ESSAYS ON SOCIAL NETWORKS:
RELATIVE CONCERNS, SOCIAL INTERACTIONS, AND UNINTENDED CONSEQUENCES

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Abstract

This dissertation is composed of a literature review, Chapter 1, an in-depth analysis of data used in the dissertation, Chapter 2, and three main essays, Chapters 3-5, on relative concerns, social interactions and unintended consequences. To uncover the nature of social interactions, Chapter 3 studies how rural residents form social networks, and what explains the recent gift spending escalation. Chapter 4 focuses on a typical market that carries significant social stigma – paid blood plasma donation in China. I explore the role of peer interactions in the networks. Building upon it, Chapter 5 evaluates how *in utero* exposures to frequent and costly social events for the impoverished families impacts early child nutrients intake and health status.

Chapter 1

This chapter reviews the recent literature on inequality and income distribution in rural China utilizing panel datasets. On the basis of the review, this chapter identifies new research areas with existing panel datasets and my new household panel dataset, i.e., the *IFPRI-CAAS*, which could shape future research.

Chapter 2

The tradition of keeping written gift record in many Asian countries offers researchers an old-fashioned but underutilized means of data collection for development and social network study. This chapter documents a long-term spontaneous household gift record I collected from the field. I discuss the data collection and network structure, highlighting its unique features for studies at household and dyadic link level.

Chapter 3

The growth rate of gift and festival spending in some developing countries has been much higher than that of consumption and income. I test three competing explanations of the phenomenon—peer effect, status concern, and risk pooling—based on the *IFPRI-CAAS* and the gift network data. I find that gift-giving behavior is largely influenced by peers in reference groups. Status concern is another key motive for *keeping up with the Joneses* in extending gifts. In contrast, risk pooling does not seem to be a key driver of the observed gift-giving patterns. I also show that large windfall income triggers the escalation of competitive gift-giving behavior.

Chapter 4

Despite the resultant disutility, people are still engaged in behavior carrying social stigma. Empirical studies on stigma behavior are rare, largely due to the formidable challenges of collecting data on stigmatized goods and services. Combining the *IFPRI-CAAS* and the gift network data, I examine frequent blood sales, widely regarded as a stigmatized behavior and the driving force of public health crises. Using a novel spatial identification strategy, I find social interactions with heterogeneous intensities affect plasma sales decisions. Peer effects are directional and work through preference interactions that reduce stigma. Families with unmarried son are more likely to sell plasma to offset costs of getting married in a tight marriage market, such as a bigger house, a higher bride price and a more lavish wedding banquet.

Chapter 5

Participating in and presenting gifts at funerals, weddings, and other ceremonies held by fellow villagers have been regarded as social norms. However, it is more burdensome for the poor to take part in these social occasions than the rich. Because the poor often lack the necessary resources, they are forced to cut back on basic consumption, such as food, in order to afford a gift to attend the social festivals. Using the *IFPRI-CAAS* and the gift dataset, this chapter shows that children born to mothers in poor families who are exposed to a greater number of ceremonies during their pregnancies are more likely to display a lasting detrimental health impact.

BIOGRAPHICAL SKETCH

Xi Chen is a Ph.D. candidate in applied economics at Cornell University. His areas of interest are Development Economics, Health Economics, Social Interactions and Networks, Applied Econometrics and Quantitative Methods.

He has experience in development studies ranging from research assistance at the International Food Policy Research Institute (IFPRI) to field work in Rural China to consulting for the United Nations University World Institute for Development Economics Research (UNU-WIDER) and the Cornell Institute for Social and Economic Research (CISER). Meanwhile, he has been offering referee service to academic journals of China study, inequality and regional science.

Both his B.S. in finance (2004) and M.S. in agricultural economics (2007) were earned from Nanjing Agricultural University, China.

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I owe much to my parents across the Pacific for all their sacrifices and firm support as always that made this dissertation a reality. Though being apart for most of the last five years, I want to express my heartfelt appreciation to my wife Bin with whom I shared the ups and downs of my life and study.

I cherish all the joys Cornell and Ithaca have offered me. Some friends are still there, some left before me. I would like to hug them one by one. The memories of time spent together are one of the most precious gifts of the PhD study.

