Social Interactions and Stigmatized Behavior: Paid Blood Plasma Donation in Rural China

Xi Chen[a]

David E. Sahn[b,*]

Xiaobo Zhang[c]

[a]Yale University, New Haven, CT, xi.chen@yale.edu

[b]Cornell University, Ithaca, NY, david.sahn@cornell.edu

[c]Peking University and International Food Policy Research Institute, China, x.zhang@nsd.pku.edu.cn

**Corresponding author*: David E. Sahn, Cornell University, 309 Savage Hall, Ithaca, NY 14853, 607/255-8921, Fax 607/255-0178

Social Interactions and Stigmatized Behavior: Paid Blood Plasma Donation in Rural China

Abstract

Despite the resultant disutility, some people, particularly the poor, are engaged in behaviors that carry social stigma. Empirical studies on stigmatized behavior are rare, largely due to the formidable challenges of collecting data on stigmatized goods and services. In this paper, we add to the limited empirical evidence by examining the behavior of donating blood plasma in exchange for cash rewards in China. We do so using two primary data sets: the first is a three-wave, census-type household survey that enables us to examine the evolving patterns and determinants of donating plasma. The second is data on detailed gift exchange records of all households in five villages. The data allow us to define reference groups, measure the intensity of social interactions, and identify peer effects, using a novel network structure-based instrumental variable strategy. We find that peer effects influence decisions to donate plasma. For example, a 1 standard deviation increase in income from donating plasma in the peer group increases the value of own plasma donation by 0.15 standard deviation. Families with sons have more incentives to donate plasma to offset the escalated costs spent in assisting their sons with marrying in a tight marriage market that favors girls.

Keywords: social stigma, social networks, peer influence, plasma donation, China

JEL: O1, Z1, R2, D8

"*Everyone in his own way is both victim and supporter of the system.*"—Václav Havel (1985, 19)

1. Introduction

Certain markets exist, especially in environments where economic concerns outweigh moral values, for goods and services that are associated with significant social stigma (Basu and Van 1998; Edlund and Korn 2002; Kim 2003; Kanbur 2004; Morris 2006). Markets for body parts, child labor, prostitution, abduction and human trafficking, drug abuse, toxic waste, and tax evasion are just some examples. Those engaged in the obnoxious markets are often the poor. Yet, not all poor people participate in the activities of obnoxious markets. Why do some poor people partake, while others not? There are few empirical economic studies on stigmatized behavior among the poor, in large part due to the difficulty in collecting relevant data.

In this paper, we aim to shed light on the question by studying a particularly stigmatized behavior in Chinese society—donating blood plasma for cash. Blood banks provide significant cash compensations to plasma donors.[1] Although donating plasma is legal (albeit often the process takes place in an under-regulated context), the behavior is imbued with stigma in China for three reasons. First, the offer of large financial incentives is seen as inducing a highly risky behavior among those in need of money. Thus, paid plasma donors are often labeled as both poor and viewed by others in the community as engaging in a desperate behavior to improve their economic situations. Related to that, relying on donating

[1] One of the attractions of blood plasma donation is that through plasmapheresis, a process to obtain blood plasma without depleting the donor of other blood constituents, the remaining components are returned to the donors. Donors are able, therefore, to more frequently give plasma. Plasma obtained by plasmapheresis stations is not used in clinical blood transfusions, but instead is sold to biopharmaceutical companies that produce high-profit human blood products, such as albumin, intravenous immunoglobulin (IVIG), anti-inhibitor coagulation complex, globulin, and hematoblasts. Since the opening of paid plasmapheresis stations in China in the early 1990s, their operations have proven highly profitable for the enterprises that run them. However, there has also been a proliferation of plasma collection operations that do not follow prescribed procedures, with standards of practice for sterilization often neglected, accurate virus detection methods not employed, and often, an improper sharing of centrifuge machines and non-disposable needles (Prati 2006).

plasma as a main source of income signals laziness. Second, people connected to plasma donors, whether they are family members or close social contacts, are concerned about the likely spread of (deadly) infectious diseases, since it is well understood that plasma donation has contributed to epidemics, including HIV/AIDS and hepatitis (Shao 2006). Third, blood has a spiritual and symbolic meaning in Chinese culture. Donating blood is essentially regarded as giving one's body, unlike in the West, where it is largely viewed altruistically and where blood is a commodity without any strong sense of it being integral to the physical or spiritual sense of self or personal identity.

In China, plasma donation is more widespread in poor rural areas than in developed regions. In the poor areas, the blood plasma donors are often concentrated in pockets of individuals, yet many poor do not donate plasma at all. We hypothesize that plasma donation becomes ethically acceptable when more people in a clan or a community become plasma donors.

We collected two unique data sets for this study. The first details gift exchange records from all households in five villages, collected in 2012, which include historical gift links within and across the five villages, as well as all gift links between the five villages and the outside world. Keeping a written record of gifts received has been a tradition in China for thousands of years (Chen 2014). The records kept by each household enable us to identify peers at the household level. Additionally, the accurate and complete network information on the size of pairwise gift exchanges effectively gauges intensity of social interactions. Using the gift records, we can define reference groups, measure intensity of social interactions, and identify peer effects.

The gift records data are matched with a larger longitudinal survey of all households in 26 villages, which includes richer information on individuals than appeared in the gift records. The matched data set enables us to track how decisions to donate plasma are affected by the nature of social networks.

One major challenge in estimating the effect of social interactions is the reflection problem (Manski 1993). To address this issue, we take advantage of a comprehensive gift-giving network data, which enables us to circumvent the reflection problem by using spatial instruments on partially overlapping peer groups. Specifically, the intuition behind our identification strategy is twofold. First, we rely on partially overlapping groups to generate peers' peers (or excluded peers), whose characteristics act as exclusion restrictions in solving the reflection problem.[2] Second, a large set of instruments, i.e., those exogenous characteristics of the excluded peers naturally generated from the group structure, correlate with peers' behavior by means of social interactions but are uncorrelated with the individual group shock. These instruments allow us to partially deal with correlated effects (De Giorgi, Pellizzari, and Redaelli 2010). Through direct and indirect peer fixed effects, an average of all relevant characteristics in a network, including those of direct peers and excluded peers, are further subtracted from each individual equation to remove unobserved characteristics and the potential impact of the institutional environment on behavior (Bramoullé, Djebbari, and Fortin 2009).

We find that in addition to poor people being more likely to donate plasma, there is strong evidence of the presence of peer influence on donating plasma. Social interactions among peers may reduce the stigma of donating plasma.

The outbreak of the COVID-19 pandemic has highlighted the relevance of our research. The surge in number of COVID-19 patients has driven up the demand for convalescent plasma from COVID-19 survivors and intensified the shortage of plasma (American Red Cross 2020). With the call for more donations (often with compensations), it is likely the poor will donate more of their plasma. This will have welfare and health consequences on the poor. Therefore, it is important to understand the stigmatized social behavior of blood plasma donation. In some developing countries, plasma donations may elevate the spread of infectious diseases. Knowing the network structure of plasma donors can help mitigate the negative health effects.

The remainder of this paper is organized as follows: in Section 2, we present the details of donating plasma for cash subsidies in rural China. Section 3 derives illustrative models for the impact of peer influence on donating plasma. Section 4 describes the longitudinal household survey and gift-exchange network data, the identification of peer influence, and

---

[2] Our approach to utilizing partially overlapping reference groups, identified from gift records, differs from co-authorship network data (Goyal, Van Der Leij, and Moraga-Gonzalez 2006), technology adoption network data (Conley and Udry 2010), and risk-sharing network data (De Weerdt and Dercon 2006), in that it possesses the feature of excluded peers. Although Bramoullé, Djebbari, and Fortin (2009) and De Giorgi, Pellizzari, and Redaelli (2010) made use of the same strategy, the former only allows a maximum of 10 people in the nominated friendship networks, and the latter has little information on social interactions.

the empirical framework. In Section 5, we report estimation results. Finally, in Section 6, we conclude.

2. Plasma Donation and Epidemics in Rural China

In China, there are separate markets for whole blood and blood plasma. The former is mainly supplied by voluntary donation and is destined primarily for hospitals and blood transfusions. Plasma donors, in contrast, are offered cash compensation, since the plasma is primarily used by commercial enterprises such as biopharmaceutical companies. Current regulations forbid pharmaceutical companies and commercial enterprises from extracting plasma from voluntarily donated whole blood, a policy designed to preserve the supply of blood for patients in need. It is therefore no surprise that, with the growing demand for plasma among commercial enterprises in this lucrative market, donating plasma is more popular than voluntarily giving whole blood.

Another reason for the popularity of plasma donation is the nature of its process. Whole blood is taken from the donor, and thereafter, the plasma is separated from the whole blood. The red blood cells are then reinjected back into the donor intravenously. To speed up the process and reduce time costs incurred by the donors, they are often given red blood cells from different, previous donors with the same blood type who were sent on their way, while their blood is being processed in a centrifuge machine to be reinjected into a later donor.

One troubling concern is that in the 1990s and early 2000s, the health status of blood plasma donors was not strictly screened, and unsanitary conditions for donating plasma were widespread (Shao 2006). This was allowed despite regulations that plasma from infected donors be segregated (Watts 2006) and presumably, not reinjected back into another donor. Consequently, some people with hepatitis and HIV infections were allowed to donate blood, resulting in outbreaks of HIV infections and hepatitis C (Wu, Rou, and Detels 2001; Prati 2006). Contamination of red blood cells during the process of obtaining plasma was associated with outbreaks of HIV infections among plasma donors as early as 1994 (Wu, Rou, and Detels 2001). In fact, donating plasma in the 1990s and the 2000s has accounted for over one-fifth of China's HIV cases (Cohen 2004; Yan et al. 2013). There has been a strong regional component to both donating plasma and the resultant outbreak of diseases. For example, a widespread HIV/AIDS epidemic in Henan province occurred in China in the 1990s, where estimates indicate that over 1.2 million people contracted AIDS, and blood transfusion in unsanitary blood banks was considered the prime suspect for this epidemic (Asia Catalyst 2007; Gao 2009).

