Spatial Identification of Stigma Behavior through Social Networks: Peer Effects on Paid Blood Plasma Donation

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ABSTRACT

Despite the resultant disutility, some people, in particular the poor, are engaged in behavior carrying social stigma. Empirical economic studies on stigma behavior are rare, largely due to the formidable challenges of collecting data on stigmatized goods and services. In this paper, I examine paid blood plasma donation in China, widely regarded as a stigmatized behavior, using two primary datasets. The first is a three-wave census-type household survey that enables us to examine the evolving patterns, and determinants of paid donations. The second is data on detailed gift exchange records of all households that allow us to define reference groups, measure the intensity of social interactions and identify peer effects using a novel spatial instrument strategy. The set of instruments, excluded peers' exogenous characteristics, are derived naturally from the structure of social networks. We find peer effects influence plasma donation decisions along all investigated outcome variables on plasma donation intensity. For example, one standard deviation more income from plasma donation in the peer group increase own plasma donation compensation by 0.15 standard deviations. Utilizing the local hepatitis epidemic as a natural experiment that provides public information on infection risks associated with plasma donation, we find that peer effects work through preference interactions that reduce stigma, not only through information transmission. Several falsification tests are conducted, including estimations using placebo peer group composition. The results also indicate that families with unmarried sons are more likely to donate plasma in order to offset costs of successfully getting married in a tight marriage market, such as a bigger house, a higher bride price and a more lavish wedding banquet.

Keywords: Social Stigma, Social Networks, Peer Influence, Paid Plasma Donation, China

JEL: D8, O1

"*Everyone was rendered both victim and supporter of the system.*" Václav Havel, 1978

1. Introduction

Certain markets exist, especially in impoverished environments where economic concerns outweigh moral values, for goods and services which are associated with significant social stigma (Kanbur, 2004; Edlund and Korn, 2002). Markets for body parts, child labor, prostitution, abduction and human trafficking, drug abuse and toxic waste are just some examples of these markets. However, empirical economic studies on stigma behavior are rare, in large part due to the difficulty in collecting the secretive data.

In this paper, I study a particular stigma behavior in Chinese society - paid blood plasma donation. More precisely, it refers to blood plasma donation where donors are rewarded with a valuable nutrition subsidy in cash. The donated plasma is extracted to produce expensive nutritional goods, rather than being used for hospital emergency. The associated stigma originates from two aspects: first, most local donors rely on the source of income once engaging in paid blood donation, signaling to people around that they are lazy and do not work in regular labor market; second, in Chinese culture blood symbols spirit, and selling blood is not essentially different from selling one's body. However, the stigma does not derive from infectious diseases that might spread out to the public.

The three decade rapid economic growth in China has been accompanied by strong demand for expensive blood products. Meanwhile, poor people across China continuously supply blood. Frequent blood donation in the impoverished and unsanitary context has had devastating impacts on human health and greatly affected agricultural production and poverty alleviation efforts. The induced HIV/AIDS crises in some regions in 1990s left thousands of children unattended. Some AIDS carriers alive have married, had children, or moved to other parts of China carrying the problem with them. However, this paper does not aim at evaluating the causal impact of paid blood donation. The question this paper attempts to answer is why paid blood donation still persists even if there has been high economic growth all over China in the past thirty years.

Poverty has been regarded as a root cause of markets for stigmatized behavior. Individuals normally justify decisions based on both notions of money-metric utility and social norms. The impoverished environment may render more weight to money-metric utility at the cost of stigma against social norms. Though unbalanced economic growth might have left some regions much poorer than others, it is still difficult to explain why paid blood donation persists in developed regions and regions with fruitful poverty alleviation.

In this paper, I argue that peer effects drives people to give more blood through endogenous social interactions. Similar to other typical stigmatized markets, the disutility associated with paid blood donation is presumably reduced when more peers engage in it. Therefore, an identification of the effects relies on understanding social interactions. However, social interactions are missing in the theoretical literature on stigmatized behavior, such as Basu and Van (1998), Edlund and Korn (2002) and Kanbur (2004). For a long time period, the literature has had difficulty extending standard models of individual utility maximization to allow pairwise, triadic and more complex interactions that shape behavior and explain social concepts (Akerlof, 1976; Basu, 1986). Until recently, the literature has started to incorporate the structure of social networks in affecting behavior (Calvó-Armengol et al., 2006 and 2009).

Despite the vast empirical literature on identifying social interactions, it remains very problematic due to the reflection problem and correlated effects that may confound the identification (Manski, 1993). Taking advantage of a social network data with partially overlapping peer groups, I am able to circumvent the reflection problem and correlated effects using spatial instruments arises from the social networks.

The intuition behind my identification strategy is twofold. First, partially overlapping groups generate peers' peers (or excluded peers) who act as exclusion restrictions in solving the reflection problem; second, a large set of instruments, i.e., exogenous characteristics of the excluded peers naturally generated from the group structure, correlate with peers' behavior by means of social interactions but uncorrelated with the individual group shock. These instruments allow me to partially deal with correlated effects (De Giorgi et al., 2010). An average of all relevant characteristics in a network, including those of direct peers and excluded peers, are further subtracted from each individual equation. The estimation solves the correlated effects (Bramoulle et al., 2009).

I collected two datasets to investigate peer effects: a three-wave census-type household survey from 26 villages enables me to examine the evolving patterns and determinants of frequent plasma donations; and the collection of detailed gift exchange records from all households were designed in five out of the 26 villages over 2000-2009 to define reference groups, measure intensity of social interactions, and identify peer effects. With the help of the matched two datasets, we are able to track how paid blood plasma donation decisions transmit via social networks (A real example with the matched datasets is presented in Appendix I.).

Many other studies worry about unobserved factors that simultaneously determine network formation and individual behavior. Fortunately, frequent gift exchange activities predate the initial introduction of blood bank to the region, mitigating the dependence of social network formation on paid blood donation behavior. The network fixed effect estimations further get rid of unobserved factors varying at the network level which simultaneously affect network formation and paid plasma donation.

To my knowledge, this is one of the very few studies that apply the novel spatial identification strategy to identify social interactions, improving upon the current problematic solutions to identification. Meanwhile, this paper is among the first successful attempts to collect the secretive data on stigmatized behavior. More importantly, to my best knowledge, this is the first empirical study that applies the rigorous identification strategy of peer effects on stigmatized behavior. This paper also uniquely measures real reference groups and tests how intensity of social interactions drives peer effect estimations.

Keeping a written record of gift received has been a tradition in China for thousands of years. This social norm has also been preserved in many neighboring countries, such as Vietnam, Korea, Japan, Thailand and Cambodia, where people engage in reciprocal gift exchanges (Chen, 2011). The record kept by each household makes sure that peer groups vary at the household level, which guarantees the presence of excluded peers. However, it is surprising that this widely available source of data has not been used in the economics literature.

My approach that utilizes partially overlapping reference groups identified from gift record is general and readily applicable to several data settings that allow excluded peers. Though coauthorship network data (Goyal et al., 2006), technology adoption network data (Conley and Udry, 2005) and risk-sharing network data (Dercon and De Weerdt, 2006) possess the feature of excluded peers, none of the peer effects study using these datasets adopts this approach. The only two exceptions are Bramoulle et al. (2009) and De Giorgi et al. (2010). However, the formal uses the Add Health data allowing a maximum of five males and five females in the nominated friendship networks, while the latter has little information on social interactions among classmates. Fortunately, the gift network data effectively gauges intensity of social interactions through accurate and complete network information on the amount of pairwise gift exchanges.

The main findings in this paper are the following: 1) there is strong evidence indicating the presence of peer influence on blood plasma donation decisions; 2) the intensity of social interactions is less relevant to peer effect identification; 3) peer effects are directional and appear to be partially driven by preference interactions that reduce stigma.

The rest of this paper is organized as follows. In section 2, plasma donation in rural China is documented. Section 3 derives illustrative models for the impact of peer influence on plasma donation. In section 4, I describe the three-wave census type survey and gift-exchange network data, the identification of peer influence and the empirical framework. In section 5 I report estimation results. Finally, section 6 concludes.

2. Paid Plasma Donation and Epidemics in Rural China

In China, the markets for whole blood and blood plasma are separate: the former is mainly supplied by voluntary donations in urban area, while the latter prevails in rural areas and offers cash compensation to blood plasma donors. The current regulation forbids pharmaceutical companies to extract plasma from voluntarily donated whole blood. The greater commercial demand for blood plasma makes it much more popular than whole blood donation. Besides significant income increase for plasma donors and booming profit for biotech companies, the plasma economy becomes a lucrative source of income for middlemen.

The national regulation for plasma and blood donations stipulates that individuals are excluded from giving if they are older than 50 or younger than 20, weigh less than 50kgs for males and 45kgs for females, or seriously disabled. In addition, an interval of 15 days between donations is required for plasma, and 3 months for whole blood (Asia Catalyst, 2007).

Once the plasma is separated from the whole blood, the red blood cells are re-injected back into the donor intravenously. To speed up the process, a donor can be given blood from previous donors with the same blood type and sent on his way while his blood is being processed in a centrifuge machine. Reports show that even people that are tested positive with Hepatitis are allowed to give blood, and their plasma is simply placed in a different pile.

In the past, contamination of red blood cells during the process of obtaining plasma was strongly suggested by the high prevalence of hepatitis C antibodies among repeat plasma donors. Outbreaks of HIV infection among commercial plasma donors from different areas occurred as early as 1994 (Wu et al., 2001). These have been attributable to the unsanitary conditions under which plasma donation has been carried out and no proper sterilization procedure implemented. Consequently, blood donors, together with injecting drug users (IDUs), have accounted for more than two thirds of China’s HIV infection (Figure 1), and as many as 250,000 blood plasma donors became infected by 2004 (Cohen, 2004). It is even estimated that by 2003, over 1.2 million people had contracted AIDS in Henan Province alone, and blood transfusion in unsanitary blood banks is regarded as the root cause (Tsang, 2003; Gao, 2009).

There has also been a strong regional component to both blood donations and the resultant outbreak of diseases, which has spurred government efforts to address this public health concern. For example, there was a widespread HIV/AIDS epidemic in Henan province in China in the 1990s which was attributed to unsanitary conditions for plasma donation. China rapidly responded to the epidemic by reducing the number of commercial blood banks and tightening regulations. Many blood banks in Henan province have since moved to southwest provinces such as Guizhou, which has become a new supplier of blood plasma in China (Yin, 2006) and is thus the area I collected data for this paper (see Figure 1). It is also one of the poorest provinces in China (Table 1).

In 2004, there were 23 blood plasma stations in Guizhou. By early 2006, they have further increased to 25 plasma stations, which accounted for 40% of the total blood plasma supply, rendering it the largest plasma market in the country. However, despite the efforts of the government to ensure greater attention to making blood donations safe, in early 2006, a rapidly growing epidemic of infectious diseases affected Guizhou.[1] In the same year, all blood banks in Guizhou were shut down due to Hepatitis C contamination.

After steps were made by the government to improve the sanitary conditions of blood donation in the region the blood banks in Guizhou were commercialized and re-opened in 2007. Since then they have aggressively moved to increase blood donations. This included raising the cash "nutrition" subsidy that was provided donors, the awarding of cash prizes to registered donors at the end of each year to attract plasma donors. In addition, donors are required to donate once every half month, with cash penalties assessed when registered blood donors delay their donation. Due to the incentive scheme, there is almost no difference in donation frequency throughout the year: donors usually donate plasma every half month. Meanwhile, there is much smaller temporal variation than cross-sectional variation in plasma donation decisions. Once a family starts to donate plasma, it rarely stops. One obvious reason is that plasma donation generates a great proportion of income that is non-substitutable, while another important reason is that regular donors often feel lack of energy to do farm work and have to rely on plasma donation eventually.

3. Conceptual Model

A static model of stigmatized behavior in a social norm is developed in which peer pressure impacts plasma donation decisions. The decision to donate plasma is subject to constraints on labor supply. Suppose that there is a continuum of agents in an economy. Each agent makes decisions on labor market participation and plasma donation engagement. Agents are heterogeneous in labor quality θ_i [2], ranging from $\theta_{\min}$ to $\theta_{\max}$ with the cumulative

1 In January of 2006, statistical data showed that the incidence, the number of deaths and the fatality rate of category B infectious disease respectively increased by 21.36%, 65.38% and 36.28% on year-on-year basis. In March of 2006, the three numbers further increased to 30.01%, 73.17% and 33.20%, respectively.