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CHAPTER 1

THE DISTRIBUTION OF INCOME AND WELL-BEING IN RURAL CHINA: A SURVEY OF PANEL DATA SETS, STUDIES AND NEW DIRECTIONS

1.1 Introduction and Overview

China has been experiencing unprecedented growth over the past thirty years, with a commensurate increase in average living standards. However, the strategy of "*Let some people get rich first*" has resulted in a huge income gap between urban and rural, east and west, coastal and inland China. There are mounting concerns that the growing inequality hinders sharing of the fruits of economic development. In addition, social unrest that accompanies worsening inequality may slow down economic transition and hinder future growth.

Most poor people still live in rural China. According to the China National Bureau of Statistics (NBS), in 2009 the rural population of China was 0.72 billion, taking up 54 percent of the total population. The official ratio of urban-rural per capita income amounts to 3.33:1. Recent household level data show that within-village inequality has grown from 0.22 in 1978 to 0.44 in 2009 (or even above 0.50 in some studies). Inequality seriously questions whether the impressive achievements in poverty reduction can equally benefit the general public in rural China. With unequal access to education, health care, the rural financial system, and non-farm work opportunities in rural China, retaining our focus on rural inequality and farmers' well-being are crucial in maintaining economic growth and social stability in contemporary China.

Rural and urban household surveys for China are largely independent. In this chapter, inequality and income distribution in rural China will be addressed. Two other sources of rising inequality in China, namely inequality between urban and rural areas and inequality within urban areas are not touched upon in this review. Nevertheless, it is worth emphasizing the importance of rural inequality in influencing the other two sources of rising inequality in China. For instance, it is found that much of the increase in the rural-urban gap appears to be the result of a growing difference in incomes between rural households in the coastal and interior provinces. Meanwhile, in standard datasets such as the Urban Household Survey (UHS) sponsored by the NBS, faster growing suburban areas are getting reclassified as urban areas and included in the urban inequality index. Massive migration from rural to urban areas caused by rural inequality might also influence urban inequality and the rural-urban gap.

Studies on rural inequality were initiated in the early 1990s when distributional snapshots with cross-sectional data became available. Extensive literature has been accumulated on the evolution of inequality in rural China since the onset of reforms in the late 1970s. The primary attention has been given to estimating the level of inequality and its changes over time, identifying the underlying sources of the inequality and its changes, and exploring aggregate (disaggregate) level effects of inequality. Since the late 1990s and the early 2000s, a second wave of inequality studies has begun to dominate the discussion as more and more panel datasets in China have become available. To our knowledge, this chapter is the first comprehensive review of studies on income distribution and well-being that use available longitudinal datasets from rural China.

Given the early focus of inequality studies using aggregate data and the fact that later available household survey datasets are not of a census type, research has largely

been silent in exploring the mechanisms of inequality and evaluating its real welfare impacts. However, people do not live on an isolated island. Though important in grasping an overall picture of the inequality situation in China, the urban-rural, east-west, and coastal-inland framework does not address the community level interactions between the rich and the poor and the resulting feeling of inequality and deprivation. It is especially the case when a rural community populated with the absolute poor is severely closed, both geographically and culturally. The rise of within-area inequality might increase the absolute poor residents' level of anxiety and hatred, as their happiness is largely anchored in comparisons to other members of their community. In addition, it has been well documented that both the poor and the rich may have been underrepresented in the official surveys. Fortunately, a newly initiated census-type household survey project might enable us to fundamentally change this situation.

The chapter is organized as follows. In part two, we begin by summarizing available panel datasets for rural China that can help explore issues on inequality and income distribution. In part three, comparisons among panel datasets are conducted. Major data issues that might act as obstacles to research and policy enforcement are then analyzed. Part four reviews the trend and spatial decompositions of rural income inequality, its major determinants, and its relationship with household welfare. Dimensions other than income inequality, such as income mobility and income polarization, are categorized and reviewed respectively. A newly established branch of discussions on inequality and health is summarized, which sheds light on our proposal for datasets of special features. On the basis of the review, Part five proposes new research areas with previous panel datasets and a new area with a new panel dataset. Part six is the conclusion.

1.2 Panel Data Sources for China

In China, five major household level panel datasets are used to explore rural inequality and distribution, which include RCRE (Research Center for Rural Economy), RHS (Rural Household Survey), CHNS (China Health and Nutrition Survey), CHIPS (Chinese Household Income Project Survey), and CAPM (Chinese Academy of Preventative Medicine). These panel data sets include both balanced and unbalanced panels, and the majority of them are unbalanced because of sample rotation or attrition.