The Chinese government responded rapidly to the epidemic by reducing the number of commercial blood banks and tightening regulations. In response, many blood banks in Henan province moved their operations to southwest provinces, such as Guizhou, where we conducted our surveys. It is not surprising that the blood banks chose Guizhou as a major source of supply of blood plasma, since it is one of the poorest provinces in China (Yin 2006). The most recent figures indicate that plasma stations in Guizhou have supplied 40 percent of the total blood plasma since 2006, rendering it the largest plasma market in the country. However, despite the efforts of the government to ensure safety of donating plasma, a rapidly growing epidemic of infectious diseases, particularly hepatitis C in early 2006, has affected Guizhou.[3] In response, the government temporarily shut down all blood banks in Guizhou, only to allow them to be reopened in 2007, after steps were taken to improve the sanitary conditions of donating plasma in the region. Since then, the commercial enterprises running the blood banks have aggressively moved to increase plasma donation, including raising cash rewards for each donation and offering bonuses to those donating regularly. In addition to the incentives for regular donation, cash penalties have been imposed on those donors who do not donate biweekly. The objective of those running the plasma stations, thus, has been to create a regular group of donors, using both incentives and penalties that encourage them to give plasma biweekly throughout the year. For those that sign up for this commitment, giving plasma thus generates a steady source and sizable proportion of their incomes. The reliance on plasma donation is further reinforced by regular donors often lacking energy to do farm work, further increasing their reliance on donating plasma.

3. Conceptual Model

Our starting point is a static model of stigmatized behavior in which peer pressure impacts plasma donation decisions, and the decision to donate is subject to constraints on labor supply. Suppose there is a continuum of agents in an economy. Each agent makes decisions on labor market participation and donating plasma. Agents are heterogeneous in labor

[3] In January 2006, statistical data showed that the incidence, the number of deaths, and the fatality rate of infectious disease increased by 21.36 percent, 65.38 percent, and 36.28 percent, respectively, on a year-on-year basis. In March 2006, the three numbers were 30.01 percent, 73.17 percent, and 33.20 percent, respectively.

productivity θ_i, ranging from $\theta_{\min}$ to $\theta_{\max}$, with the cumulative distribution function $F(\theta)$.[4] Therefore, wage income is denoted by $\theta_i w$. Donors are subject to a maximum legal donation level and, therefore, a maximum possible income for donating plasma, B. The actual level of plasma donation ranging from 0 (not donating) to 1 (donating at the biweekly level) is denoted by h_i. We follow the basic household decision model that incorporates the social stigma associated with plasma donation and an exogenous wage rate,

$$\max_{h_i} \; U(c(h_i, \theta_i, w), S(h_i, \bar{h})) \tag{1}$$

$$s.t. \; c \le \theta_i w + h_i B \;,$$

where $\mathrm{U}(\cdot)$ is the utility function. The standard assumption for utility from consumption c follows, i.e., $U_c > 0, U_{cc} < 0$. $S(\cdot)$ is the social stigma function representing disutility from donating plasma. The standard assumption $U_{cS} = U_{Sc} < 0$ follows, meaning that: (1) the greater the disutility is from donating plasma, the lower is the marginal utility of consumption; and (2) the marginal disutility from donating plasma becomes greater as consumption increases. In other words, wealthier people suffer more from an increasing social stigma than their poorer counterparts. Utility is decreasing in stigma, and the marginal disutility from stigma is increasing in stigma, i.e., $U_S < 0,\; U_{SS} < 0$.

The average level of plasma donation in the reference group is $\bar{h}$. The wage rate in the productivity term is w. A person with labor productivity θ_i receives $\theta_i w$ from labor provision.[5] The social stigma function $S(\cdot)$ satisfies two conditions: $S_h > 0,\; S_{\bar{h}} < 0;\; S_{hh} > 0,$ $S_{h\bar{h}} < 0$. The first simply states that stigma increases in own donation; the second is that stigma decreases in peers' donation. It is further assumed that a person does not have any compulsion or guilt associated with a decision not to donate plasma, regardless of the average plasma donation in the reference group, i.e., $S(0, \bar{h}) = 0$. Therefore, the only effect exerted

[4] For simplicity, in this static model, labor productivity is not a function of "donating" plasma.

[5] All the households in our census-type survey have access to only one blood bank that sets a unique price and maximum legal plasma income *B*; but human capital and, therefore, wage income vary across individuals.

by peers is operating through stigma. Thus, in combination, these conditions lead to the following proposition:

$$\frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} > 0 \qquad (2)$$

This proposition, which we test empirically and elaborate on in Appendix I, states that an individual's level of plasma donation increases with average donations in the reference group.

4. Data and Empirical Strategy

4.1 Data collection

Guizhou is one of the poorest provinces in Western China, with a population comprised of more than 20 ethnic groups. Our study uses matched gift-giving records with larger scale longitudinal household survey data collected in 26 villages in Guizhou.[6] The gift records were gathered in 2012 from all households in five randomly selected villages out of the 26 villages, including rich information on senders, receivers, and size of all cash and in-kind gifts. The records cover over 11,000 gift exchange links among households between 1994 and 2012. Matching the names that appear in these gift records with the larger 26-village household survey data, a total of 251 households in the gift-giving data set are included in the analysis, including all 184 households from the 5 villages and 67 households in 13 other villages who relate to the households in the 5 villages through gift-giving.[7] Table 1 shows their summary statistics.[8] The data were recorded by hosts at the time they were presented with gifts by guests, on the days that they hosted social events, including weddings, funerals, coming-of-age observances, childbirth, and house-moving ceremonies. Relatives were responsible for recording gifts, if the hosts were illiterate. Gift-receiving records were

---

[6] This survey was jointly conducted by the International Food Policy Research Institute (IFPRI), Chinese Academy of Agricultural Sciences (CAAS), and Guizhou University. It covered 26 villages. The study on gift records is part of the larger project.

[7] The remaining eight surveyed villages have no gift links with the five villages.

[8] In comparison with summary statistics for all households in the 26 villages in the larger project, as illustrated in Table 1 by Brown, Bulte, and Zhang (2011), they are quite similar across all measured dimensions.

routinely kept for a long period by recipients to serve as notes to reciprocate in future gift giving when attending events.[9]

Second, we have used the longitudinal survey in a larger project conducted in 2007, 2009, and 2012, including all 251 households involved in these gift exchanges. In each wave, the survey collected household-level data on demographic characteristics, cash and in-kind transfers, and incomes and consumption, in addition to rich, community-level information on public facilities, investment, and institutions. Descriptive statistics on the sample are shown in Table 1, and we present Foster-Greer-Thorbecke poverty measures on the sample in Table 2. These tables show that poverty was widespread, although, it decreased by half between 2007 and 2012. In contrast, inequality was increasing in the villages surveyed.

The three rounds of household survey included information on plasma donation, including cash received. Information on donating plasma was collected on each family member, including those who were away at the time of survey. Given the sensitivity of collecting data on donating plasma, we made great efforts to ensure the accuracy of these data, including extensive training of local enumerators to effectively communicate with and elicit accurate information from the residents in our sampled villages.

Table 3 summarizes this information, so that we can see that, in 2007, 10.3 percent of all households were engaged in plasma donation. The money received accounted for 4.5 percent of total income among all households, whether they donated plasma or not (Table 4). The 2010 follow-up survey of the same households indicated that 13.0 percent of households were engaged in plasma donation and that they contributed 8.7 percent to the total income, a doubling since 2007. This large increase was due mainly to an increase in the share of households with two or more individuals donating. By the time of the 2012 follow-up survey, 25 percent of households donated plasma, although there was a slight decline in the share of total income that those giving represented, down to 7.4 percent of the total income (Table 4). The explanation for the drop in the share of plasma donations in the total income is that the number of households with two or more donors dropped from 6.0 to 3.8 percent. Overall,

[9] Since only gift recipients keep records of senders' list for each event, we are unable to cross-check consistency of gifts in the records. That said, since some recipients mark every gift they ever repaid with a tick, we cross-check these gift exchanges within 5 villages in which we have information on both senders and recipients. More than 99.2 percent of all such gift exchange records are matched, reassuring us about the quality of gift records in this analysis.

unlike for the rich, the payment for plasma is significant, and the incentive to be a plasma donor is strong for the poor.

Appendix II depicts the dynamics of plasma donation in an example network using the matched longitudinal household survey data and the gift networks data. It is evident that households surrounded by more plasma donors in their networks are more likely to donate plasma in the following period.

4.2 Reference groups

Substantial ethnographic evidence documents social interactions at the village level in less developed rural communities. Foster (1967) argued that, when villages are small, village interactions might be a more credible assumption than studies that use city blocks, census tracks, schools, or classrooms. In a recent study, Mangyo and Park (2011) suggested that village reference groups are salient for rural residents living in close proximity. Therefore, we first define reference groups at the village level. The mountainous condition in our surveyed region further isolates connections with the outside world.

Apart from our defining the reference group by the village boundary, we exploit the rich information on gift networks to further define reference groups per each household's corresponding gift receivers, which we refer to as *alters*, in keeping with the standard terminology in social network analysis. This alternative definition of gift receivers as the reference group has the advantage over the village-based definition, since it characterizes individual social interactions with multiple, partially overlapping reference groups.

Figure 1 illustrates the gift links for one of the five villages from which we collected network data. Gift exchange networks are more intense within clans and villages, perhaps due to their lower enforcement cost. A majority of residents may have kinship ties with each other in a traditional rural community, which largely determines social norms and shapes behavior. Donating plasma becomes more acceptable when more people in a clan, and the communities in which they are concentrated, engage in what would be considered stigmatized behavior. This could explain our observation, drawn from mapping the data, that donating plasma is usually clustered among people with close social relations.

Proximity to other donors alone, however, may not compel households to become plasma donors, even if they have very similar socioeconomic characteristics, unless they are part of the same social network. To illustrate this more concretely, Figure 2 plots the positive relationship between average plasma donation decisions in the reference group (defined by village boundary) and own plasma donation decisions over the three waves of the survey.

