Peer Effect, Risk-Pooling and Status Seeking: Which Matters to Gift Spending Escalation in Rural China? †

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Xi Chen Xiaobo Zhang

Abstract

It has been widely documented that the poor spend a significant proportion of their income on gifts even at the expense of basic consumption. We test three competing explanations to this phenomenon, peer effect, status concern, and risk-pooling, based on a census-type primary household survey in three natural villages in rural China and detailed household records of gifts received in major occasions. The gift giving behavior is largely influenced by peers in the reference groups. Status concern is another key motive for "keeping up with the Joneses" in extending gifts. In particular, the poor with sons spend more on gift giving in proportion to their income than their rich counterparts in response to the tightening marriage market. In contrast, risk pooling does not seem to be a key driver of the observed gift giving patterns. Large windfall income to a large extent triggers the escalation of gift giving behavior.

Keywords: Social Network, Peer Effect, Risk-pooling, Status Seeking, Gift-giving, Ceremony
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"*If friends make gifts, gifts make friends.*" Marshall Sahlins, 1972

1. Introduction

It has been widely documented that many of the poor spend a significant portion of their limited income on social spending, such as splendid funerals (*The Economist*, 2007; Mango et al., 2009), roaring bride-prices and dowries (Rao, 1993; Dekker and Hoogeveen, 2002), lavish festivals (Banerjee and Duflo, 2007), at the expense of their basic nutrition intake (Deaton and Subramanian, 1996; Strauss and Thomas, 1997; Chen and Zhang, 2010). Peer pressures, status concerns, and risk pooling, are three notable explanations to this observed puzzle in the literature.

Many of the poor live in a closely knitted community. Their behavior is deeply influenced by their peers in the reference group. Peer effect can generate both positive and negative externality. On the positive side, peer pressure may facilitate technology adoption and social learning (Benabou, 1993; Hoxby, 2000; Glaeser and Scheinkman, 2001; Conley and Udry, 2010). However, peer pressure can also induce socially undesirable behavior, such as Juvenile delinquency (Haynie, 2001). It is likely that one's gift giving behavior is influenced by peers as well.

Gift giving may also signal wealth and social status. If a higher social status is associated with greater rewards, such as higher likelihood of marriage for offspring, then concerns for status may intensify gift giving competition. The competitive pressure is especially large for the lower tail of the distribution (Deaton, 2001; Brown et al., 2011, thereafter BBZ) because of the unfavorable marriage market conditions for the poor.

Gift giving behavior has accompanied human beings for thousands of years. Facing various natural and man-made shocks, people have used gifts giving as a means of smoothing shocks and mitigating risks. For example, funeral is very costly in many developing countries. It is hard for a family to come by the funeral expenses by itself. As a result, it is quite common that people extend gifts when attending funerals. The pooled resources can largely defray the funeral expenses. In this sense, the gift expenditures to others can be regarded as insurance premiums (Rosenzweig, 1988;

Coate and Ravallion, 1993; Townsend, 1994). It is likely risking sharing represents another key motive of gift giving.

Previous studies have investigated the behavior of gift giving separately from the angles of risk-sharing (Fafchamps and Gubert, 2007, thereafter FG), status concern and peer pressure (BBZ). In this paper, we attempt to simultaneously disentangle the three factors using a three-wave census-type household panel dataset combined with well-kept gift records for all households in three natural villages in rural China.

Our datasets have several salient features. First, because we have detailed income and expenditure information for all the households in the sampled villages over three periods, we are able to measure relative social status and examine its impact on gift giving along a wide spectrum of income distribution. Second, the complete gift records enable us to match gift givers and recipients, thereby providing us with an effective way to identify the role of risk pooling in gift giving behavior along several dimensions. Third, the long-term gift records capture the dynamics of gift giving activity, such as its recent escalation, and the resulting large variation in reference groups across occasions and over time circumvents the main identification problems. Fourth, the gift records advance the literature on network formation through gift values, since it is often that relationship intensities matter more to behavior than connections themselves.

As a preview of the main results, we find that the gift giving behavior is largely influenced by peers in the reference groups. Status concern is another key motive for "keeping up the Joneses" in extending gifts. In particular, the poor with sons spend more on gift giving in proportion to their income than their rich counterparts in responding to the increasing marriage market squeeze. In contrast, risk pooling is not a key driver of the observed gift giving patterns. Moreover, gift giving is largely reciprocal in China. After a small group of people received unexpected windfall income, they started to extend more generous gifts to others. Others have to follow suit, triggering the escalation of gift expenditure.

This paper is organized as follows. Section 2 documents the patterns of gift giving in rural China; section 3 discusses data; section 4 lays out our basic analytical framework;

section 5 discusses main issues in peer effect identification and its relevance to our strategy; section 6 specifies the empirical model; section 7 presents main results on the determinants for gift spending and its escalation; finally, section 8 concludes with further discussion.

2. Gift Giving in Rural China

Gift exchange is commonly practiced in developing countries but rarely documented in the economics literature. The Chinese society is largely relationship (*Guanxi*) based and gift exchange plays an important role in maintaining *Guanxi*. Gift giving is largely reciprocal. One is supposed to pay back previously received gifts later on according to the prevalent market price of gift giving.

The analysis of gift giving in rural China is based on our surveyed villages in rural Guizhou (Table 1). Table 2 presents gift expenditure per occasion and the number of guests in come-of-age ceremonies, weddings, and funerals over time. The average gift size has increased steadily in all the four occasions, so is the number of guests participated. However, the rising gift size is not sufficient to cover the total expenditures in these events. As shown in Table 3 on the total expenditures for the four types of events, the median expenditure of come-of-age ceremony costs more than 8,000 RMB, while on average the host of such an event nets only 3782 RMB. In other words, the host has to cover more than 54% of the expenses out of his own pocket. The gap is even much larger for wedding ceremonies among groom families: the amount of gift received accounts for only 20% of total expenditure in 2009.

Figure 1 presents the share of gift expenditure by income quartiles over our three-waves in China and other countries. The three dashed circles highlight our three-wave surveys. Over time, the share of gift and festival expenditure has increased steadily. There is an increasing spread in the share of gift and festival expenditure among four income quartiles. The poorer a household, the higher share of consumption is devoted to social spending, and the faster growth the share of gift and festival expenditure is observed between 2004 and 2009.

Figure 2 plots the annual growth rates of gift spending, consumption and income over the period of 2005-1009. Annual gift growth rates range from 18% to 45% in three villages, much higher than the 10% annual growth rate of per capita consumption. While the share of expenditures allocated to food dropped from 48 to 42 percent, the share of spending on gifts and festivals soared from 8 to 17 percent. Apparently, gift spending escalation is an acute phenomenon in this impoverished region.

3. Data Collection

3.1 Three-Wave Census Survey

The household information for this study comes from three waves of census-type household survey conducted by us in 18 selected natural villages in rural Guizhou, China.[1] They are both geographically isolated and ethnically diversified. Local residents know each other well. Most residents' kinship networks are confined in these villages. More than 20 ethnic groups are living in the area, including Han, Miao, Buyi, Gelao, and Yi. In total, ethnic minorities comprise about 20% of population.

The three rounds of surveys in 2005, 2007 and 2010 cover 801, 833 and 872 households, respectively.. The differences in sample size largely reflect demographic changes. All three waves include detailed information on household demographics, income, consumption, and transfers. Transfers include gifts received and extended.

3.2 Gift-Exchange Record Collection

Rural households usually keep the records of gift received in major occasions for a long period because they have to pay back accordingly when the gift givers hold a social event (Yan, 1996).[2] In the survey area in Guizhou, we find that all the households keep a gift book. We used digital camera to take pictures of the gifts recorded in the books for

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

[2] Yan (1996) writes, "Ritualized gift giving is also associated with the custom of making and preserving gift lists. Gift lists are homemade books on red paper (funeral gift lists are made on yellow paper) inscribed with a traditional Chinese calligraphy brush. They serve as a formal record of all gifts received by the host of a family ceremony."

major occasions (i.e. male members' wedding, female members' wedding, funeral, coming-of-age ceremony, child birth ceremony, and house-moving ceremony) in the period of 2000-2009 for all the households in three natural villages in the early 2010. The three natural villages are selected from the eighteen natural villages (three administrative villages) where the three-wave census survey was conducted (Table 1). In each administrative village, we selected the natural village with the most centered location to collect gift receiving records.

The unique Karst landform keeps the three villages isolated from the outside society. Among them, village 1 is the most remote (10 kilometers away from the county seat with poor road access), and the local custom is well preserved. To the contrary, village 3 is only 2.5 kilometers away from the county seat. It is the most vulnerable to external changes, such as the recent social spending inflation. In between, village 2 is populated with Buyi ethnic minority, who preserve the Catholic culture and ceremony tradition different from the major Han villages (e.g. village 1 and village 3). In major public ceremonies in village 2 people generally participate in the events (e.g. Halloween and Christmas) without bearing huge burden on gift exchange.[3] Since the surveyed villages are populated with Han group and ethnic minorities, we are able to explore social connections between ethnic groups.

Based on the gift record books, we identify 335 households including 160 households from the three natural villages and 175 households from the other fifteen villages covered by our large scale household survey. Once joining gift exchanges, most people remain active. A great proportion of previously inactive households become active at the end of each period.