To compare levels of inequality from a country as vast as China, it is crucial that the samples be representative of the same population, and, ideally, of all China. In principle, RHS and RCRE are the best datasets to meet this requirement, and both surveys are effectively implemented by sectors in the central government, which are the NBS and the Ministry of Agriculture (MOA) respectively. The RHS is an annual China rural household survey dating from the early 1980s. It is of high quality in many respects, including both sampling methods and the unusual effort made to minimize non-sampling errors. It covers 31 provinces, 7,100 villages, and 68,190 households. However, in-depth analysis of the RHS has been limited to selected sub-samples of provinces, and only for a few years (such as Ravallion and Chen, 1999; Tsui, 1998b). The full sample RHS data has not yet been publicly released and systematically analyzed. Similarly, the RCRE is an annual China rural household survey from the mid-1980s. It is also nationally representative, covering 31 provinces, 360 villages, and 24,000 households. Likewise, all households covered by the RCRE are asked to keep detailed diary records of household information.

Different from the RHS and RCRE, the CHNS, CHIPS, and CAPM are organized by research institutions with relatively limited geographic coverage and/or smaller samples. The CHNS is an ongoing international collaborative project between

the University of North Carolina (UNC) and the Chinese Center for Disease Control and Prevention (CCDCP). It is designed to examine the effects of the health, nutrition, and family planning policies, and programs implemented by national and local governments, and to see how the social and economic transformation of Chinese society is affecting the health and nutritional status of its population. It covers a seven-year household panel dataset in nine provinces, 100 villages, and 2000 households. Daily dietary intake is carefully measured in the dataset. The CHIPS covers around 20 provinces and 4,000-9,000 households, which is mainly sponsored by the Chinese Academy of Social Sciences (CASS). Three surveys have been conducted in 1988, 1995, and 2002, which include detailed current and retrospective information on households' income and consumption and their components. The CAPM is a 2-year social survey of 25 provinces, 138 villages, and around 8,000 households in rural China between 1978 and 1989. The first survey focuses on the relationship between nutrition and cancer; the second wave also involves multilevel socioeconomic questionnaires.

Besides the above-mentioned data, some datasets are collected for special research purposes. For example, MORDUCH, used in a study by Morduch and Sicular (2002), is a small random sample survey of 259 farm households in 16 villages in an eastern China county. The survey follows households from 1990 to 1993. The survey was tailored to deliver consistent information on income and other economic, social, and political variables. Another census-type household panel survey, the IFPRI-CAAS, is collected by the International Food Policy Research Institute (IFPRI) and the Chinese Academy of Agricultural Sciences (CAAS). The dataset focuses on three administrative villages in a western China county. The survey reveals detailed information on household incomes and expenditures

(including detailed information on social spending). Information is collected for each household member.

Given the limited availability of household panel data, macro level panel datasets are a popular tool. For instance, the RSESS-NBS (Rural Social and Economic Survey Service of the NBS) includes time series (1985–2002) and cross provincial (28 provinces) data from rural China. The RSESS-NBS can be found in books such as *Poverty Monitoring Report of Rural China* and *China yearbook of rural household survey.* Compiled aggregate level data can be found on the websites of some research institutions. For example, researchers in IFPRI compiled a dataset mainly from *China Statistical Yearbook*, *China Rural Statistical Yearbook*, *China Fixed Asset Investment Yearbook*, *China Education Expenditure Statistical Yearbook*, relevant World Bank publications, and *China Transportation Yearbook*. The dataset provides information on key economic indicators in 29 provinces from 1952 to 2001. Another convenient way to obtain a long-term aggregate panel data is through two statistical yearbooks, the *Comprehensive Statistical Data and Materials on 50 Years of China* and *Comprehensive Statistical Data and Materials on 55 Years of China*. Some long-term indicators in those two yearbooks have been adjusted to make them the most comparable over time.

1.3 Panel Data Assessment

1.3.1 Comparisons among Major Datasets

Before the 1990s, more aggregate level panel datasets were available than household level panel data. The overall household inequality was understated, since inequality *within* rural and urban areas of each province was suppressed. Analogously, when we analyze trends and the role of contributing factors to inequality such as township and village enterprises, conclusions are valid only insofar

as most rural inequality arises from differences in mean incomes across these units. Moreover, they could not say anything about the evolution of household level inequality within those areas.