Each subfigure plots one of the plasma donation factors of the peers that we investigate in this paper—that is: (1) whether to donate plasma; (2) the income earned from donating; and (3) the number of household members donating plasma—against the mean of the own plasma donation decisions in the village. The positive relationship is strongest between the number of family members donating plasma in the network and own plasma donation decisions.

4.3 Empirical strategy: Identifications of peer influence

As we discussed in the introduction, the strength of our paper rests on our ability to tackle the identification problem that arises in behaviors, so as to avoid a circularity of cause and effect. Thus, parameters in classical peer effect models are not uniquely identified (Manski 1993 and 2000). We therefore need to circumvent the reflection problem that hinders disentangling endogenous from exogenous effects in estimating the impact of peer influence on donating plasma.

The conventional instrumental variable strategy might *partially* address this challenge, since part of the difficulty arises from the endogeneity of the behavior that enters both sides of the econometric equation. Lagged community-level instruments that directly affect lagged average group behavior, but arguably have no direct link to current individual behavior under evaluation, can be employed. However, this conventional strategy assumes that individuals interact in a partitioned group with a common boundary, and no influence comes from outside the group. Peer effects in this setting may not be identifiable (Manski 1993).

There has been growing recognition that social interactions within partitioned groups are very particular and not likely to fully represent the breadth of social interactions, while interactions in *partially* overlapping groups yield an identification strategy. Lee (2007) explored the role of variations in group sizes in identifying social interactions. De Giorgi et al. (2010) assumed social interactions with multiple reference groups to identify peer effects. Following the literature in spatial econometrics (Case 1991; Anselin, Florax, and Rey 2004; Bramoullé, Djebbari, and Fortin 2009), we consider a linear-in-means peer effects model in which each household has its specific reference group, and the average behavior and characteristics of the group influence an individual's behavior. Interactions are structured through a directed social network. The relaxation of a group interactions assumption allows us to separate endogenous effects from exogenous effects and resolve the reflection problem.

Specifically, we estimate the following model for plasma donation decisions:

$$y_{i,P_i,t} = \alpha + \beta \frac{\sum_{j \in P_i} y_{j,t-1}}{n_{i,t-1}} + \gamma x_{i,P_i,t} + \delta \frac{\sum_{j \in P_i} x_{j,t}}{n_{i,t}} + \lambda_i + \phi_t + \varepsilon_{i,P_i,t} \ , \tag{3}$$

or in matrix notation,

$$Y = \alpha\iota + \beta GY + \gamma X + \delta GX + \lambda + \phi + \varepsilon \ , \tag{3'}$$

where an agent's plasma donation decision, $y_{i,P_i,t}$, is a linear function of the average behavior of its peers in a heterogeneous group P_i of size n_i, which partially overlaps with others' peer groups, own characteristics, x_i, and mean characteristics of the peer group. Agent *i* is excluded from the group defined by directed gift-exchange networks.

The term, $y_{i,P_i,t}$, denotes three indicators of donating plasma for household *i*: a dichotomous variable defined by whether one donates plasma; income from donating plasma; and number of household members engaging in donation. Both donation value and the number of members donating plasma measure engagement intensity. Average plasma donation decisions in peer groups are constructed in three ways to measure peer behavior: the first takes the simple average over peers' donation behavior; the second weighs peers' plasma donation decisions by row-normalized, pairwise gift values in the adjacency matrix and then takes the weighted average over peers' donation behavior for each individual; and the third weighs peers' plasma donation decisions by their centralities in the network.

β captures the endogenous peer effect of donating plasma, and δ, the exogenous effect of the peers' characteristics on an individual's plasma donation. The Generalized Spatial Two Stage Least Squares (GS2SLS) estimation is implemented to deal with the simultaneity in identifying peer effects β, as individual decisions might indirectly affect the average decision in the reference group. The reference groups are defined on gift networks with spatial instruments generated from the network structure. Specifically, we adopt a set of excluded peers' relevant characteristics as exclusion restrictions. Appendix III derives and illustrates this spatial instrumental variable strategy in greater detail. Standard errors in all estimations are clustered at the network level. There are 42 independent networks in the gift exchange data.

X denotes a set of covariates, including the gender of the household head, their age, education, ethnicity, and information on cadre and party membership, household size, household per capita income (excluding donating plasma),[10] ratio of local wage to per 580cc plasma price, and whether any household members experienced major health shocks, death, or death of livestock.[11] The share of all household members, comprised of unmarried sons aged 11–29, is also included, with the expectation that when this value is high, it is associated with greater expenses associated with their getting married. This is expected to raise the incentive to donate plasma. Note that the plasma donors' age profile suggests that none of the unmarried sons give plasma, avoiding any direct effect of unmarried sons as potential donors. The elderly persons (as a share of all household members) are controlled for, as official stipulation prohibits them from donating plasma. We further control for travel time to the local blood bank to capture nonmonetary cost.[12]

Unobserved variables common to households who belong to the same social environment may be correlated with households' background, which causes an additional identification problem. To address this issue, we take the difference of equation (3) for people within the same network to eliminate unobserved factors at the network level.[13] Two

---

[10] If a person is turned away because he/she looks sick, this could simultaneously affect his/her income, as the same appearance makes them look ill. Though it is unlikely that people were ever turned back from donating plasma, we replace income with its predicted value through regressing on family background and productive assets.

[11] Years between the three-wave household survey has witnessed significant changes in these characteristics, especially per capita income (due to high income growth, worsening income inequality, and high income mobility), household size (due to massive migration), relative wage (due to rapid rise in labor market wage and plasma donation compensation after the reopening of the blood bank), exposures to shocks and travel time to the local blood bank (due to improving public infrastructure that reduces time to commute), which give us sizable variations to identify the effects.

[12] Plasma donation behavior is often concentrated where local transportation conditions permit. Transportation conditions vary among villages. In villages with better road access, farmers use carts to transport people to the county seat and the nearby blood bank, while for ethnic minority groups living in the mountains, people are less likely to donate plasma regularly.

[13] Note that our approach to remove correlated effects goes further than De Giorgi et al. (2010), who argued that the instruments, i.e., characteristics of excluded peers, uncorrelated

types of within network differences can be derived: the *local* difference, which expresses the model in deviation from the mean equation of one's direct contacts, and the *global* difference, which expresses the model in deviation from the mean equation of one's direct and indirect contacts.[14] Bramoullé, Djebbari, and Fortin (2009) showed that the *global* difference imposes less restrictive conditions to obtain identification. The endogenous peer effect (β) and exogenous effect of peers' characteristics (δ) can be distinguished on most networks when the *global* difference is adopted.

This strategy, however, does not address the concern over self-selection into the networks. Though randomizing reference groups may solve the endogenous formation of the peer group, one limitation is the irrelevance of assigned groups in many interactive decisions (Fletcher 2010). Our study relies on observational social network data. Neglecting endogenous friendship selection may overestimate peer effects to a large extent (Fletcher and Ross 2011).

Our partial solutions to endogenous network formation are twofold. First, it is possible that some unobserved factors, e.g., popularity, affect both the likelihood to form links and individual plasma donations, but still differ among individuals in the same network. The network will not be exogenous, conditional on α and on x. To avoid the resulting inconsistent estimates of social interactions, we assume that these unobservables do not change over time and estimate a fixed effect model to remove unobserved factors at the household level. Results suggest that peer effects still account for within-household variations in plasma donation. Second, stigma associated with donating plasma may affect network formation and can be captured by the error term. We mitigate this concern by using the gift-exchange network data between 1994 and 2003, which predates the opening of a local blood bank. In other words, the formation of gift networks was established well before individuals were making decisions regarding whether to donate plasma.

5. Empirical Results

5.1 Main results

---

with the individual group shock, suffice to solve endogeneity due to unobserved correlated effects.

[14] Both differences assume that no household is isolated, and the results are generally valid for any row-normalized matrix *G*.

Tables 5a–5c present the main results on three plasma donation decisions, presenting OLS (column R1) and GS2SLS estimates (columns R2–R5) with the non-weighted adjacency matrix. Column R1 of Table 5a is a parsimonious specification and shows that the marginal effect of peers' decision to donate plasma on the own probability of doing so is biased upward. Columns R2 through R5 present the results of the GS2SLS estimates, with the first stage and second stage estimations of our preferred specification in column R5 presented in Appendix IV. F-tests of the excluded instruments indicate that weak instruments are not a concern. Overidentification tests fail to reject the validity of the spatial instruments.

Column R2 presents the same specification using the GS2SLS estimation strategy in which peers' average probability to donate plasma is instrumented by characteristics of excluded peers generated from the network structure. The identified peer effects in columns R3 through R5 are robust to controlling for the rich set of individual and household characteristics, contextual covariates, and network fixed effects,[15] although the marginal effect decreases as we move across the columns, especially when we add individual and household controls in column R3 and contextual controls in column R4. Our preferred specification in columns R5 controls for the extensive set of individual and household covariates, contextual factors, and network fixed effects. The results suggest that a higher rate of 10 percentage points of plasma donation among peers raises the probability of an individual donating plasma by approximately 2.5 percentage points, or 13.9 percent.

Tables 5b and Table 5c present corresponding results on plasma donation value and the number of family members donating, respectively. The GS2SLS estimates in our preferred specification in column R5 suggest that a 10.0 percent increase in peers' income from donating plasma raises individual income from donating plasma by 3.0 percent (Table 5b). Evaluated when the first family member begins giving plasma, one more peers' family member then giving plasma, on average, leads to a higher chance, by 46.9 percentage points, that a second family member in a household gives plasma (Table 5c). We should note that the actual magnitude of increase in the number of additional family members donating is still

---

[15] Beyond column R2, controlling for individual and household characteristics in column R3 reduces the peer effect estimate by 24 percent (1–0.390/0.513). Column R4 further includes contextual controls, and the peer effect estimate reduces by 23 percent (1–0.297/0.390). Further controlling for network fixed effects in our preferred column R5, the peer effect estimate drops by 16 percent (1–0.250/0.297).

relatively small, since only 25.8 percent families donating plasma have more than one member engaged in such a practice.

Throughout columns R1–R3 in Appendix IV, none of the exogenous effects, other than exposure to livestock deaths, is significant, suggesting social interactions mainly operate through peers' behavior.