Figure 3 shows a map of gift network in one of the three villages. In total, 8074 gift links during 2000-2009 are identified among 9820 potential links. These potential links include all households in the hosts' local villages and the identified links between local villages and other fifteen surveyed villages, whether there was a gift given. The assumption is that all households in the same village know each other and the dates of

[3] A major difference in this aspect between public celebrations in India and household ceremonies in China can be found in Rao (2001) and Chen (2009).

ceremonies. Given the geographic and local social environment, it is exactly the case. Meanwhile, 4611 cross-county/township gift links among 4924 potential links were recorded. These potential cross-township/county links include all the recorded cross-township/county links and zero-gift-flow links between the hosts and their brides' side blood relatives recalled by each household. Every effort was made to identify these potential but nonexistent gifts to circumvent sample attrition and sorting problem during our record collection process. Nearly all households' gift-receiving records for the ceremonies were included in this study, since less than 5 percent households reported gift book loss or damage.[4]

If all family members are illiterate, a group of two or three educated relatives usually help record gift-giving on the celebration days. However, names on the records are usually nicknames which might not be precisely identified. To solve this problem, we showed a name list to each household to facilitate their identifying the names on the records.[5] We also consulted many local people to help identify the nicknames.

Information on kinship and relatedness among villagers was also collected and matched to each gift link. The information was verified under the help of village leaders, the elderly as well as local elites. As many other rural communities, each of the three surveyed villages is resided with several major clans. Taking village 3 in Figure 3 as an example, households in the same clan usually live closer to each other due to historical reasons. Gift-exchanges are more prevalent within a clan than across clans.

4. Risk-Pooling and Network Formation: An analytical Framework

In the literature, most studies tie back pairwise link formation to individual decisions. The separability of the utility function is imposed that the utility derived from the network is equal to the sum of the utilities brought by each link, and these link-specific utilities are not affected by the structure of the network. Follow the

[4] We consulted major ceremonies with village leader and local residents to verify before going to individual families. Meanwhile, this prior information helped households recall and find gift books for us.
[5] Meanwhile, the name list made it easier to identify people who did not send gift to each family I visited and their relationships with the families, which are very important to the understanding of network formation.

conventional setting (De Weerdt, 2004; Udry and Conley. 2005; FG, 2007), we define the existence of a link (L_{ij}) between two nodes of distance d_{ij}. A link is established when the benefit from a link $(B(d_{ij},1)-B(d_{ij},0))$ exceeds its maintenance cost $C(d_{ij})$. Since distance does not explain all aspects of link formation, a residual e_{ij} exists. Specifically,

$$L_{ij}=1 \text{ if } [B(d_{ij},L_{ij}=1)-B(d_{ij},L_{ij}=0)]-C(d_{ij})+e_{ij}>0 \quad (1)$$

Social distance d_{ij} involves indicators of multiple dimensions: spatial distance, family characteristics and relatedness, shared activities and so on. The longer the social distance, the less homogeneous shocks there are, and the more monitoring and enforcement difficulties there might exist. Therefore, both the benefit and cost of link formation should increase with social distance d_{ij}, leading to a trade-off between the scope and ability to mutual insurance in the networks. Yet, the effect of multi-dimensional social distance on link formation is subject to empirical investigation.

First, income pooling should be more effective between households engaged in different activities/occupations, such as between farmers and non-farm migrant workers in our context. The former is determined by weather conditions and pest infestation, while the latter depends on economic prosperity and is expected to be uncorrelated with the former. However, households with different occupations usually have less common ground to socialize with each other.

Second, taking care of kids and elderly is another form of risk-sharing than income pooling. Young households with children are faced with different health risks from the elderly and more capable of helping each other. Therefore, households with large difference in age structure have the potential to insure each other. However, their social interactions might be limited due to differences in lifestyle.

Third, due to the potential inter-household externalities to education, links between the better educated and the less educated are more attractive to poor households than to their rich counterpart. Similarly, the poor usually have stronger motivation to link the rich. Since, link formation is directional and the incentives behind are asymmetrical, social distance should capture this trend.

Kinship may strengthen link formation as it reflects history, norms and trust in a community. Given certain geographic closeness, blood relations facilitate punishing uncooperative behavior. From a Darwinist's perspective, helping family members is a way to expand the gene pool.

Level effect should also be included in the framework (1) to explore whether households with certain common characteristics tend to link. For instance, it is expected that wealthier and higher educated people tend to link each other, and households with higher share of the elderly/kids are less likely to link. The wealth effect is captured by per capita income. Because networks affect the ability to generate income, income is endogenous to the network and is thus instrumented in the first stage estimation.[6]

The framework to this point ignores peer influence in shaping one's link formation decisions, which works in the same direction as the risk-pooling motive and may blur the identification. In a traditional rural society, peer influence matters as communities are isolated and people have close relations.

Furthermore, the framework does not clearly consider the role of status. Unlike information networks, gift networks in social occasions help climbing social ladders and mobilizing resources in the future. The fact that status seeking works in the same direction as risk-pooling and peer influence makes its identification important.

5. Peer Effect Identification

Although peer effect has been studied for decades, no consensus has been reached on its significance and magnitude due to criticisms on identification (Manski, 1993;

[6] Since social network affects the capability of income generation, income is potentially endogenous to network formation process. Households with better networks may earn higher income. Therefore, we instrument per capita income with variables predate the formation of gift links, including education of the head, size of the head's lineal family, major family productive assets (e.g. cow, horse and farming machines), inherited land size, number of working members in a household, gender of the head, whether the head is a cadre, and shocks suffered during the year. Since income enters the dyadic regressions in difference and sum, we separately instrument the difference and sum in per capita income (Appendix I). Most instruments have strong predictive power, especially land, cow, relative network size, education and shocks.. Predicted sum and difference in per capita income are used in lieu of actual income in the estimations that follow. Predicted per capita income rather than predicted wealth is used, because it is believed to be more precise than an index of wealth evaluated at subjective prices, especially in the context that a great proportion of family assets are composed of housing.

Moffitt, 2001; Brock and Durlauf, 2001). Even less is known about the mechanisms through which it operates. Three identification challenges lay in front of peer effect identification: first, the reflection problem persists as people influence each other in a group, which hinders our judge on whether one's action is the cause or the effect of peers' actions. Therefore, identification of endogenous effect from contextual effect is made possible only when strong exclusion assumption is made that an influencing factor of individual outcomes does not indirectly affect peers' outcomes; second, correlated effect confound the identification because people usually endogenously form peer group and /or are affected by common group characteristics (e.g. common shocks in the development literature and teacher effects in the studies of education) and thus behave similarly; third, the real group within which people interact with each other is *a priori* unknown.

5.1 The Reflection Problem

Many studies do not reliably tackle the reflection problem, leaving endogenous and exogenous effects entangled in the peer effect estimation. Among the two effects only the endogenous effect can generate social multiplier with policy implications, therefore studies never give up finding effective solutions.

The most frequently utilized way to isolate the two effects is to instrument peers' behavior with their lagged behavior (Hanushek et al., 2003) or the lagged treatment they received (Boozer and Cacciola, 2001). The reflection problem can also be mitigated by specifying a non-linear setting other than the linear-in-mean model (Manski, 1993; Brock and Durlauf, 2001). Recently, Bobonis and Finan (2009) attempts to apply an instrumental strategy that isolates endogenous effect under a partial-population experiment setting that directly affect the behavior of some but not all group members. More recent studies also utilize network information or partially overlapping groups to circumvent the reflection problem (De Giorgi et al., 2010).

Since peer groups are perfectly overlapped across individuals in the standard framework, it is difficult to distinguish endogenous effect from exogenous effect

(Manski, 1993). Our paper takes lagged median behavior of the group by occasion to break down the reflective influence and utilizes detailed network information to disentangle endogenous effect. Meanwhile, an alternative framework presented in this paper adopts individual-specific peer groups based on one's gift receivers. Since households in the villages sometimes attend different social events, this guarantees the existence of excluded peers that are not in one's group but are in the group of one's peers. De Giorgi et al. (2010) show how this within-group variation enables us to identify endogenous effect even without an instrumental variable approach in absence of correlated effects. Adopting the same logic, Calvó-Armengol et al. (2009) releases the excluded peers' requirement by the assumption that strength of the interactions declines with distance in the network, and the identification is still achieved.

5.2 Correlated Effects

To separate peer effect from correlated effects, some studies use randomly assigned peers (Sacerdote, 2001; Zimmerman, 2003), some use conditional variance restrictions that disentangle excess variance due to peer effect from that due to group-level sorting (Graham, 2008), and some use composition variations of adjacent cohorts within schools to identify peer effect (Hoxby, 2000; Gibbons and Telhaj, 2008; Ammermuller and Pischke, 2009).

Similar in spirit to Hoxby (2000) and Gibbons and Telhaj (2008), our peer effect identification utilizes variations in the size and composition of guests attending each social event. The longitudinal structure of the data allows us to track each household's previous peers and distinguish between new peers and old peers. The large variations in group size and that new peers account for a great proportion in each occasion provide us a chance to reliably identify peer influence. However, the presence of correlated effects in this study may come from two sources: unobservable group shocks and endogenous group formation.

To tackle the first issue of common unobservable shocks, we apply an instrumental variable approach where lagged all peers' median gift per occasion in the groups is

instrumented with median gift per occasion from out-of-township new peers. The surveyed villages are isolated from outside towns due to the unique Karst landform. On the one hand, the geographic distance limits the spread of common shocks and information sharing, which mitigate the concern for common unobserved factors. Information sharing is further restricted due to the fact that in the patrilineal culture fellow villagers attending male side ceremonies have little connection with brides' external relatives. On the other hand, new peers' median gift per occasion is highly correlated with that of all peers by construction. The two nice features of out-of-township new peers create a good instrument.

To mitigate the concern for self-selection into gift groups, reference groups are defined in line with village boundaries and brides' external blood relatives' network. The traditional patrilinear culture and land allocation system in rural China determine that most males stay in birth villages, while most females migrate out upon marriage. Brides' blood relatives are usually invited to attend major occasions. Since local geographic isolation from outside restricts social connections, most out-of-township new peers are brides' blood relatives. Meanwhile, all households in each village know each other and social events well due to close local connections for generations.