Since then, a few household level data sets have come on stream. Compared to aggregate datasets, household panel data can construct a rich, comparable panel of villages that might be used to address a host of econometric and empirical issues that trouble researchers (Benjamin et al., 2005a). Moreover, with access to household level data over time, by exploiting the household dimension of the panel, we can link the evolution of household level welfare to initial conditions in the village.

The first concern is on geographic representation. Among all panel datasets, the RHS-NBS covers the broadest areas over the longest time period. In investigating the role of geographic factors for inequality, most of the panel datasets in Table 1.1 are able to track a panel of villages, even where there has been household attrition. This guarantees geographic comparability over the complete time period. However, discrepancies still exist between datasets, for example, in the rate of growth of farm income between the RCRE and the CHNS. It might reflect the kinds of villages that are selected, with more "suburban" villages possibly included in the CHNS. The CHNS villages may have more acreage in vegetables and other cash crops, and have been less exposed to a sharp drop in grain prices that occurred after 1995.

The second concern lies in the availability of historical household data. Ideally, to analyze the evolution of inequality in contemporary China we should have a nationally representative household survey over the entire period. Among all sets of panel data employed to analyze rural inequality and income distribution in China, the RHS-NBS can be ideally representative. Unfortunately, while such household surveys have been conducted throughout the second half of the last century, they are available to researchers only for the post reform period and in any case sporadically, for

restricted years with varying but limited coverage. Only aggregate data is published and available for public use,[1] and details of the construction of the RHS-NBS income estimates and Gini coefficient is sketchy. As a result, inequality measures based on the full sample are not comparable with results derived from its sub-sample and other data sources. Besides, the publicly available aggregate RHS-NBS data does not include information on housing, subsidies, and income in kind.[2] In this sense, the major utilized household level datasets such as the RCRE, CHNS, and CHIPS are good complements that provide the aforementioned information.

Thirdly, each micro dataset has its own special focus. For example, the RCRE data has been collected from many fixed villages annually. The RHS-NBS data has an even longer time period and is nationally representative. The CHNS data is specialized to conduct nutrition and health research. The CHIPS data has more detailed information on household income. The CAMP data has gathered detailed information for nutrition, health, and medicare research.

Deficiencies of major data sets still exist. First, almost no panel datasets available (including the RHS-NBS and RCRE) contain detailed enough information at the individual level. However, since the 1990s, driven to some extent by growing policy concerns, considerable work on intra-household allocation has begun around the world. To catch up, we need to improve the quality of our panel data at the individual level and correct policy instruments that may have a gender differentiated impact. Second, refusal rates are likely to be higher among households with a high opportunity cost of time or many illiterates, but neither the RCRE nor the NBS report refusal rates. Further, by design the RHS-NBS, RCRE, and CHNS are not successful

[1] The main aggregate results can be found in: *Statistical Year Book of China*, *Rural Statistical Year Book of China*, *Yearbook of Household Survey*, *annual/quarterly statistical analysis report*, and relevant research papers.

[2] The RHS-NBS began to value in-kind components of income at approximate market prices since 1990.

in accurately estimating household incomes from family-run business.[3] A richer set of questions should be included in the surveys to track this important source of income. Underestimation of this income source might induce a significant underestimate of income inequality due to non-agricultural income growth, especially at the top end of the distribution (Benjamin et al., 2005a).[4] Finally, while the CHNS contains more details that can facilitate the exploration of the robustness of conclusions to definitions of "income", it does not have detailed expenditure data.

The fourth point relates to treatment of income. Income in the RCRE and RHS-NBS data are both defined as income earned from all enumerated sources, including both cash and imputed values for in-kind income from various sources.[5] Much of the difference between levels and trends of income among datasets can be explained by differences in the valuation of home-produced grain. For instance, relative to the RCRE, the NBS treatment of the in-kind component is likely to result in an underestimate of incomes and consumption prior to 1990, and an overestimate of the growth in incomes or consumption for 1987 to 1999 period. Given that grain income was valued at a price still systematically related to the quota price after 1990, Benjamin et al. (2005a) find a strong positive correlation between the size of the gap between the two income series and their estimate of the ratio of the market-to-quota

[3] Both the RCRE and CHNS surveys simply ask respondents for total revenue and expenditure from family businesses, while the distinction between fixed and variable costs is often lost in the enumeration process. In general, this is among the most difficult sources of income to enumerate accurately. Considerable efforts were placed in the CCAP 2000 survey by careful enumeration of balance sheets of family businesses. However, the CCAP 2000 is only a cross-sectional dataset.