Key individual and household characteristics are worth noting. Having an unmarried son is associated with a greater incentive to give plasma, which is probably due to the strong motive to earn extra money to assist the son in marrying in the competitive marriage market, with skewed sex ratios favoring females. Households with more elderly persons are less likely to donate plasma, as are those with higher income and of minority status.

Table 6 reports the impact size as a 1 standard deviation change in peers' average behavior in terms of the impact on individual behavior, as expressed in standard deviations. The effect sizes vary across 3 plasma-donating decisions, ranging from 0.124 for plasma donation probability to 0.232 for the number of family members engaged in donations. Unfortunately, the lack of empirical evidence from other similar studies on peer effects of stigmatized behavior prevents us from making a more meaningful comparison of these effects, though there is little question of their importance.

5.2 Additional analysis and robustness

Table 7 relaxes the prior assumption that all links or contacts impose the same influence over an individual under investigation. Specifically, we next assume that strength of the link matters in terms of the influence over the individual's plasma-giving behavior. In specification 2, each peer's plasma-donation decision is weighed by the size of the gift that they send to another individual. An alternative assumption we make is that peers' positions in the networks have influence over the individual, so each peer's plasma decision is weighted by measures of their network centrality, including out-degree centrality (specification 3), in-degree centrality (specification 4), and the Bonacich Centrality (specification 5; see Table 1 for summary statistics). Correspondingly, the adjacency matrices for social interactions are all row-normalized. In Table 7, GS2SLS estimations with these differently weighed adjacency matrices are compared to that with a non-weighted adjacency matrix in Tables 5a–5c. Overall, surprisingly, we do not find any larger or more significant peer effect estimates in Table 7 than the baseline results reported in Table 5. While the existence of a gift link matters to social interactions, this result may in part reflect that gift size and individual's position in the gift networks are relatively homogeneous and are indicative of the wellrecognized norm of ceremonial gifting in these traditional, agrarian communities (Chen, Kanbur and Zhang 2011).

Robustness checks are presented in Table 8. First, as a falsification test, we randomly assign households to placebo peer groups. Results from 1,000-time re-estimations with randomly assigned peer groups are performed. Peer effects are absent, reassuring us that the real gift network data we collected captures the domain of social interactions and that our identified peer effects are causal. Second, more nuanced checks are done, and the main results do not vary. For example, similar to De Giorgi, Pellizzari, and Redaelli (2010), we change the set of excluded peers' characteristics as instruments. All these checks indicate that the results on peer effects are robust to changes in the set of instruments.[16]

Studies have argued that exploiting directionality in networks is a useful identification strategy to test spurious correlations (Christakis and Fowler 2007; Bramoullé, Djebbari, and Fortin 2009). Our identification thus far relies on defining peers as people to whom one sends gifts (also known as an ego-perceived network, in which an ego identifies an alter as a friend via giving a gift). An alter-perceived network, however, consists of alters who identify egos as friends via sending gifts to egos. If contextual effects do not spuriously drive the relationship observed between the individual and peers' plasma donation behavior, we should observe a weaker or even no relationship between the two, when peer effects are identified using alter-perceived but not ego-perceived peers. Results reported in Table 8 indeed show no evidence of any effect. This provides suggestive evidence in favor of a causal interpretation regarding peer influences on donating plasma.

5.3 The potential mechanisms of peer effects

The presence of endogenous interactions arguably might be too broad to be very helpful to guide policy (Manski 2000). There are distinct channels whereby group interactions affect individual behavior. First, preference interactions determine that the disutility associated with donating plasma declines (increases) as more (fewer) peers engage in the practice, which promotes (discourages) individual plasma donation. Second, information disseminated on the profit and risk associated with donating plasma may shape expectations through social interactions. Households with more donors in their networks may increase donation if profit dominates.

[16] These results are available upon request.

Prescriptions for appropriate public policy differ between preference interactions and expectation interactions. If expectation interactions are at play, an educational intervention curbing frequent plasma donation could be useful, if information on its devastating health effects or potential risks is constrained. However, the same educational intervention becomes superfluous later on, when information is abundant and preference interactions become the major channel. More attention should then be given to policies that change preference.

Expectation interactions *alone* may not provide a satisfactory explanation in our context. In 2006, a hepatitis C epidemic affected the region, and all blood banks were shut down due to blood contamination. During the epidemic, the local government made every effort to publicize information on the situation and the associated health risks, including sending officials to speak individually with each family. An open-ended survey in 2007, designed to elicit individuals' perceptions of donating plasma, indicated that information on both benefits and costs of donating plasma had been effectively transmitted to the public through such outreach. Specifically, 96 percent of all respondents in our study correctly recalled the size of cash compensation for plasma donation; and 97 percent of respondents also listed potential devastating impacts of regularly donating plasma, such as lack of strength, disease infection, appetite loss, fatigue, nausea, and vomiting. Among migrants vulnerable to work-related accidents, almost all believed that donating plasma was riskier than an industrial injury. Other evidence that demonstrates the role played by information dissemination is that, compared to rate of plasma donation in 2006 of 31.2 percent before the shutdown of the blood bank, the rate of plasma donation dropped to 10.3 percent initially after the reopening of local blood banks in 2007. However, the doubling of plasma donation rate in five years, between 2007 and 2012, suggests that the channel of information diffusion could be seriously time-limited.

Preference interactions are likely a main mechanism at work in explaining peer effects. As we discussed previously, disutility from social stigma may decline when more peers participate, which promotes more plasma donation. What we are unable to substantiate is the exact cause of the stigma: is it that a person is labeled as being poor and lazy due to large financial incentives to donate, the potential spread of infectious diseases due to operational scandals and epidemics, or a range of possible cultural taboos? The only real empirical insight we get into this issue is based on the 2007 open-ended survey, in which approximately 90 percent of respondents (including both plasma donors and those who had never donated plasma) reported that it was difficult to talk to others about plasma donations. A majority of the plasma donors and non-donors responded that people may avoid the donors, judge them badly, or misunderstand them, and a few answered that they did not want or think people should take pity on them. Though we are not able to locate the exact stigma that may drive the identified peer effects, they all support the strong effect we observe in our analysis.

6. Conclusions

Information on stigmatized behavior is often too sensitive to collect. Combining two unique sources of primary data on long-term social networks and a rich census-type panel survey that includes data on one kind of stigmatized behavior, donating plasma in rural China, we are able to add to the limited number of empirical studies on stigmatized behavior with rich information on individual engagement. We also uniquely collected long-term spontaneous gift-receiving records kept by each household to provide early evidence on how social interactions may shape stigmatized behavior.

Our novel identification strategy relies on spatial instruments that are naturally generated from the network structure in order to gauge peer influence on donating plasma. The strategy effectively solves the reflection problem and distinguishes correlated effects that are problematic in empirical studies on peer effects. The unprecedented, rich information on real social connections through long-term gift exchanges enables us to probe into the intensity of social interactions.

We find strong evidence of peer influence, which enriches our understanding of social determinants of donating plasma. The intensity of social interactions, however, plays a trivial role in identification. Peer influences are salient in ego-perceived networks but not in alter-perceived networks, which reassures us that contextual effects may not drive the results. In addition to social interactions, poorer families tend to give more plasma. Families with unmarried sons give more plasma, presumably to create a better position for their sons in the highly competitive marriage market in China. They use the proceeds from the donation to buy bigger houses, pay higher bride prices, and throw more lavish wedding banquets. All these actions occur, despite the fact that the stigmatized behavior of donating plasma often evokes popular discomfort, distrust, and even outrage among the public.

Our results indicate that individual plasma donation may increase with peers' average donation via both expectation interactions and preference interactions. Contextual interactions and correlated effects, however, imply no such feedbacks. Programs targeting popular agents in the networks and, therefore, curbing indulgence in stigmatized behavior may be effective in reducing risky plasma donating behavior. This action may indirectly reduce plasma donation from peers with feedback to further decrease donations from the targeted households.

The issue of plasma donation under unhygienic conditions is important in its own right. It engenders devastating impacts on donors, including adverse effects on health and labor supply, and at the same time does little to alleviate poverty and intergenerational inequality. The devastation of the HIV crisis in Henan Province in China in the 1990s and the hepatitis C crisis in Guizhou Province in the 2000s, in which plasma donation contributed to both crises, are episodes that warrant careful reflection to avoid similar events in the future. Having shown the significance of social interactions, understanding its exact mechanisms and consequences will be valuable questions open to future research.

References

American Red Cross. 2020. "National Coronavirus Surge Leads to Emergency Convalescent Plasma Shortage." Press Release, July 22. https://www.redcross.org/about-us/news-and-events/press-release/2020/national-coronavirus-surge-leads-to-emergency-convalescent-plasma-shortage.html

Ammermueller, A. and Jörn-Steffen Pischke. 2009. "Peer Effects in European Primary Schools: Evidence from the Progress in International Reading Literacy Study." *Journal of Labor Economics* 27 (3): 315–48.

Anselin, L., R. Florax, and S. Rey. 2004. *Advances in Spatial Econometrics: Methodology, Tools and Applications*. Berlin: Springer-Verlag.

Asia Catalyst. 2007. "AIDS Blood Scandals: What China Can Learn from the World's Mistakes." *Research Report*, September.

Basu, K., and P. Van. 1998. "The Economics of Child Labor." *American Economic Review* 88 (3): 412–27.

Bonacich, P. 1987. "Power and Centrality: A Family of Measures." *American Journal of Sociology* 92 (5): 1170–82.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2009. "Identification of Peer Effects through Social Networks." *Journal of Econometrics* 150 (1): 41–55.

Brown, P. H., E. Bulte, and X. Zhang. 2011. "Positional Spending and Status Seeking in Rural China." *Journal of Development Economics* 96 (1): 139–49.

Case, A. 1991. "Spatial Patterns in Household Demand." *Econometrica* 59 (4): 953–65.

Chen, X. 2014. "Gift-Giving and Network Structure in Rural China: Utilizing Long-Term Spontaneous Gift Records." *PLoS ONE* 9 (8): e102104.