Based on these facts, only brides' external blood relatives among these new peers, whether they sent gifts or not, are included to construct the instrument. With the help of gift record, we are able to figure out local villagers who sent gift as well as who could but did not. All fellow villagers and brides' out-of-township blood relatives, whether they present gifts or not, are included in the peer group that defines the instrumented variable, which circumvents the endogenous group formation that confounds the identification of peer effect.

Similar to the robustness check in Dercon and Broeck (2007), group characteristics are controlled to further test the possibility that individuals endogenously sort themselves into groups due to certain unobservable characteristics or abilities.

The remaining potential problem of correlated effects arising from unobserved individual and group effect is taken care of in our longitudinal fixed effect estimations.

5.3 Reference Group Definition

In the literature, the definition of peer groups varies substantially, from the most comprehensive national population to the very restrictive grade cohorts. Besides the level and degree of social interactions specific to the context and social mechanism, the large variations in the definition reflect how hard it is to establish who influences whom *a priori*. Most studies do not have that information due to data limitation and /or a thorough understanding of the specific context and social mechanism. Instead, they assume individuals in the population (sometimes partitioned into schools or villages) as potential peers and define peer influence based on average intra-group externality that affects group members identically. Another strategy is to pick at random many sets of potential peers to build a simulated likelihood (Mihaly, 2007).

In our study, the local unique karst landform facilitates well-defined reference groups in the context of isolated rural communities. Gift record during social events provides us a good chance to study the social mechanism of peer effect. Comparing kernel density estimates among social events, gift spending in each social event clusters round a different level, suggesting peer influence works through information sharing during occasions.[7] Therefore, in our main estimation reference groups for gift spending are defined according to gift presenters in each occasion.

However, this definition leads to largely overlapping peer groups. Borrowing from recent studies that utilize rich information on social networks to construct individual-specific reference groups (Calvó-Armengol et al., 2009; De Giorgi et al., 2010; Lin, 2010), we define reference groups for gift spending based on gift receivers to whom one presents gifts per year. This definition provides partially overlapping peer groups, since households sometimes attend different social events. A comparison of estimates from

[7] Most residents give gifts in events held in their natural villages. They do share information on the gift price per occasion. On the day of a ceremony, it is often that an educated person is responsible for keeping the record of gifts received. As a result, the market information on gifts giving is largely a common knowledge within a village.

the two peer group definitions tells us if peer pressure is more intense from fellow gift presenters or from gift receivers.

6. Empirical Strategy

6.1 Model Specification

Our main empirical estimations are dyadic regressions. In network analysis, a dyad is a pair of agents. Dyadic data contains two types of information: link attributes w_{ij} between nodes i and j and node attributes z_i and z_j for nodes i and j, respectively. Therefore, the data is normally transformed into level effect ($z_i + z_j$), social distance ($z_i - z_j$) and link attributes w_{ij} to best preserve information.[8] Since gift exchanges are directional, i.e. the outcome variable y need not satisfy $y_{ij} = y_{ji}$ for any i and j. Follow FG identification, let

$$y_{i,j,c,t} = \alpha_0 + \alpha_1 m[y_{-i,j,c,t-1}] + \alpha_2(z_{i,t} - z_{j,t}) + \alpha_3(z_{i,t} + z_{j,t}) + \alpha_4 RD_{i,t} + \psi w_{i,j,c,t} + \gamma_i + \phi_t + \varepsilon_{i,j,c,t} \quad (2)$$

where -*i* denotes peers. $y_{i,j,c,t}$ is the actual gift guest i presented to the host j in an occasion c at time t. $w_{i,j,c,t}$ denotes link attributes between i and j at ceremony c and time t, such as ceremony type, cross village or not, and blood relations. $z_{i,t}$ and $z_{j,t}$ respectively denote attributes of household i and j at time t. α_1 identifies peer influence imposed on guests presenting gifts per occasion.

α_2 and α_3 are combined to test the risk-pooling motive: α_2 identifies social distance effect, while α_3 identifies level effect. The two effects are controlled to eliminate the concern that apparent assorting on gift exchange could only be due to the similarities in preferences being associated with closeness. A set of household factors are included to construct social distance and level effect indicators, including head characteristics (gender, marital status, education, age and ethnicity), family

[8] Our conditional dyadic fixed effect model assumes conditional independence for consistency, which means that gift-giving decisions are independent from each other conditional on all explanatory variables and node-specific unobserved factors.

characteristics (share of youth and the elderly, cadre, household size, land size, family assets, number of farm workers and non-farm worker), and major household shocks (natural disaster, livestock death and family member death).

However, the FG link formation framework (1=link exists; 0=link does not exist) conveys no information on how the intensity of a link is determined. The strength of links in many contexts is what really matters to an individual's well-being. It shows to what extend one can rely on networks when needed, rather than the mere existence of links could do. Therefore, we substitute actual gift one presents in an occasion for link existence as the dependent variable.

From the econometric identification perspective, FG estimations could not reliably identify level effect as the degree for a directional link from i to j is either 0 or 1. Though social differences in attributes between observations are identified, FG illustrates that low degree variation hinders the effort to identify determinants of more links, i.e., the level effect α_3. Combined with the dependence of dyadic observations, the issue is that joint likelihood of the sample cannot be decomposed into a product of single observation likelihoods. To the contrary, link intensity based on gifts amount provides much larger variation. Therefore, linear dyadic model on gift spending per occasion is estimated to circumvent the issue of indecomposable dependent dyadic observation likelihoods.

As discussed in section 5, peer effect is identified via an instrument variable approach. In the main estimations, lagged median gift spending per occasion from brides' out-of-township blood relatives, whether they sent gift or not, instruments lagged all peers' median gift spending per occasion. Adopting a non-linear peer influence setting, i.e., lagged median behavior among peers, partially overlapping groups over time and across occasions mitigates the reflection problem that confounds peer effect.

Out-of-township peers circumvent the concern for correlated effects that arises from common unobservable shocks. All fellow residents within the village boundaries and all brides' out-of-township blood relatives, whether they present gifts or not, are

included in the peer groups to mitigate another concern for correlated effects due to self-selection into gift groups.

The unique karst landform facilitates well-defined reference groups in the context of isolated rural communities. It is very likely that peer influence over gift spending in social events works through information sharing during each occasion. Therefore, in our main estimation reference groups for gift spending are defined according to fellow gift presenters in each occasion. To compare sources of peer pressure, we also define peer groups for gift spending based on gift receivers to whom one presents gifts per year.

To test FG's predictions on risk-sharing, throughout the dyadic estimations we construct social distances and level effects as FG's setting. We improve upon FG via disentangling peer effect and status seeking from risk-pooling motive. Moreover, we directly explore determinants of link intensity using long-term complete real gift networks. To the contrary, FG explores determinants of nominated informal insurance groups followed by estimating whether it predicts a small number of short-term transfers and loans in the real world.

The status seeking motive is captured by the individual-specific Deaton relative deprivation index (Deaton, 2001), the normalized difference between the average income of those with higher income and an income level x weighted by the proportion of those with income higher than the corresponding individual i. It is valued between 0 and 1. The more relatively deprived, the higher it is valued.[9] This is an improvement over BBZ that uses community-specific distributional indicators to measure status seeking.

Compared to BBZ, we further isolate the risk-sharing motive from status seeking and more rigorously identify peer effect. While BBZ restricts peer groups at the village boundary without over time variation in their composition, our long-term detailed information on gift record leads to household-specific variation in peer group over time and across events. As discussed earlier, this variation helps circumvent the reflection problem. Moreover, our instrument mitigates correlated effects that confound peer

[9] For a detailed review of a series of relative deprivation measures, please refer to Chen and Zhang (2011).

influence due to unobserved common factors and / or self-selection into groups, while BBZ does not implement an instrumental variable approach.

The main specification (2), however, does not directly account for the recent gift escalation. Manipulating the dyadic observations to difference between each pair of households with zero and nonzero gift exchanges in both directions,[10] the pairwise difference model (3) investigates how the incremental gift spending can be interpreted by three major factors: risk-sharing, changes in status and changes in peer influence. The pairwise difference model removes the unobserved pair heterogeneity. Let

$$\Delta y_{i,j,t} = \alpha_1 \Delta m[y_{-i,j,t-1}] + \alpha_2 (z_{i,t} - z_{j,t}) + \alpha_3 (z_{i,t} + z_{j,t}) + \alpha_4 \Delta RD_{i,t} + \Delta \varepsilon_{i,j,t} \qquad (3)$$

To check whether peer effect is robust to alternative IVs, we follow IV strategy in De Weerdt and Dercon (2006) that uses changes in peers' windfall income and remittance to instrument changes in peers' median gift per occasion. Changes in peers' windfall income should directly affect peers' gift spending and only exert indirect impact on one's gift spending growth via peer influence.

6.2 Dependence of Dyadic Observations

Due to the presence of node-specific characteristics common to all links containing that node, dyadic links are not independent. The non-independence feature can be expressed as $E(\varepsilon_{i,j}, \varepsilon_{i,k}) \neq 0$, $E(\varepsilon_{i,j}, \varepsilon_{k,i}) \neq 0$, $E(\varepsilon_{i,j}, \varepsilon_{k,j}) \neq 0$ and $E(\varepsilon_{i,j}, \varepsilon_{j,k}) \neq 0$ for all k. Conventional OLS estimation generates consistent coefficient but inconsistent standard errors. Monte Carlo simulations show that the corrected standard errors can be much larger, especially when the average links for nodes is large (FG, 2007).