[2] To simplify the analysis, in this static model labor quality is not a function of paid blood plasma donation.

distribution function $F(\theta)$. Therefore, their income is denoted by $\theta_i w$ and varies according to labor quality. $\underline{\theta}$ denotes the lower threshold of labor quality below which an agent engages in the maximum legal donation, while $\overline{\theta}$ denotes the upper threshold of labor quality, above which an agent spends no time donating plasma.

Since donors receive fixed cash compensation (i.e., nutritional subsidies) per donation and are subject to a maximum legal donation frequency, I denote the maximum income from plasma donation by F. h_i denotes donation intensity and ranges between 0 and 1. Following the basic household decision model setup with an exogenous wage rate as in Goto (2009),

$$\max_{h_i} U(c(h_i, \theta_i, w), S(h_i, \overline{h})) \qquad (1)$$

$$s.t.\ c \leq \theta_i w + h_i F$$

where $\mathrm{U}(\cdot)$ is the utility function, and the standard assumption for utility from consumption c is followed, i.e., $U_c > 0, U_{cc} < 0$. $S(\cdot)$ is the social stigma function which represents disutility from plasma donation. The standard assumption $U_{cS} = U_{Sc} < 0$ follows, meaning that 1) the greater the disutility is from plasma donation, the lower is the marginal utility of consumption, and 2) the marginal disutility from plasma donation becomes greater as consumption increases. In other words, the wealthier people suffer more from an increasing social stigma than their lower income counterparts. Utility is decreasing in stigma, and the marginal disutility from stigma is increasing in stigma, i.e., $U_S < 0$, $U_{SS} < 0$ [3].

$\overline{h}$ is the average intensity of paid plasma donation in the reference group. w is wage rate in quality terms. A person with labor quality θ_i receives $\theta_i w$ from labor provision.[4] The social stigma function $S(\cdot)$ satisfies $S_h > 0$, $S_{hh} > 0$, $S_{\overline{h}} < 0$, $S_{h\overline{h}} < 0$. Stigma is increasing in own engagement but decreasing in others' engagement in the group. The marginal stigma is

[3] This assumption is supported by the survey data. In the survey, subjective questions on income satisfaction, status satisfaction, and current and expected happiness status were asked to each individual household member. Appendix II plots the three main indicators on plasma donation engagement against these subjective ratings. The first and second order conditions of utility with regard to stigma are consistent with the shapes of the Appendix Figure.

[4] All the households in our census-type survey are faced with only one blood market that sets up a unique maximum blood compensation income *F*, while human resources vary a lot among people and areas. It implies equal "fluid labor" wage and unequal labor wage.

increasing in own engagement, but decreasing in others' engagement in the reference group. It is further assumed that a person does not feel guilty if one does not donate plasma regardless of the average plasma donation in the reference group, which means $S(0,\bar{h})=0$. The proposition follows. The corresponding derivation is provided in Appendix III.

Proposition: Individual engagement in stigmatized behavior is increasing in others' engagement in the reference group.

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

4. Data and Empirical Strategy

4.1 Data Collection

The dataset for this study comes from our three-wave census-type rural household survey in 26 villages in Guizhou province in Western China.[5] The local average per capita GDP is close to the median level in Guizhou. While Guizhou is one of the poorest provinces in China, it is ethnically diverse. Han is the major group. More than 20 ethnic groups live there, including Miao, Buyi, Gelao, and Yi that in total comprise about 20% of population.

We conducted the 2004 survey of all 801 households in early 2005. It collected detailed information on public facilities, investment and institutions in the villages and demographic characteristics, transfers, incomes and consumption for households. In 2004, plasma donors received a cash "nutrition" subsidy valued at 80RMB for the plasma contained in 580 cc of blood. Overall, 31.2% of households engaged in plasma donation, and the compensation accounted for 20.9% of total income (Table 2 and Table 4). Information on paid blood donation was collected on each family member, including those who were away at the time of survey. Given the sensitivity of collecting data on paid blood donation, we made great efforts to ensure the accuracy of these data, including extensive training of local enumerators who were able to effectively communicate with the residents in our sample villages. Moreover, the enumerators

[5] This survey was jointly conducted by the International Food Policy Research Institute (IFPRI), Chinese Academy of Agricultural Sciences (CAAS), and Guizhou University.

were trained to identify and probe into major discrepancies between income and expenditures, a strong indication that respondents concealed paid blood donations as an income source.

A 2006 follow-up survey of the same households was administered in early 2007 and all 833 households were interviewed. As documented earlier, blood banks in Guizhou were shutdown in early 2006 due to Hepatitis contamination in some branches. A few local residents were still able to donate through traveling to other counties nearby immediately after the shutdown of the local blood bank in 2006, as the timing of shutting down differs. However, its intensity was much smaller than before the shutdown (Table 2 and Table 4).

In early 2010, the 2009 wave follow-up survey was conducted for all 872 households. Further information on each of the family members donating plasma was collected. Since 2008 when all blood banks were reopened, they were commercialized. Nutrition subsidies have nearly doubled to 142 RMB (in real term) for the same amount of blood in an effort to encourage donors and restore trust. While by the time of our third round of data collection in 2009 the proportion of donors has recovered to 14.1% households and 6.1% of total income, it was still much less than the 2004 year level. It is also worth noting that while the payment is rather minimal to the rich, it is still a strong incentive to the poor. Over the long term, these villages where plasma donation has been pervasive are poor as indicated by the FGT poverty measures (Table 3). Plasma donation becomes a major source of income that lifts households out of poverty (Figure 2). A donor typically earns around 3600 RMB from continuous plasma donation per year, much more than from other local income generating activities.

The majority of plasma donors in a family are women. This result may reflect labor divisions to accommodate agricultural production or off-farm work, as the opportunity cost for men to engage in paid plasma donation is higher than women. However, the ratios of women donors in different villages vary significantly, reflecting different labor market situations. For example, villages with more odd job opportunities have higher proportion of female donors.

In addition to the census conducted in the 26 villages, we collected a ten-year gift-exchange record book for all households in five randomly selected villages[6] Gift-exchange data

[6] Two villages are more than 10 kilometers away from the county seat with poor road access, another two villages are within 2.5 kilometers away from the county seat, and a fifth village in between is populated with Buyi ethnic minorities, who preserve the Catholic culture different from the four Han villages.

were spontaneously recorded on the days of all social occasions when guests presented the gifts to hosts, including weddings, funerals, coming-of-age, childbirth, and house-moving ceremonies. Close relatives are responsible for recording gifts on site when hosts are busy organizing events or when they are illiterate. Gift-receiving records are usually kept for a long time in order to pay back accordingly when celebrations of other families are held. Household social links between the five villages and the other 21 surveyed villages nearby were also captured. The gift exchange record captures nearly all real within-village and cross-village connections in the long term, avoids implicitly ranking relationships in other network datasets, and is directional. In total, 8074 gift links among households during 2000-2009 were identified (Figure 3).

4.2 Reference Groups

Reference groups can be defined quite differently in specific contexts. In a developed society, information flow is fast and efficient, such that reference groups are not straightforward. However, in an impoverished traditional community, poor public infrastructure drags resource flow, and the evolution of local norms usually strengthens reciprocity. These differences facilitate a much improved definition of reference group.

In the early studies (e.g. Foster, 1967), substantial ethnographic evidence documents social interactions at the village level in less-developed rural communities. Foster (1967) argues village peer effects might be a more credible assumption than studies that use city blocks, census tracks, schools or classrooms when villages are small. In a recent study, Mangyo and Park (2011) suggest that village reference groups are salient for rural residents living in close proximity. A village is often spontaneously evolved that households within each village know each other well. Therefore, reference groups for peer behavior are first defined at the village level. In our surveyed region, the special geographic condition, *Karst* landform, further isolates local villagers' daily connections with other villages.

Apart from the reference group confined by the village boundary, rich information on 10-year gift networks enables us to redefine reference groups according to each household's corresponding gift receivers (alters) in the long run. This definition has advantage over the village-based one due to one's social interactions with multiple reference groups.

Figure 3 illustrates the 10-year gift links for one of the five villages that I collected network data. Gift exchange networks are observed to be more intense within clans and villages, since their associated enforcement cost is usually much lower than between clans and villages (Chen et al., 2011). In a traditional rural community in China, a majority of residents in a village have kinship ties with each other. Social relations often revolve around the role of the clan. Clans are integral to determining social norms which in turn play a crucial role in shaping behavior.

Though selling plasma is recognized as immoral in the Chinese culture, it becomes ethnically acceptable when more people in a clan, and the communities in which they are concentrated, engage in what would normally be unacceptable behavior. This explains my observation from the data that plasma donation activity is usually clustered among people with close social relations. Proximity to other donors, alone, does not compel households to become blood donors, even if they have very similar socioeconomic characteristics unless they are part of the social networks.

To illustrate this more concretely, Figure 4 shows the correlation between plasma donation decisions in the reference group and own donation decisions in all 26 surveyed villages, involving whether to donate and number of family members engage in, at the village level over the three-wave survey. Each point in the figure represents one village. The horizontal axes are others' plasma donation decisions in one's gift networks weighted by their network centrality and take the mean for each village. The vertical axes are average own plasma donation decisions for each village. The positive correlation is salient for both donation decisions.

4.3 Identifications of Peer Influence

The identification problem arises since behavior is determined by behavior, which brings a circularity of cause and effect. Parameters in classical peer effect models are not uniquely identified (Manski, 1993 and 2000). To estimate the impact of peer influence on plasma donation, the reflection problem that hinders disentangling endogenous effect from exogenous effect should be circumvented.

Conventional instrumental variable strategy might be able to *partially* address the problem, since part of the difficulty arises from endogeneity of the behavior that enters into both sides of the econometric equation. To compare with main spatial (network) identification, I employ lagged community level instruments that directly affect lagged average group behavior but are argued to have no direct link to current individual behavior under evaluation. However, this strategy in general is applied to models in which peers share a common boundary. In other words, individuals interact in a partitioned group, and no influence comes from outside the group. For instance, Manski (1993) studies a linear-in-expectations model, where individual behavior depends on the expected behavior of the group. Moffitt (2001) excludes individual behavior from the mean behavior, and all groups have the same size. In both cases peer effects are not identified.

There has been growing recognition that social interactions within partitioned groups are very particular and not likely to represent most forms of social interactions, while interactions in *partially* overlapping groups yield identification. Lee (2007) explores the role of variations in group sizes in identifying social interactions. De Georgi et al. (2010) assume social interactions with multiple reference groups to identify peer effect. Following the literature in spatial econometrics (Case, 1991; Anselin, Florax and Rey, 2004; Bramoullé et al., 2009), I consider a linear-in-means peer effects model where each household has its specific reference group, and the average behavior and characteristics of the group influence one's own 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.

In my estimation of peer influence, an agent's plasma donation y_i is a linear function of the average behavior among its own peers in a heterogeneous group P_i of size n_i, own characteristics x_i, and mean characteristics of the peer group. Agent i is excluded from the group defined by directed gift exchange networks. Ignoring potential correlated effects for a moment, the structural model is:

$$y_i = \alpha + \beta \frac{\sum_{j \in P_i} y_j}{n_i} + \gamma x_i + \delta \frac{\sum_{j \in P_i} x_j}{n_i} + \varepsilon_i, \qquad \mathrm{E}[\varepsilon_i \mid X] = 0 \qquad (3)$$

where β captures the endogenous effect and δ the exogenous effect. Other than assuming the strict exogeneity of the regressors, i.e., $\mathrm{E}[\varepsilon_i \mid X] = 0$, no further assumption is made on the error terms within a network. The model in matrix notation defined over all networks is:

$$y = \alpha\iota + \beta G y + \gamma x + \delta G x + \varepsilon, \quad \mathrm{E}[\varepsilon_i \mid x] = 0 \qquad (3')$$

where G is an $\mathrm{n*n}$ interaction 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:

$$y = \alpha(I - \beta G)^{-1}\iota + (I - \beta G)^{-1}(\gamma I + \delta G)x + (I - \beta G)^{-1}\varepsilon \qquad (4)$$

Bramoullé et al. (2009) show 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 and peers' peers peers characteristics G^3x 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 Georgi et al., 2010). Appendix IV illustrates the spatial instrument identification with a fictitious network.

All households in our survey are involved in their gift networks with intransitive triads, which facilitate identification. However, some households do not have a gift link of distance 3, i.e., they do not have peers' peers' peer. To avoid missing observations I take the average over all excluded peers' characteristics as exclusion restrictions.