Chen, X., R. Kanbur, and X. Zhang. 2011. "Peer Effects, Risk-Pooling and Status Seeking: What Explains Gift Spending Escalation in Rural China?" CEPR Discussion Paper #8777, Center for Economic Policy Research, London.

Christakis, N. A., and J. H. Fowler. 2007. "The Spread of Obesity in a Large Social Network over 32 Years." *New England Journal of Medicine* 357: 370–9.

Cohen, J. 2004. "HIV/AIDS in China: Poised for Takeoff?" *Science* 304 (5676): 1430–2.

Conley, T., and C. Udry. 2010. "Learning about a New Technology: Pineapple in Ghana." *American Economic Review* 100 (1): 35–69.

De Giorgi, G., M. Pellizzari. and S. Redaelli. 2010. "Identification of Social Interactions through Partially Overlapping Peer Groups." *American Economic Journal: Applied Economics* 2 (2): 241–75.

De Weerdt, J., and S. Dercon. 2006. "Risk-sharing Networks and Insurance against Illness." *Journal of Development Economics* 81 (2): 337–56.

Edlund, L., and E. Korn. 2002. "A Theory of Prostitution." *Journal of Political Economy* 110 (1): 181–214.

Fletcher, J. 2010. "Social Networks and Health Outcomes." In *The New Palgrave Dictionary of Economics*, Online Edition, edited by Steven N. Durlauf and Lawrence E. Blume. London: Palgrave Macmillan.

Fletcher, J., and S. Ross. 2011. "Estimating the Effects of Friendship Networks on Health Behaviors of Adolescents." HEDG Working Paper 11/13, Health, Econometrics, and Data Group. Department of Economics, University of York.

Foster, George M. 1967. *Tzintzuntzan: los campesinos mexicanos en un mundo en cambio*. México: Fondo de Cultura Económica.

Gao, Y. 2009. "A Report of China's HIV/AIDS Epidemic." (in Chinese) http://hi.baidu.com/80age/blog/item/d198804456bd4c8cb2b7dcb9.html

Goyal, S., M. Van Der Leij, and J. L. Moraga-Gonzalez. 2006. "Economics: An Emerging Small World." *Journal of Political Economy* 114 (2): 403–12.

Havel, Václav. 1985. *The Power of the Powerless: Citizens Against the State in Central-eastern Europe.* London: Routledge.

Kanbur, R. 2004. "On Obnoxious Markets." In *Globalization, Culture and the Limits of the Market: Essays in Economics and Philosophy*, edited by S. Cullenberg and P. Pattanaik, 39–61. Oxford: Oxford University Press.

Kim, Y. 2003. "Income Distribution and Equilibrium Multiplicity in A Stigma-based Model of Tax Evasion." *Journal of Public Economics* 87 (7–8): 1591–616.

Lee, L .F. 2007. "Identification and Estimation of Econometric Models with Group Interactions, Contextual Factors and Fixed Effects." *Journal of Econometrics* 140 (2): 333–74.

Mangyo, E., and A. Park. 2011. "Relative Deprivation and Health: Which Reference Groups Matter?" *Journal of Human Resources* 46 (3): 459–81.

Manski, C. 1993. "Identification of Endogenous Social Effects: The Reflection Problem."

Review of Economic Studies 60 (3): 531–42.

Manski, C. 2000. “Economic Analysis of Social Interactions.” *Journal of Economic Perspectives* 14 (3): 115–36.

Morris, S. 2006. “Body Mass Index and Occupational Attainment.” *Journal of Health Economics* 25 (2): 347–64.

Prati, D. 2006. “Transmission of Hepatitis C Virus by Blood Transfusions and Other Medical Procedures: A Global Review.” *Journal of Hepatology* 45 (4): 607–16.

Shao, J. 2006. “Fluid Labor and Blood Money: The Economy of HIV/AIDS in Rural Central China.” *Cultural Anthropology* 21 (4): 535–69.

Watts, J. 2006. “Censor Sees through Writer’s Guile in Tale of China’s Blood-Selling Scandal: Champion of the Poor Yan Lianke Fears He Went Too Far in Toning Down His Latest Book.” *The Guardian*, October 8.

Wu, Z., K. Rou, and R. Detels. 2001. “Prevalence of HIV Infection among Former Commercial Plasma Donors in Rural Eastern China.” *Health Policy and Planning* 16 (1): 41–6.

Yan, J., S. Y. Xiao, L. Zhou, Y. Tang, G. M. Xu, D. Luo, and Q. F. Yi. 2013. “A Social Epidemiological Study on HIV/AIDS in a Village of Henan Province, China.” *AIDS Care* 25 (3): 302–8.

Yin, H. 2006. “Guizhou Xue jiang Jing ji You si lu: An Alarming Chronicle of ‘Blood Plasma Economy’ in Guizhou Province.” *Nanfengchuang* (in Chinese). http://finance.people.com.cn/GB/4567861.html

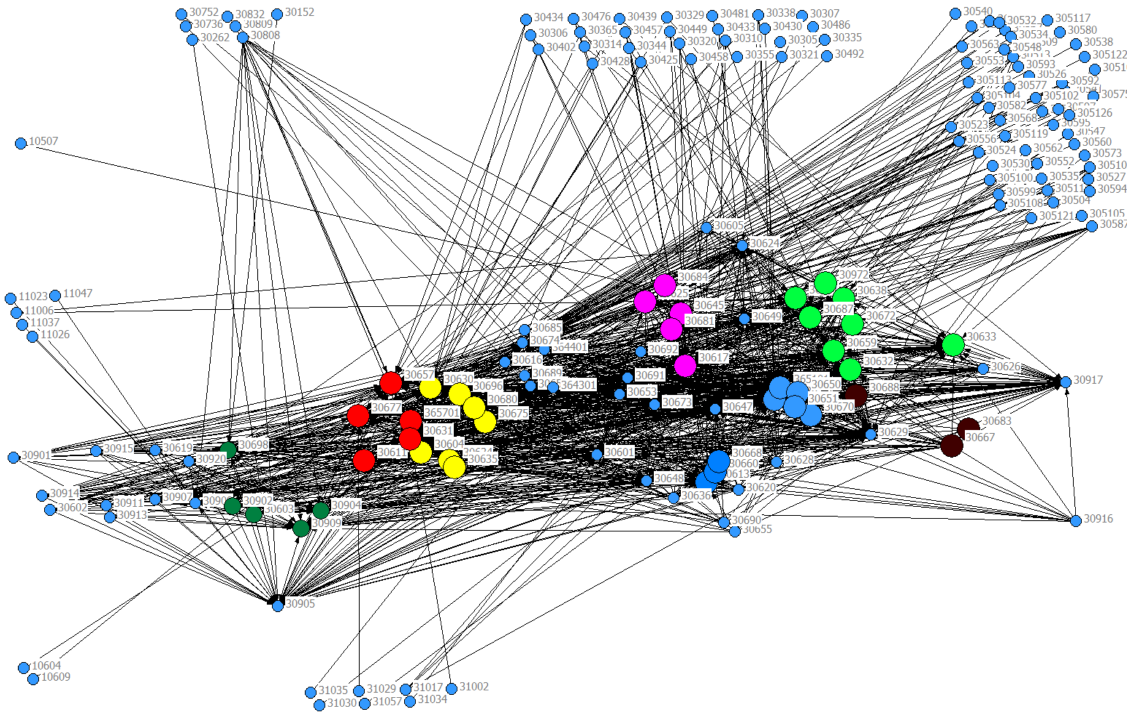


Figure 1. Long-term Gift Exchange Network in One Village

Source: Authors' gift network data from one of the five villages

Note: Dots of the same color show households in the same clan. Dots to the boundaries show households from other villages. The dots (households) are based on actual geographic locations.

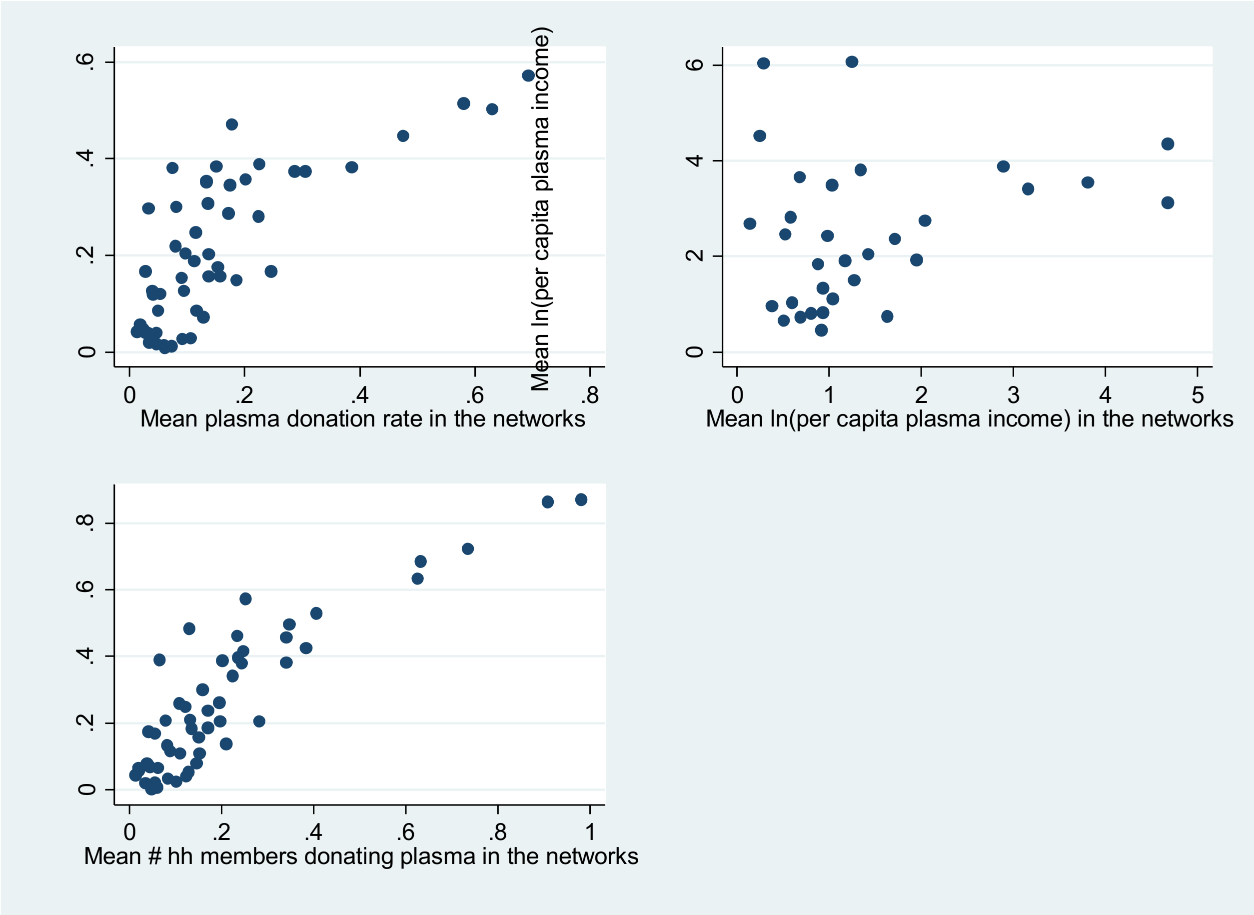


Figure 2. Association between Average Plasma "Donation" Decisions in the Networks and Own Decisions