Three general categories of approaches have been utilized to tackle the dependence of dyadic observations. The first category is to run the GLS estimation while assuming some form for the covariance matrix. However, the method has not been as thoroughly worked out as panel data (Simpson, 2001).

The second category of approaches is to correct for the understated dyadic p-values or standard errors. The conventional method have one dimension to be clustered,

[10] We restrict our dyadic links to (potential) links between households who once held social occasions.

while for dyadic data we need to simultaneously cluster two dimensions, gift presenters and gift receivers. Three corresponding methods are developed in this category. First, a multi-way clustering method is developed to allow arbitrary heteroskedasticity and intra-group correlation in distinct non-nested categories (Cameron et al., 2006; Thompson, 2009). Though applied in some setting with $E(\varepsilon_{i,j},\varepsilon_{i,k})\neq 0$ or $E(\varepsilon_{i,j},\varepsilon_{k,j})\neq 0$, the clustering does not consider $E(\varepsilon_{i,j},\varepsilon_{k,i})\neq 0$ and $E(\varepsilon_{i,j},\varepsilon_{j,k})\neq 0$. A second method, Quadratic Assignment Procedure (QAP), is widely utilized in the sociology literature. QAP uses permutation methods to adjust p-values, but it relies on bootstrapping (Simpson, 2001; Santos and Barrett, 2010). The third method corrects dyadic standard errors due to the cross-observation correlation in error terms involving certain individuals (FG, 2007). Therefore, it more thoroughly adjusts for dependence of dyadic observations.

The third category uses individual fixed effect to purge out the unobserved attributes (De Weerdt, 2004; Udry and Conley, 2005). For the dyadic data, the dyadic fixed effect model involves putting in a dummy variable for each gift presenter and gift receiver. However, a large set of dummies often leads to inefficiency or substantive parameters without estimation when the covariate does not vary much along a dimension. Meanwhile, fixed effect may not handle some forms of correlated errors (Thompson 2009). Another limitation with dyadic fixed effect is that they limit the set of covariates that can be included due to collinearity. Fortunately, the long term network record and dispersed gift spending along both dimensions allow us to identify the parameters with a large set of dummies.

Though all the three methods are effective in their own ways, there still is an assumption that the error terms of two dyads containing no mutual members are uncorrelated. We release this assumption in the robustness check through clustering the observations by time periods.

In this paper, we estimate dyadic regressions across all possible dyads using De Weerdt dyadic fixed effect correction (De Weerdt, 2004), FG standard error correction (FG, 2007) and QAP (Simpson, 2001). The absence of some dyadic observations is

perfectly predicted by never holding any ceremonies in the past few years and/or not knowing each other across villages. Therefore, there is no point including those pairs in the estimation. All estimations are based on a NxN square adjacency matrix composed of (potential) pairwise connections among ceremony organizers. Through this survey design, square adjacent matrices are built.[11]

To implement De Weerdt dyadic fixed effect correction, a set of dummy variables is introduced, one for each household in the sample indicating whether a household is involved in a pair. Every row of the data contains two dummies equal to one. Combined with the observable attribute variables, the set of dummies controls the unobserved attributes left in the error term.

The FG standard error correction uses the following formula to correct covariance matrix for the coefficient estimates β. N denotes number of dyadic observations, and K is the number of regressors. X is the matrix of all regressors, and X_{ij} is the vector of regressors for dyadic observation ij. We have $m_{ijkl} = 1$ if $i = k$, $j = l$, $i = l$ or $j = k$, and 0 otherwise. The FG method should be implemented on a NxN square adjacency matrix.

$$Var(\hat{\beta}) = \frac{1}{N-K}(X'X)^{-1}(\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N}\frac{m_{ijkl}}{2N}X_{ij}u_{ij}u_{kl}'X_{kl})(X'X)^{-1}$$

To implement QAP, the dependent variable is permuted and merged back with the independent variables. During repeated permutations, values sharing a row/column in the original data will share a row/column in the permuted data. Therefore, we preserve any dependence among elements of the same row/column but eliminate any relationship between the dependent variable and the independent variables. Then we run the estimation with the new merged data set and repeat the permutation and estimation to generate an empirical sampling distribution. If the actual coefficient is at an extreme percentile of the distribution under the null, we can reject the null hypothesis.

[11] This strategy is consistent with the standard social network survey that asks each respondent to identify a list of other households on which one could rely in case of need or to whom one gives help when called upon to do so.

7. Empirical Results

7.1 Determinants for Gift Spending Per Occasion

In Table 4, three standard error corrections are adopted in the dyadic estimation of determinants for gift spending. R1 adjusts for standard errors according to FG. We find incomplete risk-pooling: households do not purposefully insure along occupation (non-farm work and farm work), while they significantly insure each other according to income profile and weakly along education and shock dimensions. Level effects show more intense gifts among cadres, the educated and the same occupation. Families with unmarried son are motivated to link each other in exchange for insurance against large expenses in future weddings. Gift-giving is more intense between lineal relatives. Given lineal relative relationship, we find significantly less gift spending per occasion across villages, suggesting that intra-village social links are valuable. It also means that monitoring and enforcement difficulties dominate the concern for risk-pooling.[12] [13]

Peer influence is salient, with a 1% higher peers' gift spending per occasion leading to 0.24% more in gift-giving per occasion. Consistent with BBZ, status seeking is more intense for the lower tail of the distribution. The lowest ranked households spend 33% more on gift per occasion than their highest ranked counterpart.

The QAP estimation in R2 presents similar results. The differences lie in insignificant gift insurance against shocks and little level effect of occupation and education. The estimated peer effect is 0.23%, and the lowest ranked households have a 38% higher gift spending per occasion than the top households.

In R3, we report the De Weerdt dyadic fixed-effect estimations. New findings emerge: Younger families send more gifts to households with senior members.[14] Richer households exchange more gifts among themselves. 1% higher median gift spent per

[12] Our estimation of geographic proximity might be more reliable, since variations in geographic distance is larger in our dataset capturing numbers of cross-village links, while this type of link is absent in FG.
[13] There is a concern that households may self-select into a neighborhood. However, historically evolved locality of farm land in rural China prevents endogenous household placement. See Figure 3 for the typical pattern of household geographic clustering based on inherited farm land in each clan.
[14] Unlike other studies using household head age, our family demographic structure indicators in terms of share of the elderly and share of the unmarried son are controlled. The latter more directly captures potential complements in taking care of the elderly and insuring against lump-sum wedding expenditure for unmarried son, respectively.

occasion in the peer group leads to 0.48% more own gift spending, a magnitude larger than in R1 and R2. The lowest households spend 67% more on gifts per occasion than the top ones.

7.2 Determinants for Changes in Gift Spending per Occasion

Having presented the determinants for gift spending in an occasion, however, driving forces for the recent escalating gift spending are not directly addressed. In this subsection, we attempt to explore this issue. The estimation methods in R1-R3 in Table 5 correspond to R1-R3 in Table 4, respectively.

The evidence for risk-pooling on gift spending escalation is largely insignificant. We find risk-sharing responding to shocks only in R1 and that village cadres send more gifts to ordinary villagers in R1 and R2. Health and weather shocks smoothing and income pooling are even of the opposite sign in R3, suggesting that poorer households suffering from more shocks purposefully connect richer counterparts with rapid growing gifts. Under R1, gift spending among families with unmarried son or senior members experiences a higher increase. Throughout the three scenarios we do not observe gift escalation caused by risk-sharing across occupations.

The marginal peer effect is much larger in promoting gift escalation than in explaining gift spending itself. A 1% growth in peers' gift spending increases own gift expenditure per occasion by 0.74% under FG correction, 0.77% under QAP, and 0.62% under De Weerdt correction.

Being more deprived in social ladders boosts gift growth. A 1-point increase in the Deaton relative deprivation index, i.e., from the bottom to the top in the distribution, causes a 44% higher increase in gift spending per occasion under FG correction, a 40% higher increase under QAP estimation, and a 55% higher increase under De Weerdt correction.

Following the IV strategy in De Weerdt and Dercon (2006), we use changes in peers' windfall income and remittance to instrument changes in peers' median gift per occasion and conduct four robustness checks (Table 6). The F-statistic for the first stage

estimations demonstrates that the alternative IVs have large predicting power, while the p-values for Hansen J-statistic suggest that we cannot reject the null hypothesis of just-identified. All four estimations on changes in gift expenditure with alternative IVs confirm peer effect and status seeking.

First, pairwise difference models are estimated with the two alternative IVs. The identified marginal peer effects are 1.20% under FG correction, 0.76% under QAP, and 0.68% under De Weerdt correction. The identified status seeking effects are 0.54% under FG correction, 0.41% under QAP, and 0.55% under De Weerdt correction. All identified peer effect and status seeking are of high significance.

Second, instead of defining one's fellow gift presenters in each social event as peers, we identify peers as a set of gift receivers for each household over a year.[15] We conclude that peer pressure in extending gifts comes both from fellow ceremony guests and event organizers. The identified peer effect is 0.78%, closer to the QAP scenario and lying in the middle of the three pairwise dyadic regressions. The status seeking effect is 1.15%, which is larger than any of the three pairwise dyadic regressions.

Windfall income in our context includes two exogenous sources: resettlement subsidy targeting dilapidated houses and vulnerable habitats as well as land acquisitions subsidy due to urbanized projects near the local county seat. Both sources of income survive the test of their association with observable family characteristics (Appendix II), which suggests that they are largely random to household characteristics. To mitigate endogeneity that drives the effect of remittance on gift-giving, it is defined to be sent from household members migrated for at least two years.

In the first stage estimations for both pairwise dyadic regression and household fixed effect regression, changes in peers' median windfall income significantly predict changes in peers' median gift per occasion, while remittance sometimes demonstrates significant impact.