[4] Another interpretation for the underestimation of income inequality is that the much higher valuation of in-kind income in the RCRE data for the years 1993-1995 helped dampen the effect of dis-equalizing growth in wage and business incomes. The effect is temporary. However, once farm prices begin to fall, we see the sharp increase in inequality associated with falling farm incomes in the RCRE data.

[5] For instance, income from farm-household production, forestry, animal husbandry, handicrafts, gifts as well as labor earnings and income received as a gift are included. Borrowings from (or loans to) informal and/or formal sources are excluded.

price.[6] Two other differences in the income series lie in the treatment of taxes and fees and depreciation on fixed assets. Studies using the NBS usually subtract both, while typical studies applying the RCRE (e.g. Benjamin et al., 2005a) do not subtract taxes due to their focus on the earning ability of households. However, they depreciate assets themselves due to the arbitrariness of recorded depreciation expenses in the RCRE.

Furthermore, there has been concern expressed over the ability of respondents to recall past income. Records collected from the CHIPS data may rely on respondents' recall. The single-interview approach and respondents' recalling of past incomes may have errors, thus the correlation among incomes across years will embody errors in measurement. For instance, individuals may report the same incomes or the same proportion of incomes in different years, which will end up with more inertia in the income distribution data and understate the true income mobility. By contrast, the RHS-NBS data and the RCRE data are less likely to suffer from recall error, since each selected household maintains a diary over the entire year as well as two transaction books. The survey has been conducted on an annual basis. An assistant interviewer living in the county seat is supposed to visit each household every two weeks (or every month for the RCRE) to check the books. The unusual rigor applied to the collection, checking and processing of the RHS-NBS data and the RCRE data means that they are less likely to suffer from a variety of non-sampling errors common to household surveys in many other datasets.

Finally, the definition of household membership is important to note. For households in the RHS-NBS and the RCRE, household size is based on registration, but it excludes migrants. However, household membership in the CHNS data is

[6] Benjamin et al. (2005a) estimate the ratio of the market-to-quota price, which was as high as 1.46 in 1995, and then fell below 1 by 1997. After 1997, the NBS series has been directly related to the market price, and they observe some convergence in the income and consumption series.

defined more on the basis of economic attachment (residency) than registration. Household heads and family members who send remittances are included. An increasingly serious omission over time occurs as the number of people who work and live outside grows. To tackle this problem, the CHIPS 2002 included a subsample of rural migrants living in urban areas, while most datasets still exclude this increasingly important group.

In China where the market is imperfectly and unevenly developed, studies have discussed a variety of data and methodological issues for comparisons of inequality.

1.3.2 Relevant Data Issues

1.3.2.1 Measurement Errors

Inequality measures, such as the level of inequality, factor decomposition of inequality, and its change over time, are seriously affected when income or consumption is measured with error (Ravallion and Chen, 1999). Special attention should be paid to whether the underlying income concept includes income items such as imputed rents for owner-occupied dwellings, imputed incomes from home production, and in-kind income. Besides, allowing for inter-regional cost of living differences and evaluating consumption rather than expenditures (e.g. consumer durables) is important. When studying rural-urban inequality, attention should be paid to the reclassification of rural areas as urban. An adjustment of the NBS urban-rural inequality data and strictly follow a panel of rural villages over time is required.

Valuing Consumption of Own Production

A significant portion of rural household activity is directed towards production for a household's own consumption, and it tends to account for a high share of income for the poor. Its undervaluation due to the downward price bias from the market-clearing level leads to an overestimate of inequality. Meanwhile, prices used

by provincial statistics departments diverged progressively from market prices over time, which also lead to an overestimate of the rate of increase in inequality.

The process of imputed price adjustment for the RHS-NBS in the 1980s and 1990s serves as an example (World Bank, 1992; Khan et al., 1993; Ravallion and Chen, 1999).[7] Besides, Benjamin et al. (2005a) find that some localities used the same weighted average quota and above quota sales' price calculated in 1990 to value in-kind income between 1991 and 1995, which might give an additional source of downward bias in income and consumption growth between 1991 and 1995.

To correct these deficiencies, Chen and Ravallion (1996), Tsui (1998b), Ravallion and Chen (1999), and McCulloch and Calandrino (2003) apply sub-samples of the NBS data and show that all credible estimates of inequality in rural China should correct those biases. For instance, to reflect the increased marketization of the economy, following Chen and Ravallion (1996),[8] Tsui (1998b) and McCulloch and Calandrino (2003) revalue the grain kept for personal consumption. However, this revaluation can only be implemented for grain due to the lack of relevant information for other goods.