Unobserved variables common to households who belong to the same social environment may be correlated with households' background, which brings another identification problem. In this case, α becomes α_v. To address the problem of correlated effects, I further introduce appropriate differencing between structural equations to eliminate unobserved factors at the network level. Notice that my approach to get rid of correlated effects is further to De Georgi et al. (2010), which argue that the spatial instruments, i.e., the characteristics of excluded peers, uncorrelated with the individual group shock suffice for solving endogeneity due to unobservable correlated effects.

Two types of within transformations can be naturally used for this purpose: the *local* transformation which expresses the model in deviation from the mean equation of one's direct contacts and the *global* transformation which expresses the model in deviation from the mean equation of one's direct and indirect contacts.[7] Bramoullé et al. (2009) show that the global transformation imposes less restrictive conditions to obtain identification. Endogenous and exogenous social effects can be distinguished on most networks when the global network transformation is adopted. A within transformation is achieved by pre-multiplying $J = I - G = I - \frac{1}{n}\iota\iota'$, and the structural model becomes,

$$Jy = \beta JGy + \gamma Jx + \delta JGx + J\varepsilon \qquad (5)$$

where $\mathrm{E}[\varepsilon_v \mid x_v]$ is allowed to be any function of x_v. Conditional on α_v, x_v is strictly exogenous. The matrix G_v is assumed to be exogenous conditional on α_v and x_v, i.e., $\mathrm{E}[\varepsilon_v \mid x_v, G_v, \alpha_v] = 0$. The reduced form is:

$$Jy = J(I - \beta G)^{-1}(\gamma I + \delta G)x + J(I - \beta G)^{-1}\varepsilon \qquad (6)$$

The model is identified if the matrices I, G, G^2 and G^3 are linearly independent. In this case, $(JG^2x, JG^3x, ...)$ 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.

The excluded peer instruments strategy itself does not address the concern about self-selection into the networks due to endogenous gift network formation. Though randomized reference groups solve this issue, a 'relevance-endogeneity' trade-off persists. As endogeneity of a peer group diminishes due to randomization, the relevance of decision making as well as external validity of the social group is weakened (Fletcher, 2010). In this paper, I rely on observational data, and neglecting endogenous friendship selection may overestimate peer effects to a large extent (Fletcher and Ross, 2011). I will next discuss the potential concerns and my partial solutions to endogenous network formation.

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

First of all, it is possible that some unobserved factors, e.g., popularity, affect both the likelihood to form links and the individual donation behavior and differs among individuals in the same network. The network will not be exogenous conditional on α_v and x_v. To avoid the resulting inconsistent estimates of social interactions, I estimate a panel data model with household fixed effects, which further get rid of the unobserved factors at the individual household level. In this specification, I assume individual popularity does not change overtime.

Meanwhile, there is concern that the stigma associated with paid plasma donation affects network formation and is captured by the error term. Fortunately, the gift network data between 2000 and 2009 predates the initiation of blood bank to the local region in 2004 and therefore effectively mitigate this concern.

In the above spatial instrument estimations, the average peer behavior is measured with or without being weighted by amount of gifts between each pair of gift giver (ego) and gift receiver (alter). The assumption is that the intensity of gifts positively predicts alters' influence over egos. This weighting scheme is implemented via row-normalized adjacency matrix that captures information on pairwise gift exchange.

I would like to draw a cautious note on comparing the results. First, having only extensive social network data for five out of 26 villages surveyed, I have to limit both the conventional and the spatial identifications to the five village sub-sample to be comparable.

4.4 Empirical Strategy

I estimate the following household plasma donation model:

$$y_{i,P_i,t} = \alpha + \beta \frac{\sum_{j \in P_i} y_{j,t-1}}{n_{i,t-1}} + \gamma x_{i,P_i,t} + \delta \frac{\sum_{j \in P_i} x_{j,t}}{n_{i,t}} + \lambda_i + \phi_t + \varepsilon_{i,P_i,t} \qquad (7)$$

or in matrix notation,

$$Y = \alpha\iota + \beta GY + \gamma X + \delta GX + \lambda + \phi + \varepsilon \qquad (7')$$

where $y_{i,P_i,t}$ denotes three indicators of plasma donation engagement: whether a household *i* donates plasma; how much plasma household *i* donates; and how many household members donate.[8]

Two strategies are applied in identifying reference group P_i - village boundaries and gift networks. First, identification based on villages is adopted, i.e., simple average donation is taken at the village level,[9] which might be less problematic in my context due to the remote mountainous location that isolates social interactions. The validity of this treatment is based on the assumption that village boundary confines interactions and that intensity of pairwise connections is homogenous, which may not always be the case.

Fortunately, I am also able to utilize real network data that varies in the intensity of gifts, includes cross-village links, and possesses partially overlapping peer groups, which improves upon the village-based peer group identification. Group average plasma donation is constructed in two ways to measure peer behavior. The first way takes simple average over peers' donation behavior, while the second way weighs alters' donation decisions by normalized pairwise gift values and then takes the average for each ego.

Two estimation strategies are implemented to deal with simultaneity in identifying peer effects β, as individual donation decisions might indirectly affect the average donation in the reference group. The first strategy applies prior community level characteristics, i.e., average income, sanitary and transportation conditions, to instrument prior average peer donation decisions in the conventional IV estimation. The second strategy, Generalized Spatial Two Stage Least Squares Estimation (GS2SLS), defines gift networks as the reference group in the estimation with spatial instruments generated from network structure. Specifically, characteristics of peers' peers serve as instruments. For this strategy, average peer behavior is measured with and without being weighted by row-normalized adjacency matrix.

[8] Both donation value and number of family members donating blood measure donation intensity. However, we have to be cautious that donation value is a noisy measure due to respondents' recall error, numerators' calculation error and inclusion/exclusion of transportation fee, extra nutrients intake to minimize damage to health and lodging fee for donation.

[9] The household's donation decision is excluded from the average donation in the reference group.

X denotes a set of other control variables, including household head gender, age, education, ethnicity, cadre and party membership, and share of the elderly in the households. Meanwhile, household per capita income (excluding plasma donation compensation) is controlled.[10] The share of unmarried family members between age 11 and 29 is included with the expectation that its larger share corresponds to more future expenses in the marriage market and higher incentive to donate plasma. The ratio of local wage to plasma donation compensation is controlled. Other than the relative return, I further control travel time from each village to the local blood bank that captures non-money cost.[11] Shocks, such as family member death, serious diseases, natural disasters, and livestock death, are also included.

5. Empirical Results

5.1 Main Results

The main estimation results are presented in the following order: I first show evidence using both OLS and spatial IV identification strategy. Household fixed effect estimations are followed by network fixed effect, spatial estimations with non-weighed adjacency matrix is compared to those with weighted adjacency matrix, and estimations without controlling contextual effects are compared to those controlling contextual effects. Other robustness checks are then conducted and potential mechanisms discussed.

First, estimations on three blood donation indicators are reported in Table 5a-5c. Table 5a reports results on paid blood donation probability. The OLS estimation in column R1 finds peer decisions significantly determine own plasma donation decisions with a marginal influence of 0.801. This is biased upward compared to the spatial IV estimation in R2 with the same model specification.

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[10] If a donor 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 donors were ever turned back from donating blood, I replace income with its predicted value through regressing on family background and productive assets.

[11] Blood donation behavior is usually concentrated where local transportation condition permits. Transportation condition varies 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 generally unable to regularly donate blood, because after a few hour walk to the county seat it is often too late to sign up for the limited slots of donation for the day.

Estimations with spatial instruments generated from the gift network data are presented in columns R2-R5 of Table 5a, which instrument peers' average plasma donation decisions by characteristics of excluded peers generated from gift network structure.[12] Specifically, these characteristics involve per capita income, household size, cadre status, ethnicity, education, share of the elderly, share of unmarried son, relative wage, exposures to big diseases, livestock deaths and family member deaths, and travel time to the local blood bank. Standard errors in all estimations are clustered at the village level. The first stage estimation for column R5, our preferred specification, is presented in Appendix V. F-tests of the excluded instruments in the first stage indicates that weak instruments are not a concern. Over-identification tests fail to reject the validity of the spatial instruments.

Throughout columns R1-R3 of Appendix V, none of the exogenous effects other than exposure to livestock deaths are significant, suggesting that social interactions mainly operate through peers' behavior. The identified peer effects on paid plasma donation suggest that a ten percentage point increase in the rate of plasma donation among peers raises individual probability of plasma donation by 2.5 percentage. Compared to the identified marginal effect in column R2, controlling for individual and household characteristics in column R3 reduces peer effect by 24 percent (1-.390/.513). Column R4 further includes contextual controls in the network, and identified peer effect reduces by 23 percent (1-.297/.390). After further controlling for network fixed effects in our preferred column R5, the identified peer effect further drop by 16 percent (1-.250/.297). Overall, individual and household characteristics and contextual factors seem to contribute the most to the overestimated part of peer effects.

[12] The community IV strategy with perfectly overlapping groups has been widely adopted in the literature on peer effects. It might be useful to compare this conventional method with the main spatial estimation strategy in this paper. Peers' average behavior is instrumented with a series of community characteristics in the prior period: average travel time to the local blood bank, average income, average rate of access to tap water and travel time to the nearest clinics. The first stage estimations show that higher average income and higher rate of access to tap water in the village is associated with lower average engagement in plasma donation, mainly due to income effect. Besides, households more distant from clinics are less likely to donate plasma. Over-identification tests fail to reject the validity of the four instruments. F tests for excluded instruments all suggest that they are not weak instruments. In the second stage estimations, higher prior average plasma donation in the peer group significantly pushes up one's own likelihood of donation. The marginal effects are always larger than those in column R1 without IV. Compared to spatial instrument estimations, the marginal peer effects are generally larger. Our results suggest that the conventional method based on perfectly overlapping peer groups might be overoptimistic about the magnitude of peer effects.

Some individual and household characteristics are worth noting. First, the ratio of local wage to plasma donation compensation shows negative but insignificant impact. The rising wage in recent years tends to increase the opportunity cost of engaging in paid plasma donation. However, the plasma donation payment is still equivalent to 2-3 times the daily market wage. Since 2008, the plasma donation compensation has nearly doubled, offsetting the rapid wage increase. Meanwhile, labor market engagement does not prevent people from donating plasma, especially in the short run as plasma is donated every 15 days. Therefore, it is plausible that the insignificant wage ratio can be explained by both the imperfect substitution and the rapid increase in plasma donation payment.

Second, we find that having an unmarried son is associated with higher incentive to donate plasma, which is probably due to the strong motives to earn more money to get son married in the competitive marriage market with skewed sex ratios favoring females.

Besides, the official stipulation prohibits the elderly from donating plasma, which corresponds to their significantly lower probability of donation. People with higher income or of minority status significantly reduce engagement in plasma donation. Shocks such as family member death, big disease, natural disaster, livestock death and major stealing do not consistently drive people into donating plasma, even if all shocks are combined.

To test whether peer effects can be explained by within-network and within-household variations, estimations with both global network fixed effects (column R5) and household fixed effects (available upon request) are conducted. Results suggest that peer effects significantly account for both within-network and within-household variations in paid plasma donation, and identified peer effects are larger in estimations accounting for within-household variations.

Similar to Table 5a, Table 5b and Table 5c present results on value of blood donation and number of family members donating, respectively. The identified peer effects suggest that a 10 percent increase in peers' income from paid plasma donation raises individual income from plasma donation by 3 percent. Meanwhile, one more peers' family member donating plasma on average leads to .47 more own family member engaging in the activity. Two similar findings emerge in Table 5b and Table 5c. First, OLS estimations significantly overestimate peer effects.

Second, comparing spatial IV estimations in scenarios R2 through R5, individual and household characteristics seem to contribute the most to the overestimation of peer effects.

5.2 The Size of Peer Effects

In this part we assess the economic magnitude of the identified peer effects. To gauge the size of peer effects, we focus on column R5 in Table 5a through Table 5c, our preferred Generalized Spatial Two Stage Least Squares Estimation (GS2SLS) with rich individual and household covariates, contextual factors, and network fixed effects.

Taking the estimated effects at face value, peer effects estimation for the donation probability (Table 5a) informs us that a ten percentage higher peers' plasma donation rate increases own probability of donating blood by approximately 2.5 percentage. The average peer group size is 17 among which on average 3.1 peers donate plasma. Therefore, over an average of about 18% plasma donation rate, 1.7 additional average peers who donate blood increases own donation probability by about 13.9 percent.