[15] The median values are taken for a set of own gift sending links per year (i.e., the left hand side) and a set of all peers' gift sending links per year (i.e., the right hand side). The resulting dataset has one observation for each household per year, and a household fixed effect model is estimated that regresses median own gift per occasion within each year on median peers' gift spending per occasion. The model gets rid of the household unobserved factor(s) that may result in inconsistent estimation of peer effect.

There is no windfall income sharing mechanism in the eighteen villages. Therefore, changes in peers' windfall income should only exert indirect impact on own gift growth via peers' gift expenditure and their influence over own gift spending, generating spillover effect. The resettlement subsidy and land acquisitions subsidy are supposed to fulfill specific objectives. However, gift spending seems to be very responsive to these income sources, possibly due to the wealth effect that triggers gift escalation.

Rapid economic development in rural China continues to bring large windfall income opportunities, and at the same time rising wage in recent years may increase remittance. If these incomes are unevenly distributed, it is very likely that gift expenses escalation spill over to the communities with a disproportionate impact on the poor.

8. Concluding Remarks

Lavish household social spending has been widely observed, this paper studies the impoverished context where people spend heavily on gifts at the expense of basic consumption. Complementary to the literature that studies the determinants of total household social spending, we stick to the micro foundation of the behavior - how own gift spending in an event responds to relative status, peer influence and potentials to pool risks.

Our results confirm the prevalence of peer influence and status seeking motive in shaping gift spending escalation. The two effects persist upon applying different dyadic standard error corrections, adopting alternative instrument variables, changing reference groups from fellow ceremony guests to event organizers, controlling group characteristics that may correlate with network formation and own gift giving, and clustering by year to further deal with link dependence.

However, our results suggest incomplete risk-sharing to maximize potential gains from informal networks. Specifically, risk-sharing is only consistently observed via income pooling, but it is not evident via occupation diversification, education, shock smoothing and so on. Moreover, none of the above social distances accounts for the recent gift escalation.

One standard interpretation is that network maintenance cost in some dimensions is too high to sustain. Another plausible reason is that gift spending during social events is associated with status awards. Therefore, we observe that lower ranked households are more motivated to invest in gifts. In particular, households with unmarried son tend to extend gifts, but the reverse is not true. It is hardly surprising when the marriage market in China is tightening and favorable to girls. The pressure to build bigger houses, bid up bride price, and throw larger wedding banquet to improve their sons' likelihood of marriage drives them to invest early in the market.

The capability and motives for gift-giving is amplified due to massive windfall income and other opportunities amid the rapid development in China. Though received by some households, they spill over to peers and contribute to the escalating gift expenditure. For instance, the passage of Lewis turning point means significant rising wages in the labor market (Zhang et. al., 2010), which coincides with the inflating cost of ceremonies. Meanwhile, official subsidies have been implemented over the past five years, such as direct grain subsidy since 2005 and lumpy land acquisitions subsidy due to the accelerating urbanization process in rural China.

The challenge is to minimize the negative externalities caused by peer influence over gift giving and to promote more effective risk-pooling for the poor in social occasions.

References

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

Ammermueller, A. and J. 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.

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.

Benabou, R. 1993. "Workings of a City: Location, Education and Production", *Quarterly Journal of Economics*, 108(3): 619-652.

Bobonis, G and F. Finan. 2009. "Neighborhood Peer Effects in Secondary School Enrollment Decisions," *The Review of Economics and Statistics*, 91(4), 695-716.

Boozer, M. and S. Cacciola. 2001. "Inside the Black Box of project STAR: estimation of

peer e_ects using experimental data," Center Discussion Paper No. 832, Yale University.

Brock, W. and S. Durlauf. 2007. "Identification of binary choice models with social interactions," *Journal of Econometrics* 140(1), 52-75.

Brock, W. and S. Durlauf. 2001. "Interactions-Based Models", in *Handbook of Econometrics*, Heckman and Leamer (Eds), Elsevier Science B.V.

Brown, Philip H., Erwin Bulte, 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.

Cameron, A.C., Gelbach, J.B. and Miller, D.L. 2006. Robust Inference with Multi-Way Clustering. NBER Technical Working paper 327. Forthcoming, *Journal of Business and Economic Statistics*.

Chen, X. 2009. "Network for All? Understanding Private Returns to Social Spending on Household Ceremonies," working paper.

Chen, X. and X. Zhang. 2010. "Costly Posturing: Relative Status, Ceremonies and Early Child Development," working paper, Cornell University.

Chen, X. and X. Zhang. 2011. "Anatomy of Stigmatized Behavior: Peer Influence and Relative Concern," 2011 Annual Meeting, Pittsburgh, Agricultural and Applied Economics Association.

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.

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. 2004. "Risk Sharing in Rural Zimbabwe: An Empirical Analysis of Endogenous Network Formation." Unpublished, paper presented at the CSAE Conference on Growth, Poverty Reduction and Human Development.

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

De Weerdt, J. 2004. "Risk Sharing and Endogenous Network Formation." In S. Dercon, ed. *Insurance against Poverty*. Oxford: Oxford University Press.

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

Durlauf, S. and M. Fafchamps. 2005. "Social Capital." In P. Aghion and S. Durlauf, eds. *Handbook of Economic Growth*. Amsterdam: Elsevier.

Evans, W., W. Oates, and R. Schwab. 1992. "Measuring Peer Group Effects: A Study of Teenage Behavior," *The Journal of Political Economy*, Vol. 100, No. 5, 966-991.

Fafchamps, M. 1992. "Solidarity Networks in Preindustrial Societies: Rational Peasants with a Moral Economy', *Economic Development and Cultural Change*, 41: 147–74.

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

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*, 1, 215-239.

Genicot, G. and Ray, D. 2000. "Endogenous Group Formation in Risk-Sharing Arrangements." mimeo, University of California and New York University.

Ghiglino, Christian and Goyal, S. 2010. "Keeping Up with the Neighbors: Social Interaction in a Market Economy." *Journal of European Economic Association*, Vol. 8, No. 1, Pages 90-119.

Glaeser, E. and Scheinkman, J. 2001. "Measuring Social Interactions." in Social Economics (Durlauf and Young, eds.), Cambridge: MIT Press, 83-102.

Goldstein, M., and C. Udry. 1999. "Agricultural Innovation and Risk Management in Ghana." Unpublished, final report to IFPRI.

Goyal, S. 2009. "Connections: An Introduction to the Economics of Networks." Princeton University Press.

Graham, B. 2008. "Identifying Social Interactions through Conditional Variance Restrictions." *Econometrica* 76: 643-660.

Hanushek, E., J. Kain., J. Markman. and S. Rivkin. 2003. "Does Peer Ability Affect Student Achievement?" *Journal of Applied Econometrics*, 18(5): 527-544.

Haynie, D. 2001. "Delinquent Peers Revisited: Does Network Structure Matter?" *American Journal of Sociology*, 106(4): 1013-1057.

Heckathorn, D. 2002. "Respondent-Driven Sampling II: Deriving Valid Population Estimates from Chain-Referral Samples of Hidden Populations" *Social Problems* 49:11-34.

Hoxby, C. 2000. "Peer Effects in the Classroom: Learning from Gender and Race Variation," *NBER working paper #7867*.

Krishnan, P., and E. Sciubba. 2005. "Links and Architecture in Village Networks." Unpublished working paper CWPE 0462, University of Cambridge.

Lin, X. 2010. "Identifying Peer Effects in Student Academic Achievement by Spatial Autoregressive Models with Group Unobservables." *Journal of Labor Economics*, 28(4): 825-860.

Mango N, Kristjanson P, Krishna A, Radeny M, Omolo A and Arunga M. 2009. "*Why is it some households fall into poverty at the same time others are escaping poverty? Evidence from Kenya*," DP No. 16. ILRI (International Livestock Research Institute), Nairobi, Kenya.

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

Moffitt, R. 2001. "Policy Interventions, Low-Level Equilibria, and Social Interactions", Social Dynamics, eds. S. Durlauf and P. Young. MIT Press.

Murgai, R., Winters, P., Sadoulet, E. and de Janvry, A. 2000. “Localized and Incomplete Mutual Insurance.” mimeo, World Bank and University of New England and University of California.

Narayan, D., and L. Pritchett. 1999. “Cents and Sociability: Household Income and Social Capital in Rural Tanzania.” *Economic Development and Cultural Change* 47: 871-898.

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

Rao, V. 2001. “Celebrations as Social Investments: Festival Expenditures, Unit Price Variation and Social Status in Rural India,” *Journal of Development Studies*, 38: 71-97.

Sacerdote, B. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *Quarterly Journal of Economics*, 116(2): 681-704.

Santos, P. and C. Barrett. 2010. “Identity, Interest and Information Search in a Dynamic Rural Economy,” *World Development*, 38(12): 1788-1796.

Simpson, W. 2001. “QAP: the quadratic assignment procedure,” Paper presented at the North American Stata Users’ Group Meeting, March.

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

Thompson, S. B. 2009. “Simple Formulas for Standard Errors that Cluster by Both Firm and Time,” http://ssrn.com/abstract=914002.

Udry, C., and T. Conley. 2005. “Social Networks in Ghana” In C. Barrett, ed. T*he Social Economics* of Poverty: Identities, Groups, Communities and Networks. London: Routledge, Chapter 10.