A similar adjustment is conducted in the RCRE data, where grain produced for self-consumption or stored was valued at prices reflecting the quota price. Because of lower than market quota prices through the mid-1990s, income from grain production and consumption out of home production are both likely to be biased downward.

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[7] From 1991 to 1996 the NBS instructed survey teams to use an "average contract price" to value non-marketed grain from own production. This average contract price was the weighted average of the quota price and the above quota price for sales over quota to the local grain bureau. Both of these prices were administratively determined. Survey teams were further instructed to use weighted average market prices only if there were no local administrative prices (meaning no local crop procurement). It was not until 1997 that the NBS instructed survey teams to value all non-marketed agricultural commodities at market prices.

[8] Chen and Ravallion (1996) find that after revaluation of income in kind from gain production, a much larger share of the (albeit smaller) increase in rural inequality was due to grain income than past data would have suggested.

Benjamin et al. (2005a) revalue households' non-marketed grain at average village market prices.

Price Differences

Inflation/deflation is adjusted for time-series data to convert income and consumption into constant dollars (Yuan). McCulloch and Calandrino (2003) use the CPI index from the China Statistical Yearbook to deflate nominal variables. However, the published CPI uses an (unknown) mix of market and official prices, rather than market prices, to value certain goods which may underestimate the rate of increase of consumer prices and therefore overestimate the improvement in real terms.

Spatial differences may also be important. Prices in some parts of the country may be systematically different from those elsewhere, in which case estimates of inequality can be biased. However, most of the past literature has ignored spatial differences, for example, in the cost of living. Two exceptions include Chen and Ravallion (1996) and Tsui (1998b), who construct provincial-level spatial and inter-temporal spatial deflators for four and two provinces respectively. Recently, research interests have been extended to explore the rural-urban gap. However, it should be noted that adjusting for inflation over time using separate urban and rural consumer price indices does not incorporate the spatial difference at any one point in time. A constructed set of spatial price deflators documented by Holz and Brandt (2004) is widely used to adjust cross-sectional differences in urban and rural prices across provinces, and between rural and urban areas. Overall, adjusting spatial price differences might minimize the problem of overestimation of inequality and the exaggeration of the contribution of spatial disparity regarding price differences.

Durable Consumption and Income

Housing services and durables are usually relatively equally distributed at the beginning, but more unequal with different rates of accumulation of housing and an increasing share of consumption as an economy develops. Especially as durables and housing reflect consumption decisions linking permanent income, it is important to consider how they are treated in the construction of consumption and income.

The impact of durables and housing on inequality is significant. The NBS data on consumption expenditure include one-off expenditure on durables in the year in which the purchase decision was made. However, durable goods, by definition, last for a number of years. Meanwhile, owing to the infrequent purchases of consumer durables, the estimated unit values of durable goods might be based on the records of a few households and the prices may not be representative. A similar problem is encountered in relation to housing expenditure as it is difficult to include imputed rental values. The NBS only include all housing expenditure in the year in which the spending takes place, as a result of the limited rental market for housing in rural China.

Scholars have made lots of efforts in calculating and adjusting consumptions of durable goods and housing. Khan and Riskin (1998) and Khan et al. (1999) construct a revised measure for urban and rural China based on the asset valuations available in the primary survey data. Chen and Ravallion (1996) include five percent of the recorded dwelling value for housing and 10 percent for durables in total consumption. Improving upon Chen and Ravallion (1996), Tsui (1998b) adopts the available NBS price data for consumer durables, which consist of average retail price information collected by the urban survey teams of the NBS.

Utilizing the RCRE, Benjamin et al. (2005a) and Brauw and Rozelle (2008) also consider inflating the value of the stock of housing and durables to reflect the increase in prices of durable goods. McCulloch and Calandrino (2003) approximate the rental

value of the stock of durables in each year in rural Sichuan, and they also impute the rental value of housing expenditure using information about rents in the local area.