Peer effects estimation for the value of plasma donation (Table 5b) shows an one percent increase in peers' plasma donation value leads to .30 percent increase in own donation value. Table 5c indicates that evaluated at the first family member donating plasma, one more family member in the reference group engages in plasma donation leads to a 46.9 percentage higher chance that a second member in one's own family donates plasma, small in magnitude considering that only 12.9 percent of blood donating families have more than one member engaging in. The estimated peer effects suggest that disutility from stigma declines when more peers engage in plasma donation.

To facilitate comparisons with other peer effects studies using different peer measures, the size of the effects are calculated as $\sigma_{GY}\hat{\beta}/\sigma_Y$, where σ_Y indicates the variations in the own outcomes, while σ_{GY} shows variations in the peer variable. G is the adjacency matrix,[13] and GY denotes peer variable. This quantifies peer effects as the impact of a one standard

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[13] In studies that use X, an peer indicator different from Y, to proxy the peer variable, the size of the effects is $\sigma_{GX}\hat{\beta}/\sigma_Y$. An example is Ammermueller and Pischke (2009) in which the authors proxy peer variable by number of books at home, and the outcome variable is text scores.

deviation change in peer variable in terms of individual level standard deviations of the outcome variable.

The effect size measure is reported in Table 6. The effect sizes vary across different outcome variables, and variations come from own outcomes, peer variable as well as the peer coefficient. The effect sizes range from .124 to .232. However, the lack of other empirical evidence on peer effects on stigmatized behavior prevents us from a more meaningful comparison of effect sizes.

Table 7 further test whether the significance and the magnitude of identified peer effects vary much when we adopt different weights for pairwise links. In other words, we no longer assume that all existing pairwise links have the same strength. Rather, we make use of pairwise gift sizes and network centrality. F-tests of the excluded instruments in the first stage still rule out the possibility of weak instruments, and over-identification tests verify instruments' validity. However, results on the three major outcome variables weighted by gift size suggests smaller and less significant pattern. When weighted by network centrality, three measures are adopted, i.e. the out-degree centrality, the in-degree centrality, and the Bonacich centrality, which measure influence over peers, popularity in the network, and overall how central one is in the network, respectively. The formal definitions of these centrality measures are in the note of Table 7. It is concluded that spatial instrument estimations find larger and more significant peer influence without incorporating link intensity or network centrality. While the existence of a pairwise link suggests social interactions, the intensity of each link (measured by gift size) or the centrality of individual network position may not indicate the strength of influence in social interactions.

Robustness checks are presented in Table 8. First, I construct placebo peer groups via randomly assigned groups. Specifically, in this falsification test I randomly select five alternative households to construct a reference group for each household. Peer effects disappear, suggesting that real networks capture the domain of social interactions. Second, we find that peer effects are directional, which suggests that the effect is causal. More directionality and causality issues are discussed in the next subsection. Third, more nuanced checks are done and the main results do not vary. For example, similar to De Giorgi et al. (2010), I reduce the original large set of excluded peers' characteristics as instruments. I drop the distance to the local blood bank due to the concern of geographic homogeneity in the communities, but peer effects remain. Alternatively, I drop age profile from the instrument list as regulation on donation age may not be strictly enforced, but peer effects are still there. Additionally, people may concern that participating in funerals may not suggest popularity or influence. Instead, it might only reflect a norm of mutual assistance in a community. Gift links due to funerals are dropped when defining reference groups, but peer effects are still significant. All the above checks indicate that the reference group definition and peer effects identification are robust.

To further support our argument of exogenous network formation regarding blood plasma donation decisions in subsection 4.3, in Table 9 we test peer effects based on kinship network. Similar to gift and loan networks that precede the initiation of the blood bank to the local region, kin relationships are also independently formed from plasma donation decisions. While our estimations confirm peer effects along kinship networks, they do not exist for non-kinship networks. Furthermore, significant peer effects are found in in-kind gift networks, they seem less significant in cash gift networks.

5.3 The Potential Mechanism of Peer Effects

To understand from where peer effects are originated, I first test the direction of influences. Are peer effects from gift presenters (egos), gift receivers (alters) or both? The above estimations of peer effects all assume that influences flow from gift receivers to gift presenters, but not necessarily vice versa. A gift, especially in impoverished regions, means that a relationship matters to gift givers. New work in the econometrics of networks and sociology confirm that exploiting directionality in networks is a useful identification strategy (Freeman, 1979; Bramoulle et al., 2009). Fortunately, the gift record allows us to test the directional hypothesis.

Unlike the identified peer effects that gift presenters' plasma donation decisions are driven by their gift receivers' actions, estimations in Table 8 do not find evidence that gift receivers' plasma donation is affected by gift presenters, providing additional evidence in favor of the causal interpretation regarding social influence in donation behaviors. If contextual effects are spuriously driving the relationship between gift presenters and gift receivers, there is no reason to expect a directional result. In other words, gift senders in the context should appear to have an influence on gift receivers. Since no such a significant effect is found, the evidence is suggestive of a causal effect.

Having been able to verify peer effects in shaping individual behavior and the asymmetric flow of peer influences from gift receivers to gift presenters, the presence of endogenous interactions might arguably be too broad to be very helpful if empirical analysis is to guide policy (Manski, 2000).

There are distinct endogenous channels whereby group behavior affects individual behavior. For example, preference interactions may persist such that the disutility associated with plasma donation declines as more peers engage in. In this case, an individual's preference toward stigmatized behavior is largely shaped by peers' behavior. Alternatively, an individual may learn about the attractiveness of plasma donation from peers in terms of large income generation with "little" effort. In this case, positive information disseminated shapes expectations through interactions. What is the main mechanism at work, preference interactions or expectation interactions?

A public crisis during the three-wave survey might help us understand the basic processes. In 2006, Hepatitis C infected Guizhou and blood banks were shutdown. The epidemic directly hit some blood banks in the province but not our surveyed one, while the government shut down all of them. Therefore, the shock was purely exogenous to local households. The lower rate of donation two years after the reopening of local blood bank suggests that awareness of potential risks may affect individual donation. If negative information dominates the process, during the period after shock we should not observe an increasing pattern of individual blood plasma donation for groups with more donors. However, the data suggests that almost no household which had engaged in plasma donation after the shock withdrew from donation in 2009. In contrast, a number of households were newly involved in the activity, especially in the communities where donation had been prevalent. Moreover, the estimation dropping observations before the blood bank shutdown suggests even stronger peer effects than the whole sample estimation (Table 8).

In early 2006 when infectious diseases came, the local government made every effort to publicize information on epidemic situation. Information on potential risks should be already embodied in donation decisions after the shock. Therefore, a salient increase in individual plasma donation due to group influences over two time points after the shock is most plausibly attributed to preference interactions that reduce stigma, rather than expectation interactions. Prescriptions for appropriate public policy differ between preference interactions and expectation interactions. My result infers that an educational intervention showing devastating effects of frequent plasma donation might be useful before the epidemic crisis if expectation interactions are at play, and superfluous later on when preference interactions stand out. More attentions should be given to policies that change preference, rather than just providing information on potential risks.

6. Conclusions

Datasets on stigmatized behavior are often too sensitive to collect. Fortunately, combining two sources of data I collected in the field, i.e., a unique 10-year gift network data and a primary census-type panel data in rural China with detailed information on stigmatized behavior, I study one kind of such behavior—frequent plasma donation with cash compensation. This paper is among the first empirical studies on stigmatized behavior. To my knowledge, this is the first paper that utilizes dyadic social network to identify social interactions in shaping stigmatized behavior.

A novel identification strategy, i.e., spatial instruments naturally generated from the network structure, is implemented to gauge peer influence on plasma donation decisions. The strategy effectively solves the reflection problem and distinguishes correlated effects that are puzzling empirical studies on peer effects.

The unprecedented rich information on real social connections through long-term pairwise gift exchanges enables me to probe into the intensity of social interactions.

I find strong evidence of peer influences in blood donation decisions, which enriches the general understanding about poverty and paid plasma donation. The intensity of social interactions plays a unimportant role in the identification. Peer effects are directional. It is only imposed from gift recipients to gift presenters, suggesting that receiving more gifts indicates higher popularity in the networks. The results also indicate that peer influences identification using perfectly overlapping groups tends to be overoptimistic in finding the effects.

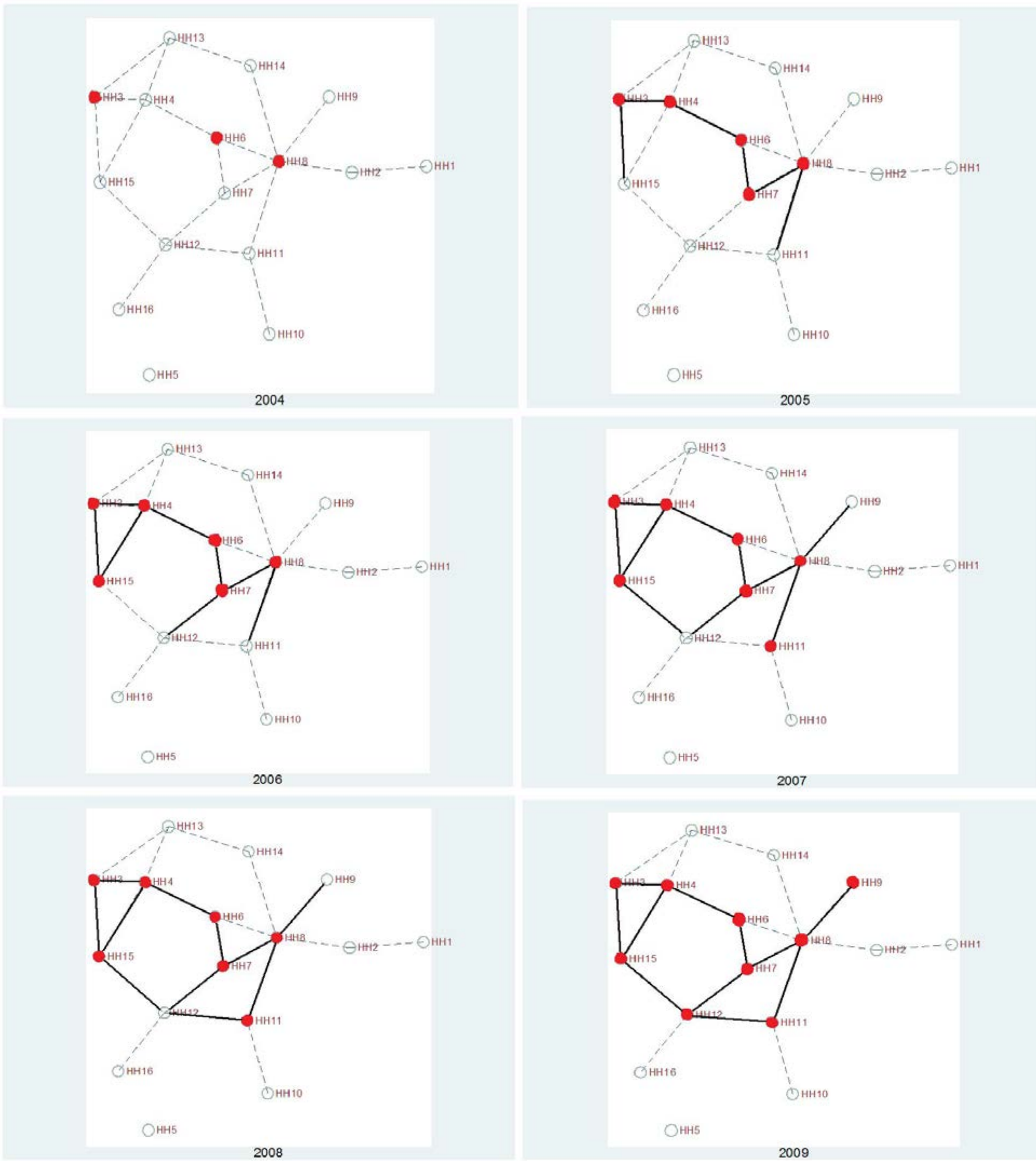
The identified endogenous social interactions provide parameter for large-scale interventions with general equilibrium effects. Due to negative externalities associated with the behavior, individual donation level increases with peers' average donation. Contextual interactions and correlated effects, however, imply no such feedbacks. Programs aiming at targeting popular agents in the networks and therefore curbing indulgence in stigmatized behavior tend to be very effective. In the case of paid plasma donation, this action may indirectly reduce donation from others in the group with a feedback to further decrease donation from the targeted households.