Source: Authors' survey data

Notes: The horizontal axes denote peers' mean plasma donation decisions, including whether to donate plasma, income earned from donating plasma, and the number of household members who donate plasma. The vertical axes denote own plasma donation decisions. Each dot represents one village, which takes the mean of own plasma donation decisions and peers' mean plasma donation decisions at the village level. There are 5 villages randomly selected for gift record collection, plus 13 other villages in which households relate to those in 5 villages through gift-giving. Some dots may partially or even completely overlap due to their similarity in values.

Table 1. Summary Statistics (2007–2012)

Variables	*Mean*	*S.D.*
Distance to the county seat (km)	5.58	3.25
Share of minority households (%)	0.32	0.47
No. of household members	4.30	1.64
Household head age (years)	47.12	12.81
Village leader or party member (Y/N)	0.09	0.29
Share of household members aged 11–29, unmarried	0.21	0.23
Share of household members aged 60 and above	0.13	0.27
Male head of household (dummy)	0.93	0.26
Education of household head (year)	4.15	3.20
Per capita cultivated land (mu)	1.05	1.05
Own farm machine (Y/N)	0.01	0.11
Own cow (Y/N)	0.24	0.65
Own horse (Y/N)	0.03	0.23
No. of occurrences of major disease among family members in last 2 years	0.46	0.68
No. of occurrences of livestock deaths in last 2 years	0.38	0.60
Normalized in-degree centrality (popularity)	0.04	0.22
Normalized out-degree centrality (influence)	0.04	0.06
Normalized Bonacich Centrality	7.56	15.60

Source: Authors' survey data

Notes: Summary statistics for the 251 households after matching the gift-giving data and the social survey data.

Table 2. Summary Statistics on Poverty and Income Inequality (2007–2012)

Poverty and income inequality measures	*Total* *2007*	*2010*	*2012*
Per capita annual income (RMB)	1,817.3	2,795.7	3,004.2
Income inequality (Gini)	48.2	55.2	57.1
Income inequality excluding donating plasma (Gini)	49.0	56.6	58.3
Income below poverty line of 892 RMB (%) (P0)	36.3	22.4	18.3
Poverty-gap below poverty line of 892 RMB (P1)	15.0	10.1	8.5
Squared poverty-gap below poverty line of 892 RMB (P2)	8.3	6.4	5.5

Source: Authors' survey data.

Table 3. Summary Statistics on Households Donating Plasma (2007–2012)

	2007	*2010*	*2012*
Participation rate in donating plasma (%)	10.3	13.1	25.0
% households with one plasma donor	7.6	7.1	21.2
% households with two or more plasma donors	2.7	6.0	3.8
Mean per capita income from donating plasma (RMB per year)	82.2	242.4	222.5
Gross cash benefit from donating plasma (per 580cc)	150	150	150

Source: Authors' survey data

Note: The gross cash benefit from donating plasma (per 580cc), 150 RMB, is before deducting any cost incurred around each plasma donation. However, all direct costs incurred around plasma donation, such as transportation fee, lodging fee, and basic nutrients intake to minimize damage to health, are to be deducted to generate the mean per capita income from donating plasma (RMB per year).

Table 4. Main Sources of Income (Percent) (2007–2012)

	Total		
	2007	*2010*	*2012*
Main Sources of Income (percent)			
Farming	31.4	33.1	33.3
Livestock	6.8	6.9	8.1
Local non-farm and self-employment	30.0	23.8	24.0
Remittance from migrants outside the county	13.1	8.8	8.0
Disaster relief, anti-poverty programs, deforestation subsidies	2.0	5.4	2.8
Gift income	9.1	8.2	6.6
Income from donating plasma	4.5	8.7	7.4
Other income (including land leasing)	3.1	5.1	9.8

Source: Authors' survey data.

Table 5a. Impact of Peer Effects on Probability of Donating Plasma (2007–2012)

	R1	*R2*	*R3*	*R4*	*R5*
	Network Peer Group + Link				
	OLS	*GS2SLS*	*GS2SLS*	*GS2SLS*	*GS2SLS*
Lagged peers' mean rate of plasma donation	0.801***	0.513***	0.390**	0.297**	0.250**
	(0.097)	(0.100)	(0.175)	(0.128)	(0.125)
Individual and household controls	No	No	Yes	Yes	Yes
Contextual controls	No	No	No	Yes	Yes
Direct and indirect network fixed effects	No	No	No	No	Yes
F test excluded instruments	–	103.13	61.20	11.83	12.13
p-value over-identification test	–	0.265	0.186	0.184	0.247
(Pseudo) R2	0.064	0.198	0.330	0.339	0.363
N	753	753	753	753	753

Notes:

[1] Linear probability models (LPM) are estimated. Marginal effects from LPM are presented.

[2] Robust standard errors are clustered at the network level. *significant at 10%; **significant at 5%; ***significant at 1%.

[3] Excluded instruments in the GS2SLS estimations include the following characteristics of peers' peers: per capita income excluding plasma donation compensation, household size, ethnicity, education, share of the elderly, share of unmarried son, relative market wage to plasma donation compensation, cadre status, travel time to the local blood bank, and major shocks (including major diseases, livestock deaths, natural disasters, and family member deaths).

[4] Village fixed effects and year fixed effects are included in individual and household controls.

Table 5b. Impact of Peer Effects on Income from Donating Plasma (2007–2012)

	R1	*R2*	*R3*	*R4*	*R5*
			Network Peer Group + Link		
	OLS	*GS2SLS*	*GS2SLS*	*GS2SLS*	*GS2SLS*
Lagged peers' mean income from donating plasma	0.834***	0.558***	0.445***	0.367***	0.303**
	(0.101)	(0.101)	(0.173)	(0.127)	(0.123)
Individual and household controls	No	No	Yes	Yes	Yes
Contextual controls	No	No	No	Yes	Yes
Direct and indirect network fixed effects	No	No	No	No	Yes
F test excluded instruments	–	103.17	61.34	11.36	11.65
p-value over-identification test	–	0.223	0.136	0.143	0.197
(Pseudo) R2	0.078	0.208	0.329	0.344	0.366
N	753	753	753	753	753

Notes:

[1] Robust standard errors are clustered at the network level. *significant at 10%; **significant at 5%; ***significant at 1%.

[2] Village fixed effects and year fixed effects are included in individual and household controls.

Table 5c. Impact of Peer Effects on Number of Household Members Donating Plasma (2007–2012)

	R1	*R2*	*R3*	*R4*	*R5*
	Network Peer Group + Link				
	OLS	*GS2SLS*	*GS2SLS*	*GS2SLS*	*GS2SLS*
Lagged peers' mean no. of household members donating plasma	0.924***	0.673***	0.537***	0.525***	0.469**
	(0.130)	(0.122)	(0.195)	(0.135)	(0.135)
Individual and household controls	No	No	Yes	Yes	Yes
Contextual controls	No	No	No	Yes	Yes
Direct and indirect network fixed effects	No	No	No	No	Yes
F test excluded instruments	–	123.37	60.72	14.67	15.00
p-value over-identification test	–	0.447	0.104	0.397	0.535
(Pseudo) R2	0.110	0.225	0.358	0.361	0.384
N	753	753	753	753	753

Notes:

[1] Marginal effects are presented. Robust standard errors are clustered at the network level. *significant at 10%; **significant at 5%; ***significant at 1%.

[2] Village fixed effects and year fixed effects are included in individual and household controls.

Table 6. Effect Sizes

	(1)	*(2)*	*(3)*	*(4)*
	S.D. Plasma Donation σ_Y	*S.D. Peers' Plasma Donation* σ_{GY}	*Peer Effects* $\hat{\beta}$	*Effect Size* $\sigma_{GY}\hat{\beta} / \sigma_Y$
Plasma donation probability	0.368	0.182	0.250	0.124
Plasma donation value (log)	2.488	1.241	0.303	0.151
No. of household members donating	0.496	0.245	0.469	0.232

Notes: The estimates of peer effects in column (3) are taken from the scenario R5 in Table 5 (a) – (c).

Table 7. Peer Effects with Alternative Weightings

	R1	*R2*	*R3*
Lagged Peers' mean rate of plasma donation	*Donate or not*	*Donation value*	*No. of hh members donating*
1. Baseline	0.250**	0.303**	0.469**
	(0.125)	(0.123)	(0.135)
2. Weighed by pairwise link intensity (gift size)	0.153	0.205*	0.297**
	(0.119)	(0.117)	(0.129)
3. Weighed by out-degree centrality based on	0.236**	0.284**	0.438***
number of links	(0.121)	(0.119)	(0.129)
4. Weighed by in-degree centrality based on	0.234**	0.280**	0.381***
number of links	(0.115)	(0.113)	(0.123)
5. Weighed by Bonacich Centrality based on	0.249**	0.298**	0.501***
pairwise link	(0.127)	(0.125)	(0.135)

Notes:

[1] In-degree centrality is defined as (normalized) number of links the respondent receives from peers, which measures one's influence over peers.