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

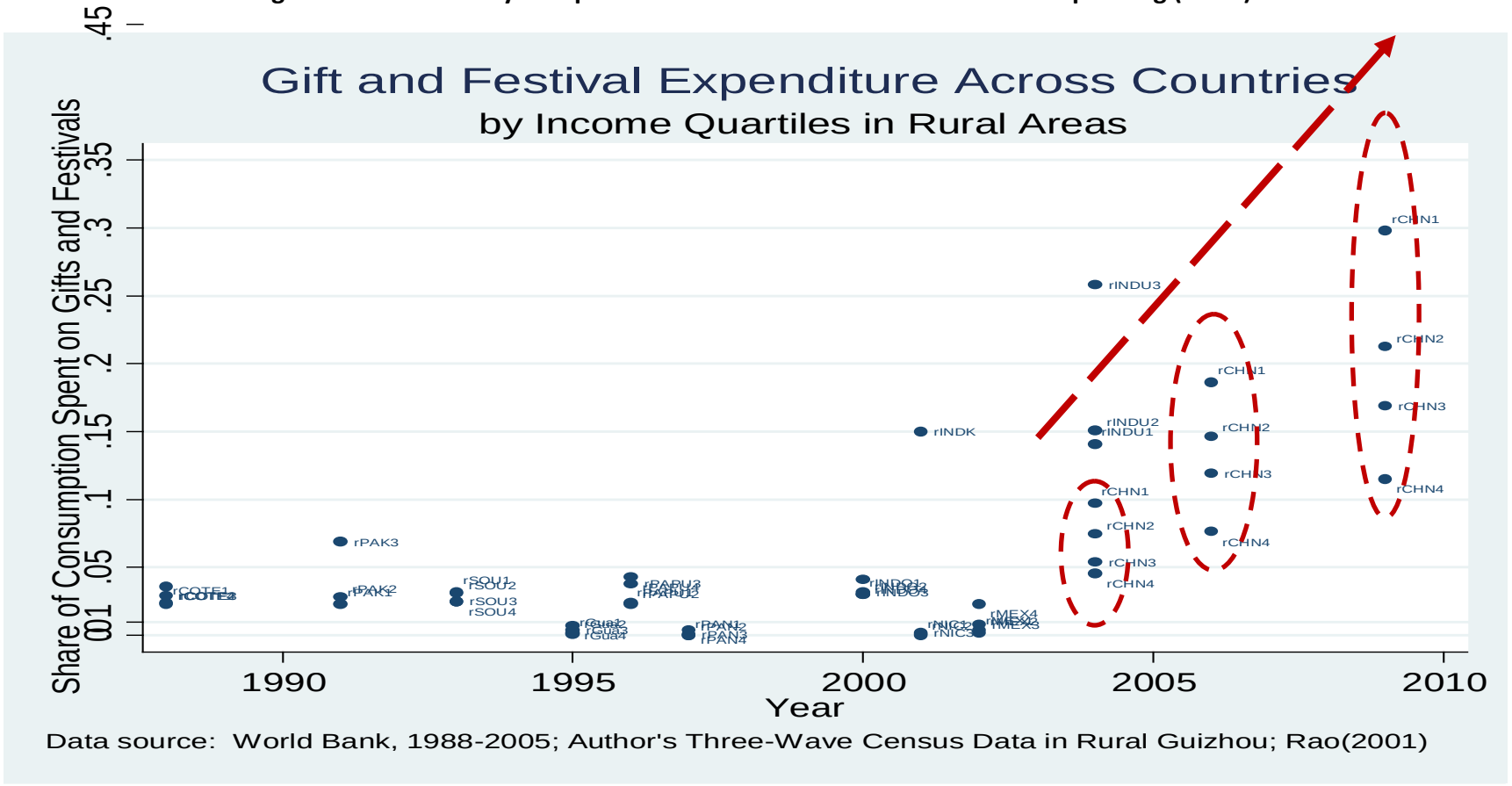
Zhang, Y. 2009. “Interpersonal Trust and Social Interaction between People of Different Regions Sizes.” Working paper, The Chinese University of Hong Kong.

Hoxby, C. 2000. “Peer effects in the classroom: Learning from gender and race variation,” *NBER Working Papers No. 7867*.

Gibbons, S and S. Telhaj. 2006. “Peer effects and pupil attainment: Evidence from secondary school transition,” *CEE Discussion Papers 0063*, Centre for the Economics of Education, LSE.

Zimmerman, D. 2003. "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment", *Review of Economics and Statistics*, 85(1): 9-23.

Figure 1 Cross-Country Comparison on the Share of Household Social Spending (Rural)

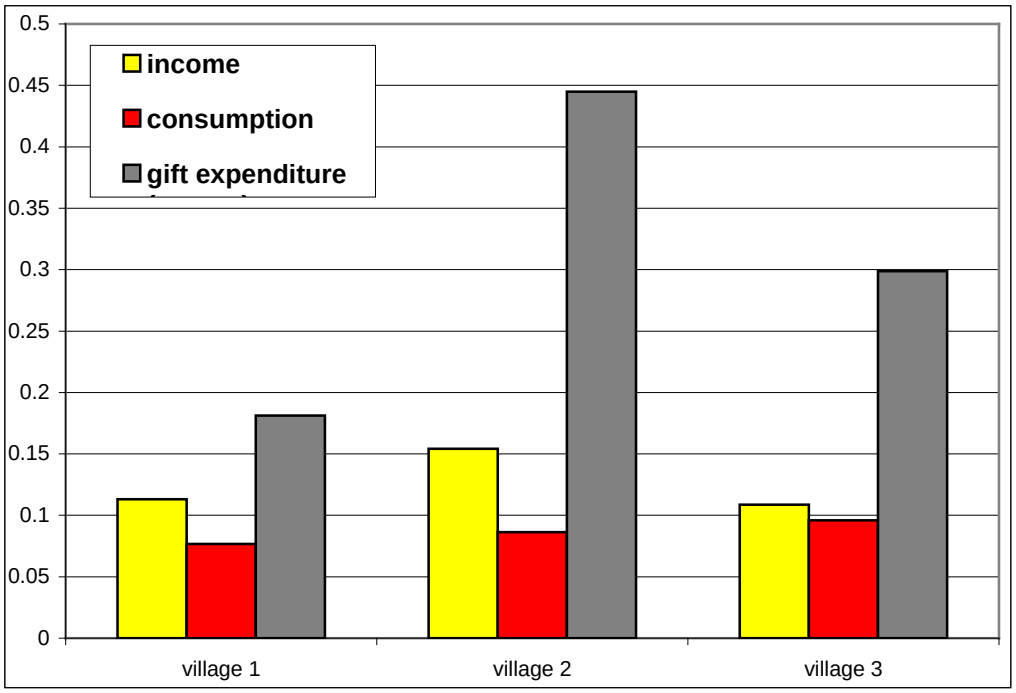


Notes: 1. The categorization for rural China (rCHN1, rCHN2, rCHN3, rCHN4) is based on the same four quartiles as other datasets, i.e. less than $1 per day (denoted as "1"), $1-$2 per day (denoted as "2"), $4-$6 per day (denoted as "3") and $6-$10 per day (denoted as "4"). The poverty lines are adjusted according to 2005 PPP rate from http://iresearch.worldbank.org/PovcalNet/jsp/index.jsp.

2. Notation: CHN: China, Gua: Guatemala, INDU: India-Udaipur, INDO: Indonesia, INDK: India-Karnataka, COTE: Cote d'Ivoire, MEX: Mexico, NIC: Nicaragua, PAK: Pakistan, PAN: Panama, PAPU: Papua New Guinea, SOU: South Africa, INDH: India-Hyderabad. "r" denotes rural area.

3. The dashed circle and the arrow show rapid increase in the share of gift and festival expenditure in our three-wave Guizhou survey.

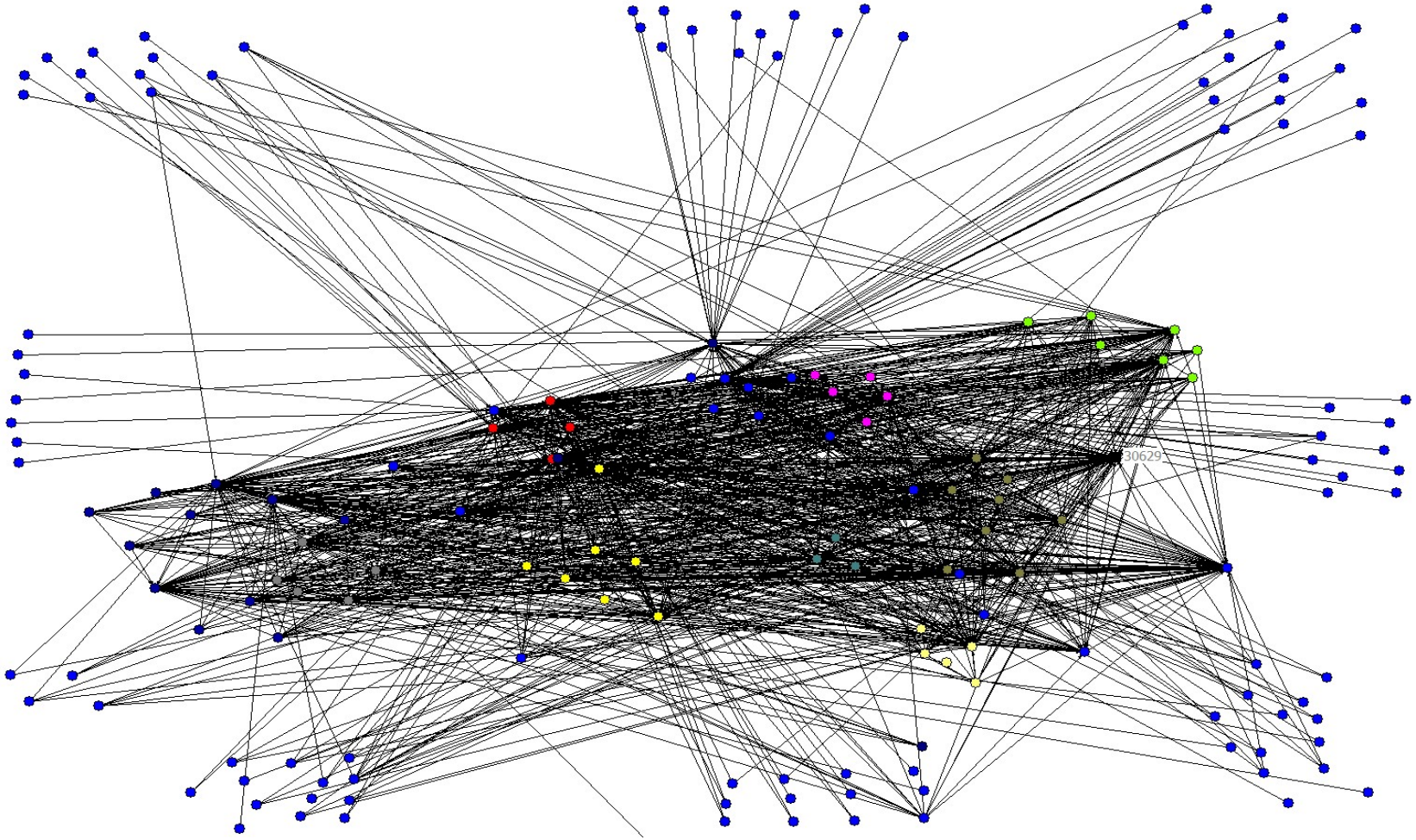
Figure 2 Annualized Growths of (Per Capita) Income, Consumption and Gift Spending