My results further infer that identified peer effects might be originated from preference interactions that reduce stigma. Expectation interaction may drive peer effects, especially at the initial stage of the epidemic, through the dissemination of information on potential risks associated with plasma donation.

Moreover, social pressure is especially salient for households with unmarried sons, suggesting tightening unbalanced marriage market in contemporary China. This particular finding suggests some adjustments to one child policy.

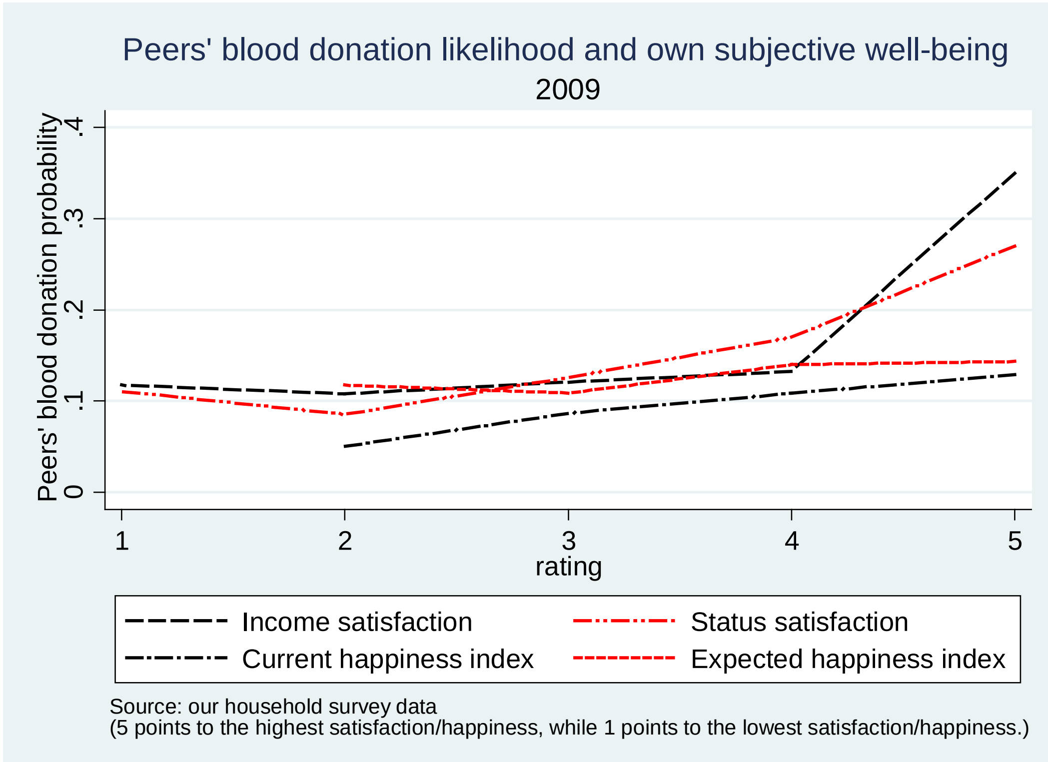
This paper suggests that the study of plasma donation is important on its own right. It engenders devastating impacts on people who engage in, such as on human physical and mental health, agricultural production, poverty alleviation and inter-generational inequality. The HIV crisis in Henan Province in China in the 1990s and Hepatitis C crisis in Guizhou Province in the 2000s are some of the hard lessons we should learn from. Moreover, stigma explains the difference between obnoxious markets and a regular market. Stigmatized behavior often evokes popular discomfort, distrust and even outrage among the public. It brings all kinds of negative externalities to the society. Having convincingly shown the significance of peer effects in this paper, understanding the mechanism that underlies social interactions and the consequences of stigmatized behavior will be a valuable question open to future research.

Appendix I: Paid Blood Donation Decisions Transmitting via Gift Networks

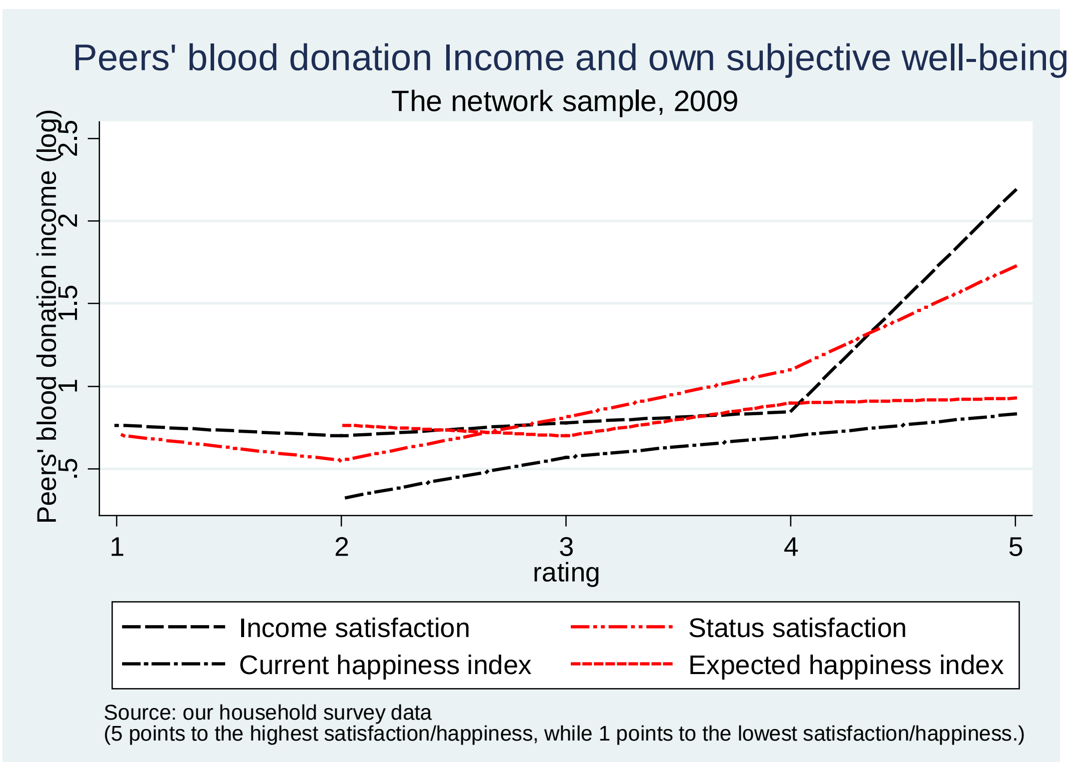


Data: Author's household survey data matched with gift networks data.
Notes: A real example of paid plasma donation decisions Transmitting via Gift Networks during 2004-2009. The red dots denote households engaging in paid plasma donation. Households near these households in the networks are more likely to follow donation decisions.

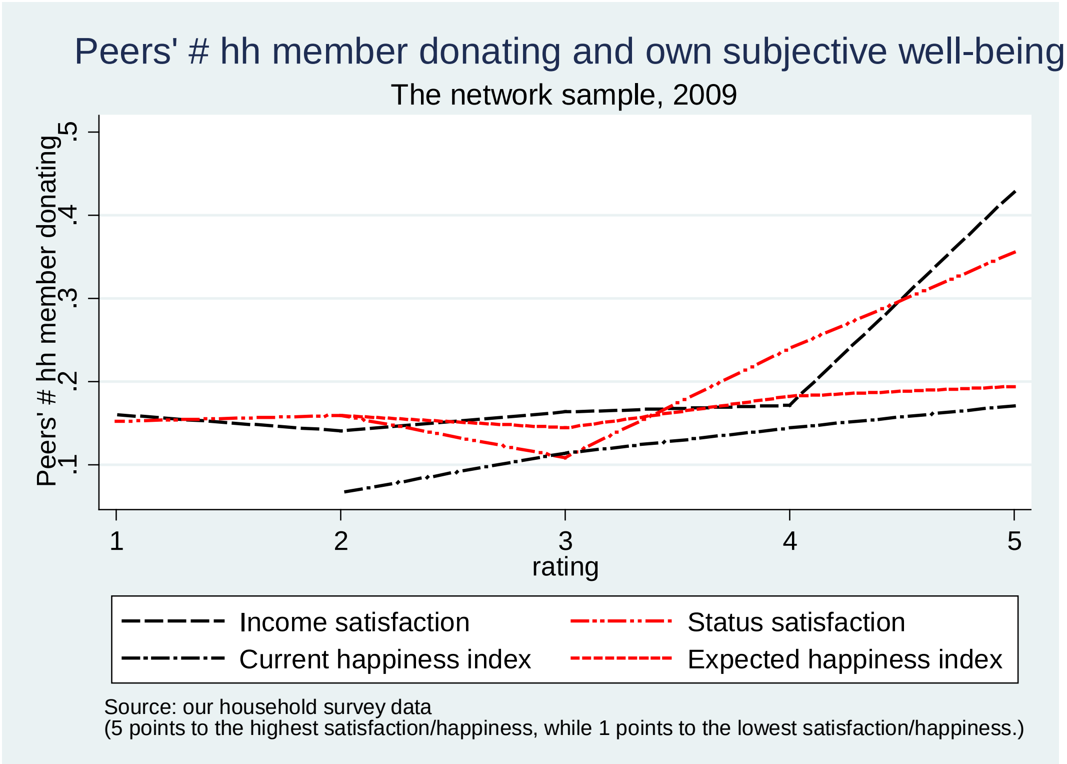
Appendix II: Peers' Paid Blood Donation and Own Subjective Well-being



Data: Author's household survey data.



Data: Author's household survey data.



Data: Author's household survey data.

Appendix III: Proof of the Proposition

The first order condition for an interior solution is:

$$F\frac{\partial U(c(h_i,\theta_i,w),S(h_i,\overline{h}))}{\partial c}+\frac{\partial U(c(h_i,\theta_i,w),S(h_i,\overline{h}))}{\partial S}\frac{\partial S(h_i,\overline{h})}{\partial h_i}=0 \qquad \text{(A1)}$$

which solves optimal intensity of plasma donation $h^*(\theta_i,\overline{h},w)$ given the labor quality (θ_i), the average intensity of plasma donation in the reference group ($\overline{h}$), and the wage rate (w). The second order condition is satisfied.

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

$$F\frac{\partial U(c(1,\theta_i,w),S(1,\overline{h}))}{\partial c}+\frac{\partial U(c(1,\theta_i,w),S(1,\overline{h}))}{\partial S}\frac{\partial S(1,\overline{h})}{\partial h_i}\geq 0 \qquad \text{(A2)}$$

where the labor quality is low enough that the marginal utility of consumption dominates the marginal disutility of social stigma for the whole range of h. The above equality holds with $\underline{\theta}$. In contrast, if the labor quality 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 $\overline{\theta}$.

$$F\frac{\partial U(c(0,\theta_i,w),S(0,\overline{h}))}{\partial c}+\frac{\partial U(c(0,\theta_i,w),S(0,\overline{h}))}{\partial S}\frac{\partial S(0,\overline{h})}{\partial h_i}\leq 0 \qquad \text{(A3)}$$

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 that expectation.

$$\overline{h}=\int_{\theta_{\min}}^{\theta_{\max}} h_i(\theta,\overline{h},w)dF(\theta) \qquad \text{(A4)}$$

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

Differentiating LHS of (1) with respect to w yields

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

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

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

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

Therefore, both the rising wage rate (w) and labor quality (θ_i) have a negative impact on plasma donation. 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

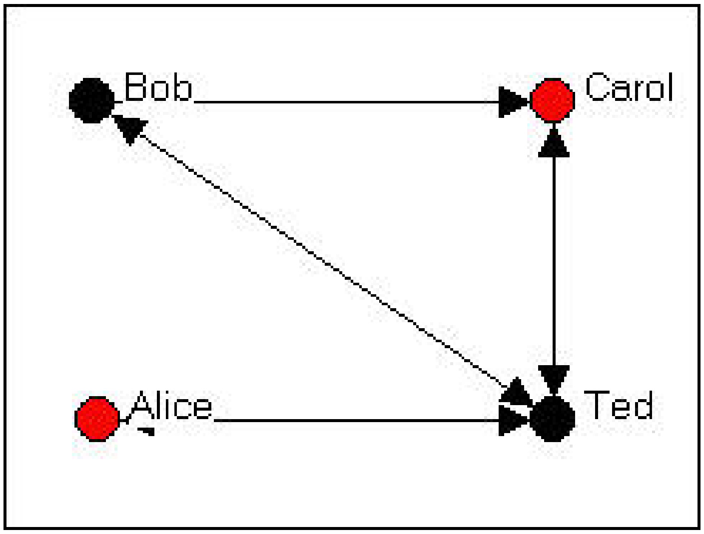
$$\begin{aligned} &FU_{cc}c_h \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + FU_{cS}[S_h \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + S_{\bar{h}}] + U_S[S_{hh} \frac{\partial h_i(\theta_i, \bar{h}, w)}{\partial \bar{h}} + S_{h\bar{h}}] \\ &+ S_h[U_{Sc}c_h \frac{\partial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

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

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

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

Appendix IV: An Illustration of Spatial Instruments Identification



My peer group definition is directional, depending on whether a gift is sent or not. In this fictitious case, Bob sends gift to Carol and Ted, but not Alice; Carol only sends 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 peers' peers. 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.