[2] Out-degree centrality is defined as (normalized) number of links the respondent sends out to peers, which measures one's popularity in the network.

[3] Centrality comprehensively measures direct and indirect connections one has in one's neighborhood. In addition to direct links, the more connections the actors in one's neighborhood have, the more central one is (Bonacich 1987).

Table 8. Other Tests on Peer Effects

	R1	*R2*	*R3*
Lagged peers' mean plasma "donation"	*Donate or not*	*Donation value*	*No. of hh members donating*
1. Baseline	0.250**	0.303**	0.469**
	(0.125)	(0.123)	(0.135)
2. Testing using placebo peer groups	–0.124	–0.098	–0.067
(1,000 times, with bootstrap standard errors)	(0.106)	(0.102)	(0.093)
3. Testing peer effects using alter-perceived but not	0.099	0.128	0.120
ego-perceived peers	(0.167)	(0.164)	(0.163)

Notes:

[1] Robust standard error in parentheses.

[2] Other notes follow Table 5a

ONLINE APPENDIX

Appendix I. Proof of the Proposition

The first order condition for an interior solution is:

$$B\frac{\partial U(c(h_i,\theta_i,w),S(h_i,\bar{h}))}{\partial c}+\frac{\partial U(c(h_i,\theta_i,w),S(h_i,\bar{h}))}{\partial S}\frac{\partial S(h_i,\bar{h})}{\partial h_i}=0, \tag{A1}$$

which solves optimal level of donating plasma $h^*(\theta_i,\bar{h},w)$, given the labor productivity (θ_i), the average level of donating plasma in the reference group ($\bar{h}$), and the wage rate (w). The second order condition is satisfied. Let $\underline{\theta}$ denote the lower threshold of labor productivity below which an agent "donates" the maximum legal level, while $\bar{\theta}$ denotes the upper threshold of labor productivity, above which an agent does not donate plasma.

Considering the corner solutions for h, if an individual "donates" the maximum legal plasma ($h \to 1$), according to Kuhn-Tucker condition we have:

$$B\frac{\partial U(c(1,\theta_i,w),S(1,\bar{h}))}{\partial c}+\frac{\partial U(c(1,\theta_i,w),S(1,\bar{h}))}{\partial S}\frac{\partial S(1,\bar{h})}{\partial h_i}\geq 0, \tag{A2}$$

where the labor productivity is low enough that the marginal utility of consumption dominates the marginal disutility of social stigma for the whole range of h. The equality (A2) holds with $\underline{\theta}$. In contrast, if the labor productivity is high enough that the marginal utility of consumption is dominated by the marginal disutility of social stigma for the whole range of h, the following inequality holds. The following equality holds with $\bar{\theta}$:

$$B\frac{\partial U(c(0,\theta_i,w),S(0,\bar{h}))}{\partial c}+\frac{\partial U(c(0,\theta_i,w),S(0,\bar{h}))}{\partial S}\frac{\partial S(0,\bar{h})}{\partial h_i}\leq 0. \tag{A3}$$

Finally, to achieve the interior market equilibrium of peer Influence, an ex-ante expectation of average plasma donation should coincide with the resulting average plasma donation given the expectation:

$$\bar{h} = \int_{\theta_{\min}}^{\theta_{\max}} h_i(\theta, \bar{h}, w) dF(\theta) \ , \tag{A4}$$

where $\theta_{\min} < \underline{\theta} < \bar{\theta} < \theta_{\max}$. Meanwhile, a stable equilibrium of the peer Influence requires that $\partial h_i / \partial \bar{h} < 1 \quad \forall \theta_i, \bar{h}, w$.

Differentiating LHS of (1) with respect to w yields:

$$B[U_{cc}(c_h \frac{\partial h_i}{\partial w} + c_w) + U_{cS} S_h \frac{\partial h_i}{\partial w}] + U_S S_{hh} \frac{\partial h_i}{\partial w} + S_h [U_{Sc}(c_h \frac{\partial h_i}{\partial w} + c_w) + U_{SS} S_h \frac{\partial h_i}{\partial w}] = 0 \tag{A5}$$

Collecting the term $\partial h_i / \partial w$, we have:

$$\frac{\partial h_i}{\partial w} = -\frac{B\theta_i U_{cc} + S_h U_{Sc}\theta_i}{BU_{cc}c_h + BU_{cS}S_h + U_S S_{hh} + S_h U_{Sc} c_h + (S_h)^2 U_{SS}} = -\frac{B\theta_i U_{cc} + S_h U_{Sc}\theta_i}{SOC} < 0 \tag{A6}$$

$$sign(\frac{\partial h_i}{\partial w}) = sign(\frac{\partial h_i}{\partial \theta_i}) < 0 \tag{A7}$$

Therefore, both the rising wage rate (w) and labor productivity (θ_i) have a negative impact on donating plasma. First, growth in consumption induces a fall in marginal utility of consumption; second, a rise in consumption makes marginal disutility of the social stigma greater.

To derive the impact of peer pressure on plasma "donation", we differentiate LHS of (A1) with respect to $\bar{h}$, which yields:

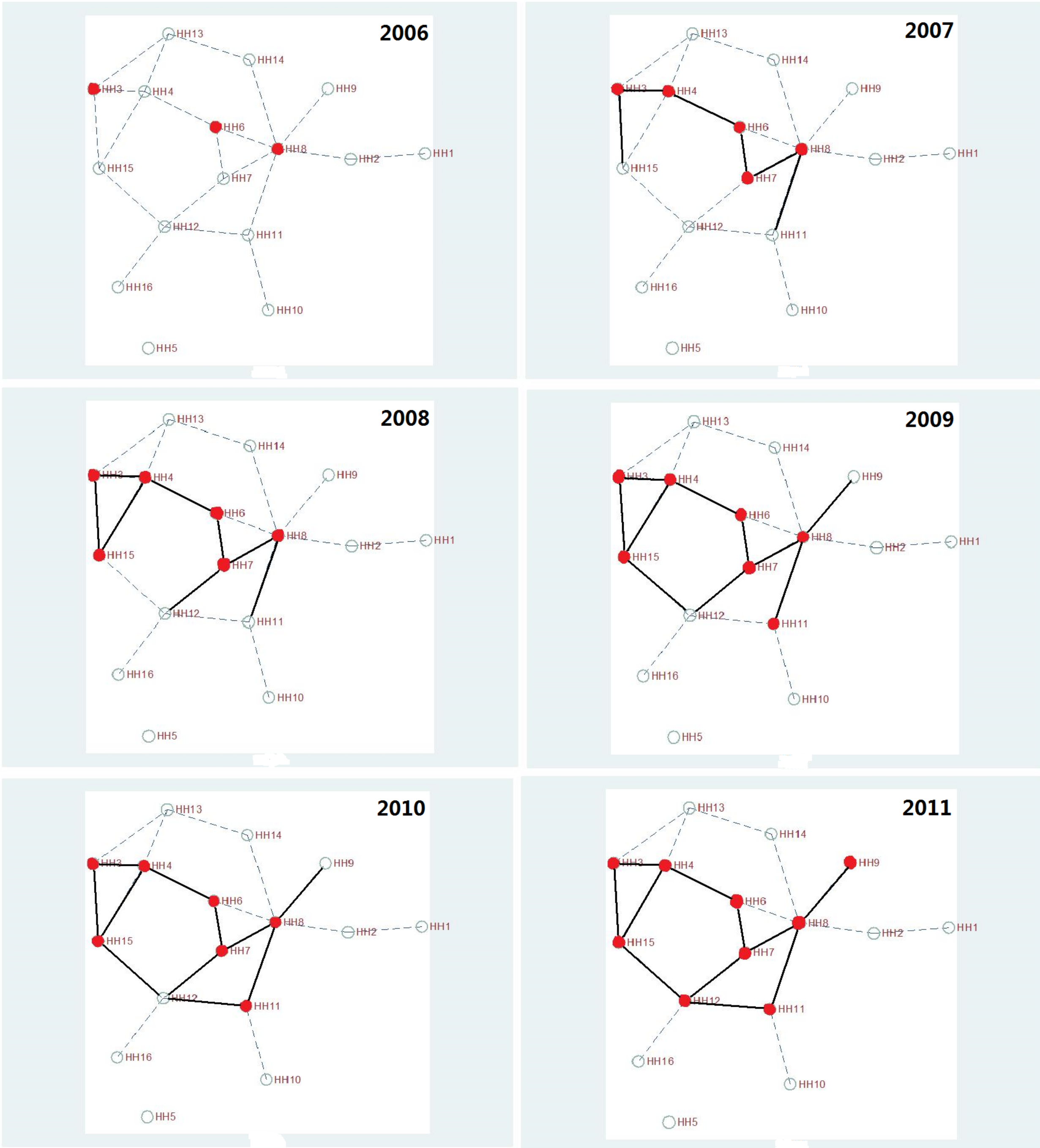
$$\begin{aligned} &BU_{cc}c_h \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + BU_{cS}[S_h \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + S_{\bar{h}}] + U_S[S_{hh} \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + S_{h\bar{h}}] \\ &+ S_h[U_{Sc}c_h \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + U_{SS}(S_h \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + S_{\bar{h}})] = 0 \end{aligned} \tag{A8}$$

Collecting the term $\partial h_i / \partial \bar{h}$, we get:

$$\frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} = -\frac{BU_{cS}S_{\bar{h}} + U_S S_{h\bar{h}} + S_h U_{SS} S_{\bar{h}}}{BU_{cc}c_h + BU_{cS}S_h + S_{hh}U_S + S_h U_{Sc}c_h + (S_h)^2 U_{SS}} = -\frac{BU_{cS}S_{\bar{h}} + U_S S_{h\bar{h}} + S_h U_{SS} S_{\bar{h}}}{SOC} > 0 \quad \text{(A9)}$$

More intense plasma donation in the neighborhood induces *i* to more actively donate plasma.