1.3.2.2 Sample Attrition Bias

Attrition bias is present in panel data collection for several reasons. First of all, in some data sets, such as the RCRE, RHS-NBS, and CHIPS, whole villages drop out because they are annexed into a city. In some other cases when panel datasets are based on written records collection, sample attrition may reflect the fact that maintaining diaries of their households' incomes and expenditures makes it difficult for illiterate households to participate and the opportunity cost of keeping records for the rich are high. Some rich residents might leave their villages for an entire year, some people might show unwillingness to make efforts, and some people do not want to reveal their personal information. To the poor, attrition may also be endogenous to shocks (Lokshin and Ravallion, 2001). It is difficult to distinguish such households from those that change too much to keep in the panel or those who were replaced by the surveyors for certain reasons (Ravallion and Jalan, 2001). However, to the poor endogenous attrition may be minimized, since sampled households in the RHS-NBS are paid to participate. Khor and Pencavel (2005) find that unmarried, younger and older people are less likely to be represented in the CHIPS 1995. Benjamin et al. (2005a) and Brauw and Giles (2008) compare cross sections of the RCRE and RHS-NBS with overlapping years of the CHNS and CCAP 2000 that are not based on diary record.

Comparing with other surveys in which households are known to be randomly sampled, a disproportionate number of households at both ends of the income distribution are excluded from the NBS, CHNS, and RCRE data, which might lead to an underestimate of income inequality (Benjamin et al., 2005a). Sometimes the numbering of the replacements is not properly handled, since a considerable amount

of replacements are assigned the same ID number of the survey units as those that are replaced (Shen and Yao, 2008). To check the accuracy of the original ID and the continuity of the RCRE, Hoken et al. (2006) develop data matching methods, construct new panel databases and test the sample attrition biases. They demonstrate that a large number of spurious continuities of panel survey appear to exist in the original ID. To compensate for sample attrition, the 1997 CHNS includes all newly-formed as well as additional households in original communities to replace households lost. Faced with more severe attrition such as a drop out of an entire community, a new community in the original province would be added (Chen, 2005).

1.3.2.3 Units of Measurement

In evaluating inequality, per capita estimates are usually imputed to all members within a given household. Higher levels of aggregate analyses base their units of measurement at the village, township, county, or provincial level, which underestimate inequality because it ignores the internal inequality arising from differences in welfare among households within these administrative units. This simplified treatment also forms a poor basis upon which to evaluate the contribution of cross-unit inequality to the total. This issue has not been effectively addressed in studying inequality in rural China as individual consumption or income data are rarely available.

To deal with the problem of equalizing all family members within each household, estimates of household income and consumption expenditure were divided by the number of adult equivalents in the households using the World Health Organization adult equivalence scale (McCulloch and Calandrino, 2003). This scale is derived from detailed studies of the nutritional requirements of males and females of different ages in developing countries. Meanwhile, income or consumption should be

adjusted by household size, as the relative need of different sized households is different. Chen and Ravallion (1996) provide an example of integrated adjustments.

The unit of measurement also affects the estimated effect of inequality on growth. The dependence of growth rate at household level on the initial log of indicators such as capital stock can induce spurious effects after aggregation process (Ravallion, 1998). Even when the growth rate is linear in the initial capital stock, a term for the change in inequality will be found in the residual of the usual aggregate growth rate regression. More complex forms of nonlinearity and alternative functional forms for the inequality measure relevant to the micro-level externality can yield further spurious effects of measured inequality.

1.3.2.4 Adjustment for Income Volatility

The impact of income and consumption volatility on inequality has received limited attention in the literature. Compared to urban income, volatility of rural income is substantially higher in China. At present, poor rural households either have no access to capital markets or only have access at prohibitively high borrowing rates, which limits their ability to smooth income. Thus, it is vital to adjust for rural income volatility when constructing measures of inequality to obtain a more realistic inequality estimate and to build a more comparable basis for rural-urban inequality. Previous studies on income volatility in rural China (Jalan and Ravallion, 1998; Li et al., 2005) do not make direct adjustments to welfare measures. Whalley and Yue (2006) use the CHIPS for rural residents to construct measures of certainty equivalent income and calculate summary distributional measures for the modified income data.

1.4 Main Findings from Panel Data

1.4.1 Rising Income Inequality and Economic Development

From 1987 to 1999, income distribution improved by most measures during the early part of the period, as average incomes rose substantially with only a modest increase in inequality. However, the distribution worsened significantly over the late 1990s and the early 2000s, with rising inequality and falling absolute incomes, especially at the bottom end of the income distribution (Benjamin et al., 2005a). This situation was attributed to collapsed agricultural income and uneven growth of non-farm income due to the contribution of non-farm family businesses. Within the non-farm incomes category, local income was relatively disequalizing, while income from outside the village was relatively equalizing (Benjamin et al., 2005b). Almost no studies using household data show the recent trajectory of rural income inequality.