Source: Gift record data (2005-2009) and three wave survey data.

Notes: Annualized growth rates have adjusted for inflation based on recent years' *China Statistics Year Book* issued by NBS.

Figure 3 Dyadic Links and Gift Exchange Networks



Source: Authors' social network data from one of the three 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.

Table 1 Summary Statistics by Natural Village (2009)

	Village 1	Village 2	Village 3	Total
Total number of households	48	27	80	155
Total population	203	96	295	594
Distance to the county seat (km)	10.0	11.0	2.5	7.8
Per capita cultivated land (mu)	0.87	0.16	1.10	0.71
Share of flat land (%)	40.0	20.7	80.0	53.4
Male head of household (dummy)	93.5	94.8	91.6	92.8
Education of household head (years)	2.87	3.06	3.98	3.44
Minority head of household (dummy)	2.9	90.1	5.9	18.9
Share of household members aged 11-29, unmarried (%)	15.9	15.7	14.7	16.6
Share of household members aged 60 and above (%)	14.2	17.9	12.5	14.1

Source: Authors' survey data for three out eighteen villages where we collected gift records.

Table 2 Gift Spending and Sizes of Ceremonies (2000-2009, per Occasion)

Year	Come-of-age			Male Wedding			Female Wedding			Funeral		
	Mean gift (RMB)	Gift SD	Mean # guests	Mean gift (RMB)	Gift SD	Mean # guests	Mean gift (RMB)	Gift SD	Mean # guests	Mean gift (RMB)	Gift SD	Mean # guests
2000-2004	28.8	18.1	35.5	41.7	20.3	31	41.6	21.1	22	23.5	17.2	31
2005	25.1	12.3	34	45.9	27.2	38	-	-	-	28.7	17.4	49
2006	27.6	8.0	41	55.4	29.4	34.3	58.1	24.7	31	21.8	13.3	61.9
2007	46.6	27.8	46	50.5	25.9	40	53.3	24.1	26.3	-	-	-
2008	-	-	-	53.6	34.8	35.5	59.7	29.2	36	83.4	42.1	56
2009	73.3	41.6	51.5	90.6	52.3	37.3	68.4	39.7	45	37.9	23.6	75.5

Source: Authors' gift exchange data from three natural villages.

Notes: All gifts spent have been adjusted for inflation based on China Statistic Year Book published by NBS. "-" means no ceremony occurred during that year.

Table 3 Median Expenditures (RMB) in Organizing Major Ceremonies (1996 – 2009)

Year	Come-of-age	Wedding (Groom's Family)	Wedding (Bride's Family)	Funeral Expenditure
1996	-	4500 (**3.00**)	3157 (**2.10**)	2688 (**1.79**)
1997	-	3852 (**2.84**)	3100 (**2.29**)	3471 (**2.56**)
1998	-	5211 (**3.85**)	3025 (**2.23**)	3170 (**2.34**)
1999	-	3634 (**2.64**)	3829 (**2.79**)	4328 (**3.15**)
2000	-	6250 (**4.85**)	2929 (**2.27**)	4393 (**3.41**)
2001	-	7371 (**5.81**)	5644 (**4.45**)	3388 (**2.67**)
2002	-	7347 (**5.20**)	4536 (**3.21**)	3402 (**2.41**)
2003	-	7891 (**6.22**)	5143 (**4.05**)	4655 (**3.67**)
2004	-	10423 (**8.24**)	4243 (**3.35**)	6150 (**4.86**)
2005	3208 (**1.95**)	9486 (**5.76**)	7633 (**4.63**)	5156 (**3.13**)
2006	3387 (**2.62**)	11805 (**9.14**)	7502 (**5.81**)	6175 (**4.78**)
2007	4284 (**2.75**)	8569 (**5.50**)	4927 (**3.16**)	8096 (**5.20**)
2008	8046 (**5.50**)	13983 (**9.56**)	5833 (**3.99**)	7561 (**5.17**)
2009	8154 (**5.51**)	15066 (**10.18**)	7766 (**5.25**)	7151 (**4.83**)

Source: Authors' survey data.

Notes: [1] All spending have been adjusted for inflation based on *China Statistic Year Book* published by NBS. All values are in RMB. [2] Recall data on organizing come-of-age ceremony were only collected since 2005. [3] Numbers in brackets denote expenditure as times of average per capita income in the 18 villages.

Table 4 Dyadic Regression on Gift Expenditure per Occasion

	R1		R2		R3	
	FG (2007) SE Correction		Quadratic Assignment Procedure (*p-value*)		De Weerdt (2004) SE correction	
Social Distances (def(Zi , Zj))						
Cumulated shocks	-0.178**	(0.08)	-0.319	(0.20)	-0.131*	(0.08)
Head minority status	-0.028	(0.06)	-0.019	(0.47)	-0.233	(0.49)
Household size	0.089**	(0.04)	0.049*	(0.09)	-0.069	(0.08)
Number of farm workers	0.047	(0.04)	0.031	(0.25)	0.081	(0.17)
Number of non-farm workers	-0.024	(0.02)	-0.018	(0.37)	-0.032	(0.06)
Head education	-0.026*	(0.02)	-0.022	(0.18)	-0.040	(0.03)
Head gender	-0.072	(0.19)	-0.081	(0.35)	-0.422	(0.41)
Cadre	0.237	(0.15)	0.233*	(0.08)	-0.207	(0.19)
Head marital status	0.086	(0.12)	0.083	(0.31)	-0.086	(0.31)
Head age	0.010***	(0.00)	0.010**	(0.02)	0.071**	(0.03)
Share of the elderly	-0.239	(0.18)	-0.269	(0.16)	-1.054**	(0.44)
Share of unmarried son	-0.135	(0.15)	-0.155	(0.15)	-0.099	(0.29)
Per capita income (predicted, log)	0.468***	(0.13)	0.617**	(0.02)	0.245***	(0.03)
Level Effect (sum(Zi , Zj))						
Cumulated shocks	0.057	(0.05)	0.040	(0.27)	0.084	(0.06)
Head minority status	0.067	(0.10)	0.076	(0.26)	1.779***	(0.54)
Household size	0.065*	(0.04)	0.075**	(0.03)	0.112	(0.07)
Number of farm workers	0.067*	(0.04)	0.037	(0.24)	0.021	(0.06)
Number of non-farm workers	0.039**	(0.02)	0.044	(0.18)	-0.114*	(0.06)
Head education	0.019*	(0.01)	0.016	(0.23)	0.050*	(0.03)
Head gender	-0.050	(0.08)	-0.037	(0.38)	-0.002	(0.38)
Cadre	0.261**	(0.10)	0.274*	(0.07)	0.282	(0.18)
Head marital status	-0.061	(0.06)	-0.059	(0.39)	-0.638**	(0.30)
Head age	0.001	(0.01)	0.001	(0.40)	-0.047	(0.03)
Share of the elderly	0.388**	(0.17)	0.369	(0.11)	0.409	(0.45)
Share of unmarried son	0.320**	(0.12)	0.321**	(0.05)	0.310*	(0.17)
Per capita income (predicted, log)	0.109	(0.17)	0.073	(0.31)	0.775***	(0.08)
Link Attributes						
Lineal relatives or not	1.611***	(0.12)	1.757***	(0.00)	1.550***	(0.13)
Across villages or not	-2.430***	(0.16)	-2.297***	(0.00)	-1.778***	(0.09)
Peer Influence						
Peers' median gift (per occasion, lag, log)	0.241**	(0.12)	0.234**	(0.04)	0.480**	(0.23)
Status Seeking						
Deaton Relative Deprivation	0.337*	(0.19)	0.375**	(0.04)	0.671***	(0.15)
R2 / N	0.442 / 3136		0.446 / 3136		0.519 / 3136	

Notes: Dyadic standard errors are reported in R1 and R3, and QAP p-values are reported in R2. * significant at 10%; ** significant at 5%; *** significant at 1%. Village and year fixed effects are controlled.