Appendix II. Plasma Donation Decisions Transmitting through Social Networks



Data: Authors' household survey data matched with gift networks data.

Notes: This appendix provides a real example of plasma donation transmitting via gift networks during 2006–2011. Each dot represents a household, and red dots indicate that the households donate plasma. Each (dashed or solid) line represents a gift. There are four cases: (1) a solid line between two red dots means a gift between two plasma donors; (2) a solid line between a red dot and an empty dot means a gift between a current plasma donor and a future donor; (3) a dashed line between two empty dots means a gift between two non-donors; and (4) a dashed line between a red dot and an empty dot means a gift between a plasma donor and a non-donor.

Appendix III. Derivation and Illustration of Spatial Instruments Identification

Appendix IV derives and illustrates our spatial instrumental strategy to overcome the reflection problem. We also discuss the additional strategy to mitigate correlated effects that may complicate our peer influence identification.

Ignoring correlated effects for a moment, our structural model for plasma donation decisions is:

$$y_i = \alpha + \beta \frac{\sum_{j \in P_i} y_j}{n_i} + \gamma x_i + \delta \frac{\sum_{j \in P_i} x_j}{n_i} + \varepsilon_i, \qquad \mathrm{E}[\varepsilon_i \mid X] = 0$$

The meanings of mathematical notations follow equation (3) in Section 4.3. Other than assuming the strict exogeneity of the regressors, i.e., $\mathrm{E}[\varepsilon_i \mid X] = 0$, no assumption is made on the error terms within a network. The model in matrix notation defined over all networks is:

$$y = \alpha\iota + \beta G y + \gamma x + \delta G x + \varepsilon, \quad \mathrm{E}[\varepsilon_i \mid x] = 0,$$

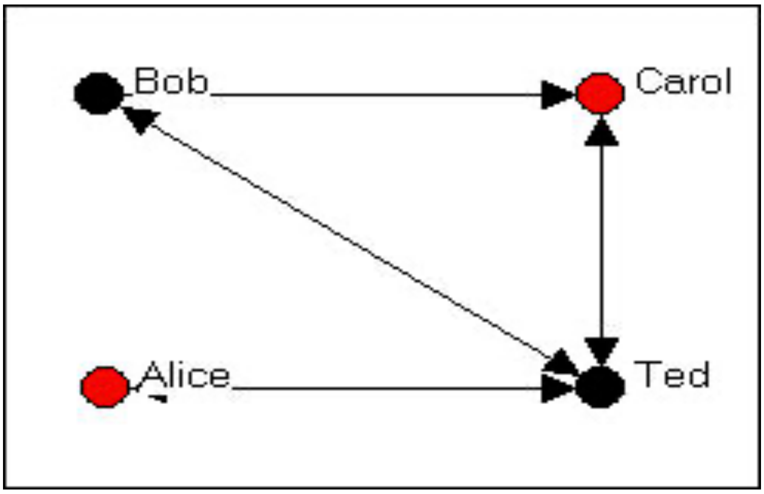
where G is an $\mathrm{n{*}n}$ interaction matrix (or *adjacency matrix*) with $G_{ij} = 1/n_i$ if *i* send gifts to *j* and 0 otherwise. ι is a $\mathrm{n{*}1}$ vector of ones. The corresponding reduced form is:

$$y = \alpha(I - \beta G)^{-1}\iota + (I - \beta G)^{-1}(\gamma I + \delta G)x + (I - \beta G)^{-1}\varepsilon$$

$\sigma_{Gy}\hat{\beta} / \sigma_y$ quantifies peer effects as the impact of a one standard deviation (SD) change in peers' average behavior in terms of SDs of the individual behavior. σ_y indicates variations in own behavior, σ_{Gy} shows variations in peers' average behavior, and Gy denotes peers' average behavior (Ammermueller and Pischke 2009).

Bramoullé, Djebbari, and Fortin (2009) showed that the model is identified if $E[Gy \mid x]$ is not perfectly collinear with (x, Gx). A necessary condition for identification is that the matrices I, G, and G^2 must be linearly independent. If so, peers' peers' characteristics, G^2x, are valid instruments. A sufficient condition for identification is that individuals interact through a heterogeneous network that has an intransitive triad. In other words, there are individuals whose peers' peers are not all their friends (De Giorgi et al. 2010).

We illustrate the identification with a fictitious network example. Our peer group definition is directional, depending on whether a gift is sent or not. In this fictitious case, Bob sends a gift to Carol and Ted, but not Alice; Carol only sends a gift to Ted; Ted sends to Bob and Carol and Alice; and Alice only sends to Ted. For Bob, Carol and Ted are in the peer group, while Alice is a peers' peer. For Carol, Ted is in the peer group, while Alice and Bob are peers' peers. For Ted, all other agents are in the peer group. For Alice, only Ted is in the peer group, while Bob and Carol are peers' peers. For all four agents, their excluded peers' characteristics can serve as instruments for their own peers' characteristics.



To remove correlated effects, a within network difference is taken by pre-multiplying $J = I - G = I - \frac{1}{n}\iota\iota'$, and the structural model becomes:

$$Jy = \beta JGy + \gamma Jx + \delta JGx + J\varepsilon,$$

where $\mathrm{E}[\varepsilon \mid x]$ is allowed to be any function of x. Conditional on α, x is strictly exogenous. The matrix G is assumed to be exogenous, conditional on α and x, i.e., $\mathrm{E}[\varepsilon \mid x, G, \alpha] = 0$. The reduced form is:

$$Jy = J(I - \beta G)^{-1}(\gamma I + \delta G)x + J(I - \beta G)^{-1}\varepsilon$$

The model is identified if the matrices I, G, and G^2 are linearly independent, and JG^2x are valid instruments. It is sufficient to conclude that peer effects are identified when the diameter of a network (i.e., maximal gift exchange distance) is greater than or equal to 3, meaning, for example, that at least two agents, i and j, are separated by a friendship network of distance 3.

Appendix IV. Spatial Identification on Peer Effects (Full Results, 1st and 2nd stages)

	R1		*R2*		*R3*	
	Donate or not		*Donation value*		*No. of hh members donating*	
Endogenous Social Effects = (I–G)Gy	0.250**	(0.125)	0.303**	(0.123)	0.469**	(0.135)
Own Characteristics = (I–G)x						
Per capita income	–0.042***	(0.014)	-0.282***	(0.098)	-0.072***	(0.021)
Cadre status	–0.05	(0.045)	-0.429	(0.289)	-0.111**	(0.056)
Household size	0.026**	(0.011)	0.134*	(0.076)	0.033**	(0.015)
Education	0.004	(0.003)	0.026	(0.023)	0.005	(0.004)
Ethnicity status	–0.164***	(0.061)	-1.100***	(0.394)	-0.299***	(0.075)
Share of elderly	–0.062	(0.079)	-0.525	(0.581)	-0.139	(0.106)
Share of unmarried son	0.180**	(0.077)	1.234**	(0.517)	0.204**	(0.098)
Ratio of farm wage to plasma income	–0.183	(0.145)	-1.279	(0.979)	-0.277	(0.173)
Exposure to big diseases	–0.051*	(0.030)	-0.328	(0.205)	-0.033	(0.043)
Exposure to livestock deaths	–0.033	(0.030)	-0.21	(0.202)	-0.026	(0.044)
Exposure to family member deaths	–0.007	(0.051)	-0.114	(0.341)	-0.087	(0.061)
Exogenous social effects = (I–G)Gx						
Mean per capita income	–0.044	(0.065)	–0.266	(0.444)	0.042	(0.099)
Mean cadre status	0.236	(0.259)	1.797	(1.817)	0.644	(0.471)
Mean household size	–0.077*	(0.043)	-0.451	(0.278)	-0.074	(0.047)
Mean education	0.008	(0.034)	0.046	(0.220)	-0.008	(0.042)
Mean ethnicity status	–0.122	(0.177)	-1.189	(1.189)	-0.125	(0.191)
Mean share of elderly	0.208	(0.452)	1.127	(3.176)	0.226	(0.566)
Mean share of unmarried son	–0.397	(0.290)	-2.814	(2.036)	-0.471	(0.431)
Mean ratio of farm wage to plasma income	–0.122	(0.341)	-1.048	(2.559)	-0.054	(0.627)
Mean exposure to major diseases	0.431	(0.270)	2.808	(1.820)	0.375	(0.362)

Mean exposure to livestock deaths	0.585***	(0.199)	3.746***	(1.288)	0.692**	(0.312)
Mean exposure to family member deaths	0.364	(0.343)	2.448	(2.354)	0.616	(0.475)
Excluded Instruments – Exogenous Characteristics of Excluded Peers (I–G)G²x						
Mean per capita income	-0.068*	(0.036)	-0.013	(0.236)	-0.066	(0.042)
Mean cadre status	-0.031	(0.174)	-2.877***	(1.128)	-0.170	(0.205)
Mean household size	0.063*	(0.036)	1.355***	(0.257)	0.100**	(0.046)
Mean education	-0.054**	(0.027)	-0.732***	(0.179)	-0.044	(0.032)
Mean ethnicity status	-0.273	(0.197)	-1.934	(1.288)	-0.283	(0.231)
Mean share of elderly	-1.250***	(0.225)	-3.348**	(1.476)	-1.335***	(0.265)
Mean share of unmarried son	0.545***	(0.144)	5.483***	(0.941)	0.419***	(0.159)
Mean ratio of farm wage to plasma income	0.038	(0.097)	0.359	(0.635)	0.023	(0.114)
Mean exposure to big diseases	0.601***	(0.116)	2.324***	(0.758)	0.667***	(0.136)
Mean exposure to livestock deaths	0.398***	(0.107)	0.116	(0.700)	0.451***	(0.126)
Mean exposure to family member deaths	0.203	(0.183)	-0.654	(1.201)	0.017	(0.216)
Network, Year, Village Fixed Effects	Yes		Yes		Yes	
N	753		753		753	

Notes: The full estimations in Columns R1, R2, and R3 correspond to column R5 in Table 5a, Table 5b, and Table 5c, respectively.