Appendix V: Spatial Identification on Peer Effects (Full Estimation Results, 1st and 2nd stages)

	R1		R2		R3	
	Donate or Not		Donation value		# hh members donate	
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 big 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)G^2x						
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 and Village Fixed Effects	Yes		Yes		Yes	
N	552		552		552	

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

References

Akay, A., Martinsson, P., and H. Medhin. 2011. “Does Positional Concern Matter in Poor Societies? Evidence from a Survey Experiment in Rural Ethiopia” *World Development*, forthcoming.

Akerlof, George A. 1976. “The Economics of Caste and of the Rat Race and Other Woeful Tales,” *The Quarterly Journal of Economics*, vol. 90(4), 599-617.

Anagnost, S. 2006. “Strange Circulations: the Blood Economy in Rural China,” *Economy and Society*, 35:4, 509-529.

Anderson, S. 2007. “The Economics of Dowry and Bride Price.” *Journal of Economic Perspectives* 21(4): 151-74.

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): 315-348.

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

Arrow K. 1972. “Gifts and Exchange,” *Philosophy and Public Affairs,* 1, 4, 343-362.

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

Ballester, C., Calvó-Armengol, A. and Y. Zenou. 2006. “Who’s Who in Networks. Wanted: The Key Player,” *Econometric*s 74: 1403–1417.

Banerjee, A. V. and E. Duflo. 2007. “The Economic Lives of the Poor,” *Journal of Economic Perspectives* 21(1): 141-167.

Basu, K. 1986. “One Kind of Power,” Oxford Economic Papers, Volume 38 (2): 259-282.

Basu, K. and P. Van. 1998. “The Economics of Child Labor,” *American Economic Review* 88(3): 412-427.

Bonacich, P. 1987. “Power and Centrality: A Family of Measures.” *The American Journal of Sociology*, Vol. 92, No. 5. pp. 1170-1182.

Bowles, S. and Y. Park. 2002. “Emulation, Inequality, and Work Hours: Was Thorstein Veblen Right?” Santa Fe Institute mimeograph.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2009. “Identification of peer effects through social networks.” *Journal of Econometrics*, vol. 150(1): 41-55.

Brown, Philip H., Bulte, E. and Xiaobo Zhang. 2011. “Positional Spending and Status Seeking in Rural China.” Forthcoming, *Journal of Development Economics*.

Calvó-Armengol, A., Patacchini, E. and Y. Zenou. 2009. "Peer Effects and Social Networks in Education," *Review of Economic Studies*, 76 (4): 1239-1267.

Case, A. 1991. “Spatial patterns in household demand.” *Econometrica* 59(4): 953-965.

CHAIN, 2006: “Mai Xue Lao Ren De Yan Lei He Wei Sheng Guan Yuan De Bao Ma: Guizhou Sheng ‘Xue Jiang Jing Ji’ You Si,” (in Chinese), http://www.chain.net.cn.

Chakravarty, S. R. 1990. “Social Ethical Index Numbers,” Springer, Berlin, 1990.

Chen, X. 2011. “Gift Escalation and Network Structure in Rural China: Utilizing A Unique Long-term Spontaneous Gift Record," working paper, Cornell University.

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.

Chen, X. and X. Zhang. 2011. “Costly Posturing: Relative Status, Ceremonies and Early Child Development,” *forthcoming*, UNU-WIDER Discussion Paper.

Clark, A. and A. Oswald. 1996. “Satisfaction and Comparison Income,” *Journal of Public Economics*, 61, pp. 359-381.

Cohen, J. 2004. “HIV/AIDS in China: Poised for Takeoff?” *Science* 304(5676): 1430-1432.

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

Deaton, A. 2001. “Relative Deprivation, Inequality, and Mortality,” *NBER Working Paper* #8099, Cambridge, MA: National Bureau of Economics Research.

Deaton, A. 2003. “Health, Inequality, and Economic Development,” *Journal of Economic Literature* 41, 113-58.

De Brauw, A. and S. Rozelle. 2008. "Migration and household investment in rural China," *China Economic Review*, Elsevier, vol. 19(2), pages 320-335, June.

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.

Dekker, M. and H. Hoogeveen. 2002. “Bridewealth and Household Security in Rural Zimbabwe,” *Journal of African Economies* 11(1): 114-145.

Dercon, S. and J. De Weerdt. 2006. “Risk-sharing networks and insurance against illness,” *Journal of Development Economics* 81(2), 337-356.

Duesenberry, J. 1949. “*Income, Saving, and the Theory of Consumer Behavior,”* Cambridge, Mass.: Harvard University Press.

Easterlin, R. 1974. “Does Economic Growth Improve the Human Lot? Some Empirical Evidence,” in *Nations and Households in Economic Growth,* ed. by David, P. and Reder, M., pp. 89-126. Academic Press, New York.

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

Fafchamps, M. and F. Gubert. 2007. “The Formation of Risk Sharing Networks,” *Journal of Development Economics* 83: 326-350.

Fafchamps, M. and F. Shilpi. 2008. "Subjective welfare, isolation, and relative consumption," *Journal of Development Economics*, vol. 86(1), pages 43-60, April.

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

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

Foster, George M., Tzintzuntzan: los campesinos mexicanos en un mundo en cambio (Colo Bosqua del Pedregal, Me´xico: Fondo de Cultura Econo´mica, 1967).

Frank, R. 1985. “*Choosing the Right Pond*,” New York: Oxford University Press.

Frank, R. 1997. “The Frame of Reference as a Public Good,” *Economic Journal,* 107: 1832-1847.

Freeman, L. 1979. “Centrality in social networks: Conceptual clarification.” *Social Networks*, Vol. 1, 215-239.

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

Gerdtham, U. and M. Johannesson. 2004. “Absolute income, relative income, income inequality, and mortality,” *Journal of Human Resources* 39 (1): 228–248.

Goto, Hideaki. 2009. “Social Norms, Distributional Shifts of Adult Labor Efficiency, and Child Labor,” *Working Paper #16*, National Graduate Institute for Policy Studies, Japan.

Goyal, S., Van Der Leij, M., and J.L. Moraga-Gonzalez. 2006. “Economics: An emerging small world,” *Journal of Political Economy* 114 (2), 403-412.

Jackson, M. 2008. “*Social and Economic Networks*,” Princeton University Press.

Kanbur, R. 2004. “On Obnoxious Markets,” in S. Cullenberg and P. Pattanaik (editors), *Globalization, Culture and the Limits of the Market: Essays in Economics and Philosophy*. Oxford University Press.

Kaplan, G.A., E.R. Pamuk, J.W. Lynch, R.D. Cohen, J.L. Balfour. 1996. “Inequality in Income and Mortality in the United States: Analysis of Mortality and Potential Pathways,” *British Medical Journal* 312: 999-1003.

Kawachi, I., B.P. Kennedy, K. Lochner, and D. Prothrow-Stith. 1997. “Social Capital, Income Inequality, and Mortality,” *American Journal of Public Health* 87(9): 1491-1498.

Kempen L. 2003. “Status consumption and ethnicity in Bolivia: evidence from durables ownership,” *International Journal of Consumer Studies* 31(1): 76-89.

Knack, S. and Keefer, P. 1997. “Does Social Capital Have an Economic Payoff? A Cross-Country Investigation,” *Quarterly Journal of Economics*, Vol. CXII, Issue 4.

Lee, L.F. 2007. “Identification and estimation of econometric models with group interactions, contextual factors and fixed effects,” *Journal of Econometrics* 140(2), 333-374.

Levine, A., Frank, R. and D. Oege. 2011. “Expenditure Cascades,” working paper, Cornell University.

Li, H. and Y. Zhu. 2006. “Income, Income Inequality, and Health: Evidence from China,” *Journal of Comparative Economics*, 34(4): 668-693.

Ling, D. 2009. “Do the Chinese ‘Keep Up with the Joneses’? Implications of Growing Economic Disparities and Relative Deprivation on Health Outcomes among Older Adults in China,” *China Economic* Review, vol. 20, Issue 1, 65-81.

Liu, X. 2000. “*In One’s Own Shadow: An Ethnographic Account of the Condition of Post-Reform China*,” Berkeley: University of California Press.

Luttmer, E. 2005. “Neighbors as Negatives: Relative Earnings and Well-Being,” *Quarterly Journal of Economics* 120: 963-1002.

Mangyo, E. and A. Park. 2011. “Relative Deprivation and Health: Which Reference Groups Matter?” *Journal of Human Resources* 46(3):459-481.

Manski, C. 1993. “Identification of Endogenous Social Effects: The Reflection Problem.” *Review of Economic Studies* 531-542.

Manski, C. 2000. “Economic Analysis of Social Interactions,” *Journal of Economic Perspectives*, 14(3): 115-136.

Neumark, D. and A. Postlewaite. 1998. “Relative income Concerns and the Rise in Married Women’s Emplyment,” *Journal of Public Economics*, 70, pp. 157-183.

Putnam, R. 2000. “*Bowling Alone: The Collapse and Revival of American Community*,” New York: Simon and Schuster.

Rao, V. 1993. “The Rising Price of Husbands: a Hedonic Analysis of Dowry Increases in Rural India,” *Journal of Political Economy,* 101: 666-677.

Ravallion, M. and M. Lokshin. 2010. "Who cares about relative deprivation?" *Journal of Economic Behavior and Organization* 73(2): 171-185.

Rawls, J. 1971. “*A Theory of Justice*,” Cambridge, MA: Harvard University Press.

Robson, A. 1996. "The Evolution of Attitudes to Risk: Lottery Tickets and Relative Wealth." *Games and Economic Behavior* 14(2): 190-207.

Runciman, W.G. 1966. “*Relative Deprivation and Social Justice,”* London: Routledge & Kegan Paul.

Sen, A. 1983. “Poor, relatively speaking,” *Oxford Economic Papers*. New Series, Vol. 35, No. 2, pp. 153-169.

Sen, A. 1985. “The Moral Standing of the Market,” in Paul, E.F., Miller, F.D. Jr, Paul, J. (Eds), *Ethics and Economics*, Basil Blackwell, Oxford.

Shao, J. 2006. “Fluid Labor and Blood Money: The Economy of HIV/AIDS in Rural Central China,” *Cultural Anthropology,* Volume 21 Issue 4, 535-569.

Singer, E. 1981. “Reference Groups and Social Evaluations," in M. Rosenberg & R.H. Turner (eds.)

Social Psychology: Sociological Perspectives. New York: Basic Books, Inc.

Solnick, S. and D. Hemenway. 1998. “Is More Always Better? A Survey on Positional Concerns,” *Journal of Economic Behavior and Organization*, 37(3), 373-383.

Stark, O. and J.E. Taylor. 1991. “Migration incentives, Migration Types: The Role of Relative Deorivation,” *Economic Journal* 101: 1163-11178.

Steiner, P. 2003. “Gifts of Blood and Organs: the Market and “Fictitious” Commodities,” *Revue française de sociologie,* Volume 44, 147-162.

Stutzer, A. 2004. “The Role of Income Aspirations in Individual Happiness,” *Journal of Economic Behavior and Organization* 54(1): 89-110.

The Economist. 2007. “Can Ghanaians afford such splendid funerals?” May 24.

Titmuss, R. 1970. “*The Gift Relationship*,” Allen and Unwin, London UK; Reprinted 1997., LSE Books, London, UK.

Tsang, K. 2003. "Blood Plasma Economy Accelerates AIDS Crisis in China," *Sing Tao Daily*. August 01.