Table 5 Pairwise Dyadic Regression on *Changes in* Gift Expenditure per Occasion

	R1		R2		R3	
	FG (2007) SE Correction		Quadratic Assignment Procedure (*p-value*)		De Weerdt (2004) SE correction	
Social Distances (def(Zi , Zj))						
Cumulated shocks	-0.179**	(0.07)	-0.101	(0.18)	0.47**	(0.21)
Head minority status	0.226***	(0.04)	0.139*	(0.06)	-1.208	(0.84)
Household size	0.024	(0.02)	0.016	(0.25)	0.052	(0.08)
Number of farm workers	0.012	(0.01)	0.010	(0.32)	0.014	(0.02)
Number of non-farm workers	0.002	(0.02)	0.001	(0.46)	0.088	(0.06)
Head education	-0.010	(0.01)	-0.005	(0.36)	-0.015	(0.04)
Head gender	-0.035	(0.07)	-0.025	(0.40)	-2.452	(1.53)
Cadre	0.259***	(0.09)	0.128*	(0.15)	-0.056	(0.26)
Head marital status	0.097	(0.06)	0.058	(0.31)	-0.109	(0.38)
Head age	0.002	(0.00)	0.001	(0.39)	0.016	(0.02)
Share of the elderly	0.061	(0.11)	0.048	(0.36)	0.445	(0.54)
Share of unmarried son	-0.147**	(0.06)	-0.092	(0.21)	0.093	(0.36)
Per capita income (pred, log)	0.248	(0.16)	0.137	(0.30)	-0.834**	(0.40)
Level Effect (sum(Zi , Zj))						
Cumulated shocks	-0.021	(0.03)	-0.002	(0.51)	0.055	(0.08)
Head minority status	-0.155***	(0.04)	-0.083	(0.11)	-2.281**	(0.92)
Household size	-0.057***	(0.02)	-0.031*	(0.06)	-0.043	(0.08)
Number of farm workers	0.031*	(0.02)	0.031	(0.23)	0.025	(0.02)
Number of non-farm workers	-0.042**	(0.02)	-0.022	(0.14)	-0.094	(0.06)
Head education	0.016*	(0.01)	0.011	(0.15)	0.014	(0.04)
Head gender	-0.168**	(0.07)	-0.092	(0.13)	-2.627***	(1.02)
Cadre	-0.211***	(0.07)	-0.133*	(0.07)	0.038	(0.21)
Head marital status	0.096	(0.06)	0.060	(0.25)	-0.050	(0.36)
Head age	-0.003	(0.00)	-0.001	(0.33)	-0.023	(0.03)
Share of the elderly	0.223**	(0.10)	0.145	(0.14)	0.812	(0.52)
Share of unmarried son	0.158**	(0.06)	0.107	(0.15)	0.363	(0.33)
Per capita income (pred, log)	0.012	(0.05)	-0.016	(0.43)	0.199*	(0.12)
Change in Peer Influence						
Peers' median gift (per occasion, lag, log)	0.736***	(0.13)	0.767***	(0.00)	0.621***	(0.09)
Change in Status Seeking						
Deaton Relative Deprivation	0.438**	(0.21)	0.397***	(0.00)	0.554***	(0.13)
R2 / N	0.18 / 3136		0.11 / 3136		0.21 / 3136	

Notes: Dyadic standard errors are reported in R1 and R3, and QAP p-values are reported in R2.

* significant at 10%; ** significant at 5%; *** significant at 1%. Village and year fixed effects are controlled.

Table 6 Pairwise Dyadic Regression on *Changes in* Gift Expenditure with Alternative IV

(*Changes in* peers' windfall income and remittance as IVs)

	marginal effect	standard error
Pairwise Dyadic Regression - Second Stage		
1.Pairwise Difference Model (under FG standard error correction)		
Δ Peers' median gift (per occasion, lag, log)	1.200***	(0.35)
Δ Deaton Relative Deprivation	0.538***	(0.19)
2. Pairwise Difference Model (under Quadratic Assignment Procedure)		
Δ Peers' median gift (per occasion, lag, log)	0.761***	(0.00)
Δ Deaton Relative Deprivation	0.414***	(0.01)
3. Pairwise Difference Model (under De Weerdt standard error correction)		
Δ Peers' median gift (per occasion, lag, log)	0.683***	(0.13)
Δ Deaton Relative Deprivation	0.551***	(0.20)
Pairwise Dyadic Regression - First Stage		
1st stage: Δ peers' windfall income (lag, log)	0.071***	(0.02)
Δ peers' remittance (lag, log)	0.013	(0.19)
F-statistic for joint significance	19.28	
p-value for Hansen *J*-statistic	0.26	
Household Fixed Effect Regression - Second Stage		
4. Household First Difference Model (DV: average gift per occasion in each year; gift receivers as peers)		
Δ Peers' median gift (per occasion, lag, log)	0.779**	(0.34)
Δ Deaton Relative Deprivation	1.149***	(0.41)
Household Fixed Effect Regression - First Stage		
1st stage: Δ peers' windfall income (lag, log)	0.134***	(0.03)
Δ peers' remittance (lag, log)	0.085***	(0.03)
F-statistic for joint significance	15.58	
p-value for Hansen *J*-statistic	0.35	

Notes: Dyadic standard errors are reported in scenarios 1 and 3 in the second stage, and scenario 2 in the first stage reports QAP adjusted *p-values*. Scenario 4 reports robust standard errors. * significant at 10%; ** significant at 5%; *** significant at 1%. The instrument variables strategy in all scenarios follows De Weerdt and Dercon (2006) except that we adopt a more exogenous remittance definition that is only relevant for family members migrated for at least two years.

Appendix I Instrumenting Income

	sum of per capita income	difference in per capita income
	All regressors as sums	All regressors as differences
land (*mu*)	0.02***	0.02**
	(0.00)	(0.01)
machine (*dummy*)	-0.23***	0.09
	(0.06)	(0.18)
cow (*#*)	0.05***	0.11***
	(0.01)	(0.03)
horse (*#*)	-0.06	0.06
	(0.04)	(0.13)
Hhsize (*# members*)	-0.07***	-0.15***
	(0.01)	(0.02)
network size (# *lineal relatives, log*)	1.22***	0.13
	(0.20)	(0.61)
edu (*years*)	0.01**	0.08***
	(0.01)	(0.02)
sex (*dummy*)	-0.16***	0.31**
	(0.05)	(0.15)
cadre (*dummy*)	-0.04	-0.49***
	(0.04)	(0.12)
shocks (*# time*s)	-0.19***	-0.14***
	(0.01)	(0.04)
Year dummies	Y	Y
Village dummies	Y	Y
r2	0.83	0.45
N	7239	7239

Note: Dyadic standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix II-1 Summary Statistics for Windfall Income & Non-earned Income

Year	Mean*	Median*	Sd*	N*
	Direct grain subsidy (targeting grain growing area)			
2004	-	-	-	-
2006	24.67857	20.5	9.81	14
2009	120.5333	90	62.57	105
	Remittance (from hh members migrated for at least 2 years)			
2004	1385.588	980	686.47	34
2006	3357.313	2000	1685.53	67
2009	3635.147	3000	2656.85	68
	Resettlement subsidy (targeting dilapidated houses and vulnerable habitats)			
2004	-	-	-	-
2006	441.1692	396	321.01	13
2009	902.5333	600	678.51	15
	Land acquisitions subsidy (targeting hhs involved in projects near county seat)			
2004	-	-	-	-
2006	8896	10000	5548.74	5
2009	60147.5	55000	35341.32	18

Source: Authors' survey data.

Notes: *households who received the specific subsidies/remittances. "-" denotes no occurrence.

Appendix II-2 Windfall Income and Family Characteristics

	I	II	III	IV
	resettlement subsidy (Logit)		land acquisitions subsidy (Logit)	
lrmrelatives_normcenvill	0.00	0.01	-0.09	-0.07
	(1.00)	(0.77)	(0.54)	(0.50)
hhsize	0.02	0.02	0.40	0.40
	(0.93)	(0.90)	(0.45)	(0.31)
shrmigr	-1.08	-0.76	1.81	3.62
	(0.45)	(0.58)	(0.52)	(0.24)
sex	-1.00	-0.91	-0.72	-0.65
	(0.18)	(0.21)	(0.49)	(0.23)
minority	-0.54	-0.21	-1.21	0.73
	(0.46)	(0.67)	(0.35)	(0.41)
edu	-0.02	0.00	-0.07	0.26
	(0.84)	(0.95)	(0.82)	(0.17)
cadre	0.69	0.62	0.31	0.42
	(0.26)	(0.30)	(0.22)	(0.24)
age	0.04	0.03	0.22	0.15*
	(0.11)	(0.26)	(0.12)	(0.06)
shelder	-1.75	-0.50	-5.24	0.26
	(0.19)	(0.67)	(0.36)	(0.93)
shyouth	0.54	2.22**	-0.03	0.76
	(0.61)	(0.02)	(0.99)	(0.81)
land	-0.01	-0.04	0.28	-0.01
	(0.85)	(0.56)	(0.24)	(0.96)
cow	0.02	0.16	-1.66	-0.02
	(0.95)	(0.55)	(0.19)	(0.98)
horse	-0.01	-0.14	-0.21	-0.32
	(0.99)	(0.88)	(0.36)	(0.71)
shocks	-0.40	-0.25	-0.01	-0.01
	(0.54)	(0.70)	(0.99)	(1.00)
Year Fixed Effect	Y	N	Y	N
Village Fixed Effect	Y	N	Y	N
Pseudo R2	0.157	0.077	0.379	0.245
N	616	616	607	609

Notes: Resettlement subsidy targets dilapidated houses and vulnerable habitats due to natural disaster. Land acquisitions subsidy targets households affected by public construction projects near the local county seat.