Van de Stadt, H., A. Kapteyn, and S. Van de Geer. 1985. “The Relativity of Utility: Evidence from Panel Data,” *Review of Economics and Statistics*, 67(2), pp. 179-187.

Veblen, T. 1899. “*The Theory of the Leisure Class*,” MacMillan, New York.

Wasserman, S. and Faust, K. 1994. “*Social Network Analysis: Methods and Applications*,” Cambridge: Cambridge University Press.

Wei, S. and X. Zhang. 2011a. “The Competitive Saving Motive: Evidence from Rising Sex Ratios and Savings in China,” *Journal of Political Economy*, 119(3): 511-564.

Wei, S. and X. Zhang. 2011b. "Sex Ratios, Entrepreneurship, and Economic Growth in the People‘s Republic of China," *NBER Working Papers 16800*.

Wildman, J. 2003a. “Modeling Health, Income and Income Inequality: the Impact of Income Inequality on Health and Health Inequality,” *Journal of Health Economics,* 22: 521-538.

Wildman, J. 2003b. “Income Related Inequalities in Mental Health in Great Britain: Analyzing the Causes of Health Inequality over Time.” *Journal of Health Economics,* 22: 295-312.

Wilkinson, R.G. 1997. “Health Inequalities: Relative or Absolute Material Standards?” *British Medical Journal* 314: 591-595.

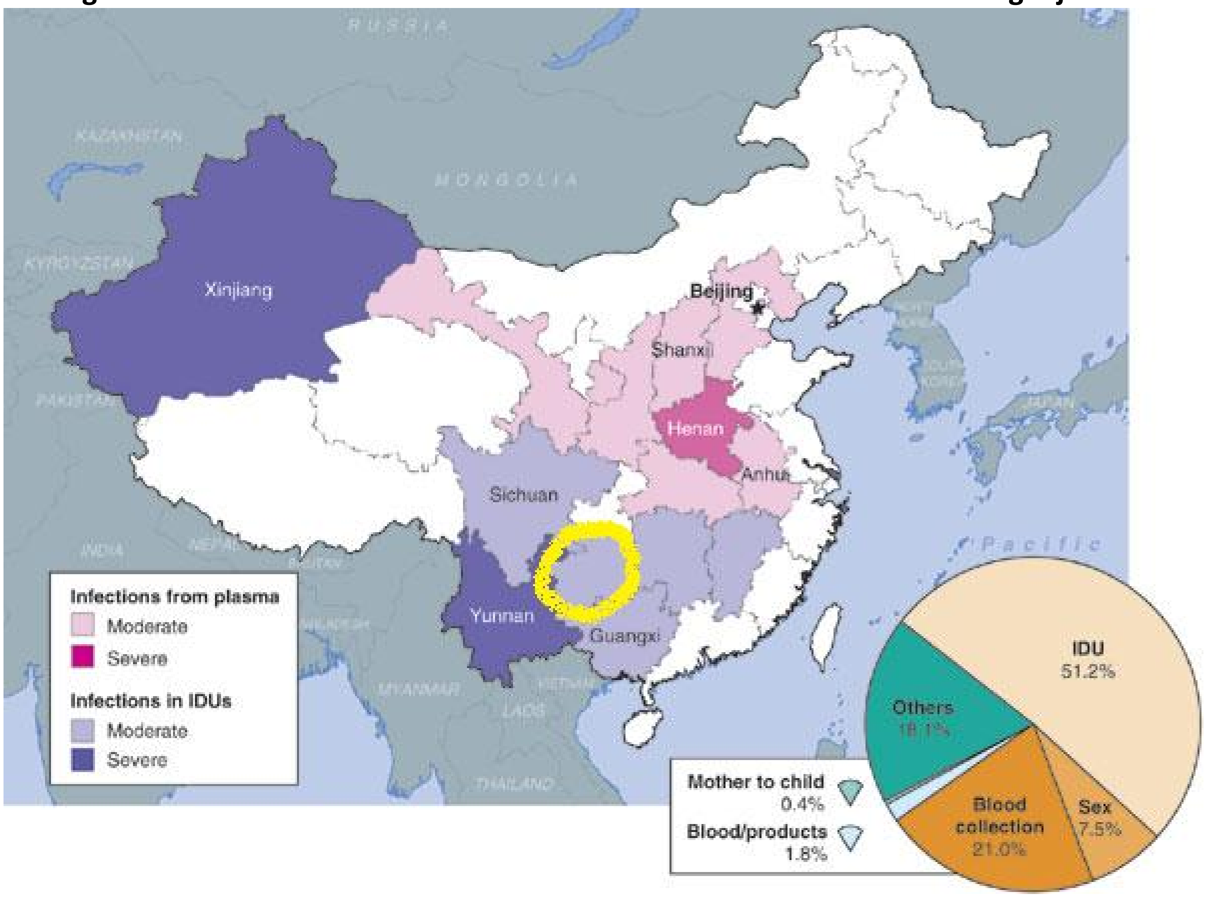
Wu, Z., K. Rou, and R. Detels. 2001. “Prevalence of HIV infection among former commercial plasma donors in rural eastern China,” *Health Policy and Planning*, 16: 41-46.

Yan, Y. 1996. “*The Flow of Gifts: Reciprocity and Social Networks in a Chinese Village,”* Stanford: Stanford University Press.

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://www.nfcmag.com/ReadNews.asp?NewsID=5831.

Yitzhaki, S. 1979. “Relative Deprivation and the Gini Coefficient,” *Quarterly Journal of Economics* 93(2), 321-24.

Figure 1 Prevalence of HIV-AIDS Infected from Blood Collection and Drug Injection



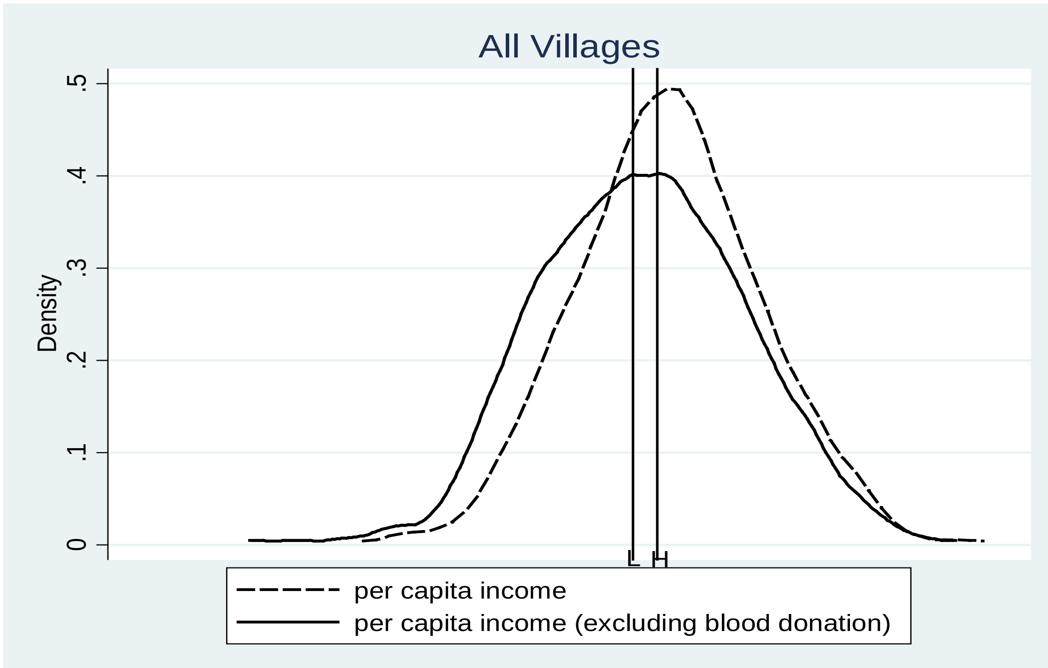
Source: Cohen (2004).

Notes:

[1] This figure describes the situation of HIV infection up to 2004. Outbreaks of HIV infection in China have been mainly caused by drug injection (IDUs) and plasma collection, which altogether have accounted for more than two thirds of China's HIV infection, and 250,000 blood plasma donors became infected by 2004 (Cohen, 2004). The infected population is distributed in specific regions: the pink area is mainly affected by plasma collection, while the blue area is mainly influenced by drug injection. The darker the color, the more severe infection there is.

[2] The area in yellow is Guizhou province, which was not a major HIV infected area due to either drug injection or plasma collection up to 2004.

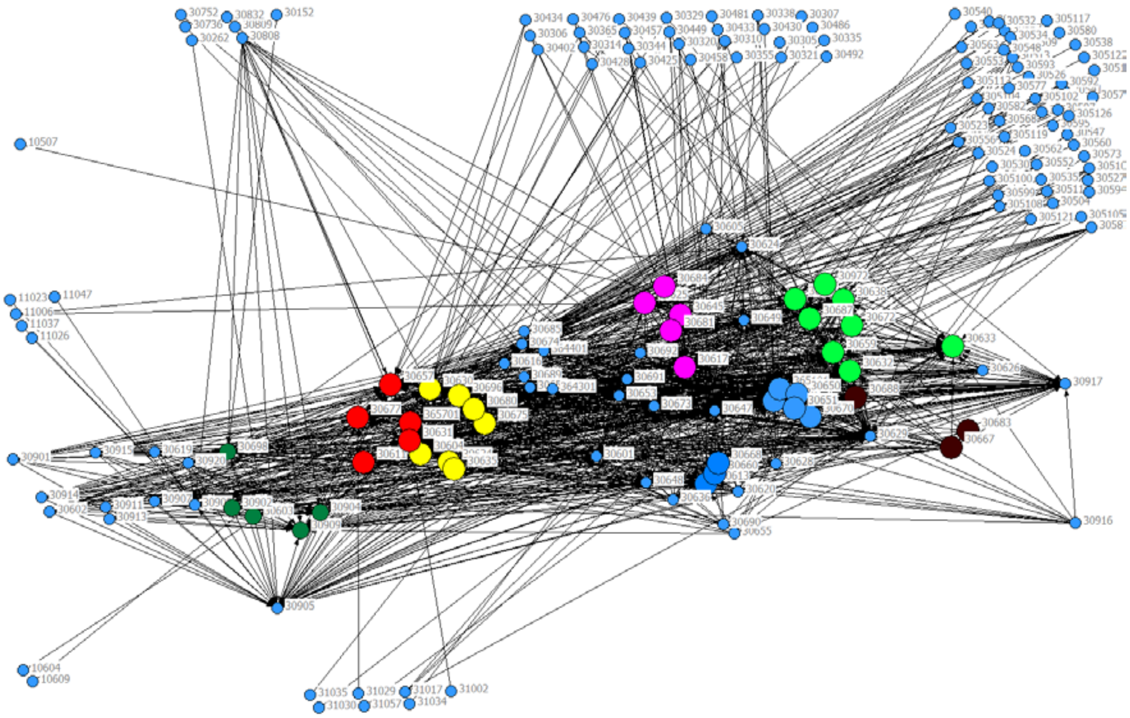
Figure 2 Distribution of Per Capita Income Including / Excluding Plasma Donation



Source: Authors' 2004 survey data

Note: Two vertical lines, "L" and "H", refer to the low (668RMB) and high (892RMB) official poverty lines stipulated by the Chinese government.

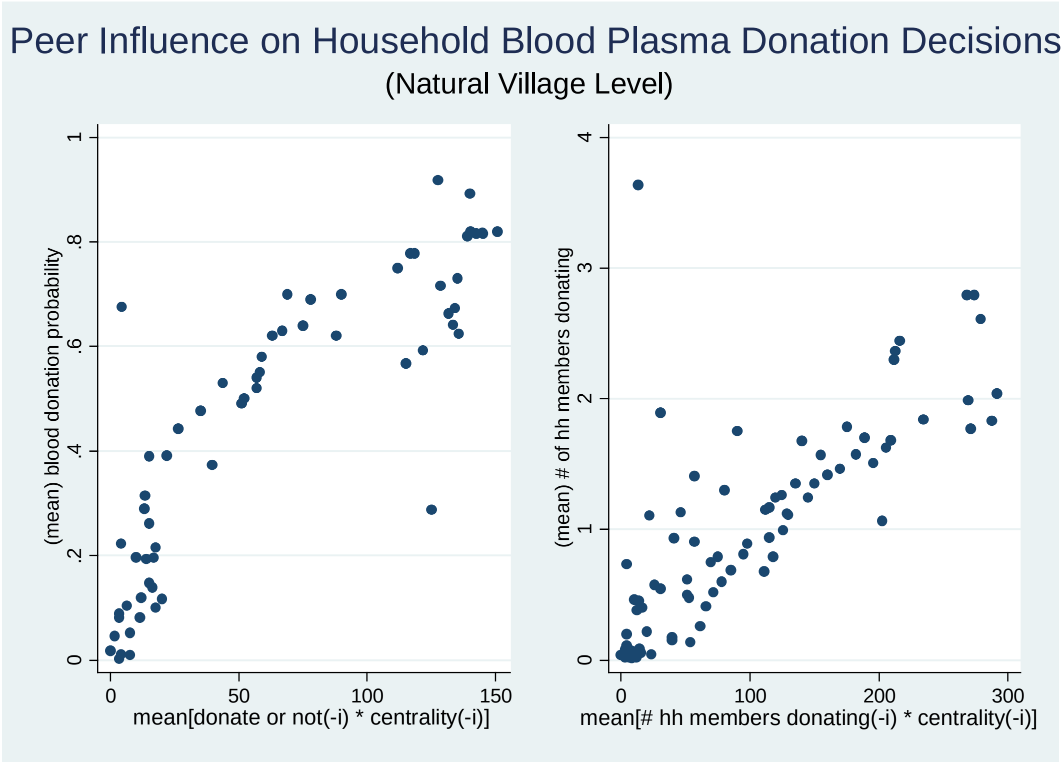
Figure 3 Long-term Gift Exchange Network in One Village



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 4 Peer Influence on Household Plasma Donation

(Probability and Number of Donors)



Source: Authors' survey data

Notes: The horizontal axis weights each peer's plasma donation decisions, including whether to donate (left figure) and how many household members engage in (right figure), by its gift network centrality and takes the mean value. Mean value is further taken at the village level. The vertical axis takes the mean of own plasma donation decisions at the village level. Each dot represents one village.

Table 1 Baseline Summary Statistics (2004)

	Total
Number of villages	26
Distance to county seat (km)	6.8
Number of households	801
Total population	3073
Share of minority households (%)	30.8
Share of household members aged 60 and above (%)	14.1
Share of households with migrants (%)	41.4
Share of household members who migrate (%)	12.4
Male head of household (%)	92.8
Education of household head (years)	4.44
Household average year of schooling	2.97
Per capita cultivated land (mu)	0.98
Percentage of flat land (%)	53.4
Land rental rate (Yuan per mu)	60
Share of households with TV (%)	50.3
Share of households with bicycles or motorcycles (%)	10.9
Share of households with phones (%)	17.2
Having difficulty with access to drinking water	59.9
Share of households with local non-farm jobs (%)	56.6
Share of households with self-employment (%)	6.6

Source: Authors' survey data

Table 2 Summary Statistics on Income and Consumption Components (2004-2009)

	Total		
	2004	2006	2009
Main Sources of Income (Percent)			
Farming	33.3	31.4	33.1
Livestock	8.1	6.8	6.9
Local non-farm and self-employment	24.0	30.0	23.8
Remittance from migrants outside the county	8.0	13.1	8.8
Disaster relief, anti-poverty programs, deforestation subsidies	2.8	2.0	5.4
Gift income	5.6	9.1	8.2
Plasma donation income	20.9	4.3	6.1
Main Expenditures (Percent)			
Food	47.8	42.2	35.5
Clothing	4.0	4.6	4.2
Fuel	8.4	8.3	7.5
Telephone	1.4	3.0	5.5
Medical care	16.4	15.8	13.5
Education	8.7	11.7	12.9
Gift and festival spending	7.9	13.9	15.2

Source: Authors' survey data.

Table 3 Summary Statistics on Poverty and Income Inequality (2004-2009)

	Total		
	2004	2006	2009
Per capita annual income (RMB)	1404	1817	2855
Income inequality (Gini)	43.1	48.2	55.2
Income inequality excluding plasma donation (Gini)	46.3	49.0	56.6
Income below poverty line of 892 RMB (%) (P0)	37.3	36.3	22.4
poverty-gap below poverty line of 892 RMB (P1)	14.5	15.0	10.1
squared poverty-gap below poverty line of 892 RMB (P2)	7.5	8.3	6.4

Source: Authors' survey data.

Table 4 Summary Statistics on Paid Plasma Donation (2004-2009)

	Total		
	2004	2006	2009
Participation rate in donating plasma (%)	31.2	10.1	14.1
Mean per capita plasma donation (RMB)	163.2	28.6	93.8
Cash compensation (nutrition subsidy) for plasma donation (580cc)	80	80	150
# households without plasma donor	552	749	749
# households with one plasma donor	235	66	97
# households with two or more plasma donors	15	18	26

Source: Authors' survey data

Table 5a The Impact of Peer Effects on Paid Blood Donation Probability (2004-2009)

	R1	R2	R3	R4	R5
	Network Peer Group + Link				
	OLS	GS2SLS	GS2SLS	GS2SLS	GS2SLS
Lagged peers' Mean plasma donation probability	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 & indirect network fixed effects	No	No	No	No	Yes
F test excluded instruments	-	103.13	61.20	11.83	12.13
p-val over-identification test	-	0.265	0.186	0.184	0.247
(Pseudo) R2	0.064	0.198	0.330	0.339	0.363
N	552	552	552	552	552

Notes:

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

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

[3] The identification strategy follows (Bramoullé et al., 2009). The excluded instruments used in each estimation are the following characteristics of excluded peers: per capita income excluding blood donation compensation, household size, ethnicity, education, share of the elderly, share of unmarried son, relative market wage to blood donation compensation, cadre status, travel time to the local blood bank, and major shocks (including big 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 The Impact of Peer Effects on Income from Paid Blood Donation (2004-2009)

	R1	R2	R3	R4	R5
	Network Peer Group + Link				
	OLS	GS2SLS	GS2SLS	GS2SLS	GS2SLS
Lagged peers' Mean income from plasma donation	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 & indirect network fixed effects	No	No	No	No	Yes
F test excluded instruments	-	103.17	61.34	11.36	11.65
p-val over-identification test	-	0.223	0.136	0.143	0.197
(Pseudo) R2	0.078	0.208	0.329	0.344	0.366
N	552	552	552	552	552

Notes:

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

[2] The identification strategy follows (Bramoullé et al., 2009). The excluded instruments used in each estimation are the following characteristics of excluded peers: per capita income excluding blood donation compensation, household size, ethnicity, education, share of the elderly, share of unmarried son, relative market wage to blood donation compensation, cadre status, travel time to the local blood bank, and major shocks (including big diseases, livestock deaths, natural disasters, and family member deaths).

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

Table 5c The Impact of Peer Effects on Number of Family Members Engaging in Paid Blood Donation (2004-2009)

	R1	R2	R3	R4	R5
	Network Peer Group + Link				
	OLS	GS2SLS	GS2SLS	GS2SLS	GS2SLS
Lagged peers' Mean # family members donating	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 & indirect network fixed effects	No	No	No	No	Yes
F test excluded instruments	-	123.37	60.72	14.67	15.00
p-val over-identification test	-	0.447	0.104	0.397	0.535
(Pseudo) R2	0.110	0.225	0.358	0.361	0.384
N	552	552	552	552	552

Notes:

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

[2] The identification strategy follows (Bramoullé et al., 2009). The excluded instruments used in each estimation are the following characteristics of excluded peers: per capita income excluding blood donation compensation, household size, ethnicity, education, share of the elderly, share of unmarried son, relative market wage to blood donation compensation, cadre status, travel time to the local blood bank, and major shocks (including big diseases, livestock deaths, natural disasters, and family member deaths).

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

Table 6: Effect Sizes

	(1)	(2)	(3)	(4)
	S.D. Blood Donation σ_Y	S.D. Peer Blood Donation σ_{GY}	Peer Effects $\hat{\beta}$	Effect Size $\sigma_{GY}\hat{\beta} / \sigma_Y$
Blood donation probability	0.368	0.182	0.250	0.124
Blood donation income (log)	2.488	1.241	0.303	0.151
# family members donate	0.496	0.245	0.469	0.232

Notes: The estimates of peer effects in column (3) are taken from the scenario R4 in Table 5 (a)-(c).

Table 7 Peer Effects with Alternative Weightings

Peers' mean prior paid donation behavior	R1 Donate or Not	R2 Donation value	R3 # hh members donate
1. Baseline (weighed by pairwise link)	0.250**	0.303**	0.469**
	(0.125)	(0.123)	(0.135)
2. Weighed by pairwise link intensity	0.153	0.205*	0.297**
	(0.119)	(0.117)	(0.129)
3. Weighed by out-degree centrality based on number of links	0.236**	0.284**	0.438***
	(0.121)	(0.119)	(0.129)
4. Weighed by out-degree centrality based on link intensity	0.202*	0.259**	0.394***
	(0.122)	(0.120)	(0.130)
5. Weighed by in-degree centrality based on number of links	0.234**	0.280**	0.381***
	(0.115)	(0.113)	(0.123)
6. Weighed by in-degree centrality based on link intensity	0.173	0.220**	0.281**
	(0.110)	(0.109)	(0.118)
7. Weighed by Bonacich centrality based on pairwise link	0.249**	0.298**	0.501***
	(0.127)	(0.125)	(0.135)
8. Weighed by Bonacich centrality based on link intensity	0.219*	0.283**	0.331***
	(0.117)	(0.113)	(0.123)

Note:
[1] Indegree centrality measures number (intensity) of links the respondent receives from peers.
[2] Outdegree centrality measures number (intensity) of links the respondent sends out to peers.
[3] Bonacich Centrality measures direct and indirect connections one has in one's neighborhood. Besides direct links, the more connections the actors in one's neighborhood have, the more central one is.

Table 8 Other Tests on Peer Effects

	R1	R2	R3
Peers' mean prior paid donation behavior	Donate or Not	Donation value	# hh members donate
1. Baseline	0.250**	0.303**	0.469**
	(0.125)	(0.123)	(0.135)
2. Testing reference groups: using placebo groups	-0.095	-0.102	-0.055
	(0.118)	(0.118)	(0.117)
3. Testing potential mechanism: expectation interactions that diffuse information or preference interactions that change stigma?	0.499***	0.528***	0.620***
	(0.167)	(0.164)	(0.163)

Notes:

[1] Robust standard error in parentheses;*significant at 10%;**significant at 5%;***significant at 1%.

[2] It is hypothesized that influence flows from the gift receiver to gift presenter, but not necessarily vice versa. A gift, especially in impoverished regions, means that a relationship matters to the gift giver. New work in the econometrics of networks and sociology confirm that exploiting directionality in networks is a useful identification strategy (Freeman, 1979; Bramoulle et al., 2009). Fortunately, the gift record allows us to test the directional hypothesis.

[3] In this table, there is no evidence that gift receivers are influenced by gift presenters, providing additional evidence in favor of the causal interpretation regarding social influence in plasma donation behaviors. If contextual effects are spuriously driving the relationship between ego (gift sender) and alter (gift receiver), there is no reason to expect a directional result. The context should cause both sides to move up and down simultaneously; hence, if I find a significant effect in one direction, I should also find it in the other: the gift sender should appear to have an influence on the gift receiver. Since no such a significant effect is found, it is believed that the evidence from the gift record is suggestive of a causal effect.

[4] Panel 3 uses sample after the shutdown and reopen of local blood bank (2007 - 2009). Only households after the outbreak of Hepatitis C epidemic and who are informed are included in the estimations.

[4] Other notes follow Table 5a.

Table 9 Various Social Ties and Paid Blood Donation

	R1 Donate or Not	R2 Donation Value	R3 # family Members Donate
	Panel A: Kinship Networks		
Peers' mean prior paid donation	0.067	0.096	0.252**
	(0.118)	(0.115)	(0.123)
	Panel B: Close Kinship Networks		
Peers' mean prior paid donation	0.240**	0.268**	0.290***
	(0.114)	(0.110)	(0.112)
	Panel B: Non-Kinship Networks		
Peers' mean prior paid donation	0.060	0.112	0.260*
	(0.125)	(0.123)	(0.139)
	Panel C: Cash Gift Networks		
Peers' mean prior paid donation	0.137	0.190*	0.297**
	(0.119)	(0.116)	(0.129)
	Panel D: In-Kind Gift Networks		
Peers' mean prior paid donation	0.282**	0.325***	0.359***
	(0.121)	(0.118)	(0.129)
N	552	552	552

Notes: follow Table 5a.