1.4.1.1 Determinants of Income Inequality

Studies on determinants of income inequality can be categorized into two major branches, inequality by income sources and assets and inequality by geography. The first category emphasizes declining agricultural income, disequalizing non-farm income (especially family businesses), egalitarian land distribution, and physical and human capital. Inequality determinants classified by geographic hypotheses are briefly summarized and followed by an extensive review of spatial decompositions. Besides the above-mentioned two branches, crucial events and development strategies in rural China can explain some of the inequality trend, including urban-biased development policy, rural industrialization, rural financial development, fiscal decentralization, market fragmentation, globalization processes, grassroots democracy, and the role of political power and connections.

Determinants of Rural Inequality by Income Sources and Assets

In general, changing structure and composition of income generates higher inequality (Tsui, 1998a), which recently has been followed by more specific studies

on different components of income and their contributions to inequality. It is unclear whether equality of farm income due to the current egalitarian land distribution policy is necessarily good for overall income inequality, since more inequality of farm income might actually reduce overall income inequality (Benjamin et al., 2006). However, Chen (2005) verifies the negative role that farm income plays in inequality. Within farm income, grain production plays the most important role in rising inequality, and non-farm income plays the secondary role, while other farm incomes have a decreasing effect on inequality (Ravallion and Chen, 1999; Benjamin et al., 2005b). Wan and Zhou (2005) conclude that cropping pattern is more crucial than labor and human capital inputs based on disequalizing income from non-farm family businesses and the failure of non-farm labor markets in constituting rising income inequality.

Decomposing inequality into land category, farm assets and human capital shows several things: first, farm assets are inequality-reducing over the period because of their diminishing rate of return cross section and over time (Ravallion and Chen, 1999); and second, constraints on farm size implicit in the Chinese administrative allocation of land together with agricultural goods price change may ease its contribution to overall inequality (Wan and Zhou, 2005; Benjamin et al., 2006). Although land inequality grew from 1987 to 2002, it is still low by developing country standards (Benjamin et al., 2005b). However, land area is a poor measure of land endowment, given the usual negative correlation between land capacity and farm size. Higher return over time to good quality farm land is inequality-increasing (Ravallion and Chen, 1999). Thus, spatial decompositions based on cultivated area alone exaggerate differences in land across space. Third, education is found to have little effect on inequality (Wan and Zhou, 2005) but is gaining importance (Wan, 2007). The Rising intra-regional and urban-rural differential distribution of education

and entrepreneurial attributes leads to more intra-regional and urban-rural inequality (Benjamin et al., 2002; Guo, 2007). Improving education and off-farm job market simultaneously leads to success in family businesses and labor markets (Benjamin et al., 2002).

Determinants of Rural Inequality by Geography

When encompassing weather, infrastructure, and other natural resources, geography would account for a very significant share of total rural inequality. Using provincial level data, Wan (2007) finds that location and location-related factors comprise the largest contributor to total regional inequality, although its percentage contribution has decreased over time. Utilizing household survey data, Ravallion and Chen (1999) find that the differences in income between those living in mountainous rural areas and those on the plains have been an important source of rising inequality. However, Benjamin et al. (2005a) rule out geography as the most important factor for understanding the dispersion of incomes; rather, the prevailing inequality is due to inequality between neighbors within a village.

Determinants of Rural Inequality by Developmental Strategy

Firstly, urban-biased development policies help us understand the picture behind spatial rural inequality. Before the economic reform, the role of the state sector was important in the interior. However, since then growth of the non-state sector in the interior provinces has been much slower as more resources have gone to support a larger population tied to the state sector. It has handicapped the growth and labor demand in the rural secondary and tertiary industry. In contrast, much faster growth in the non-state sector in coastal provinces has helped provide a wide array of job opportunities for both rural and urban areas there. The unbalanced spatial job creation and fragmented capital market have significant negative effect on rural inequality (Zhang and Tan, 2007). Due to the still fragmented factor markets, fast growing

international trade and foreign capital investments have been concentrated in the more developed coastal region rather than vast inland areas, leading to further aggravating regional rural inequality (Zhang and Zhang, 2009).

Evidence shows that most of the rising inequality in rural industrialization is spatial and has increasingly contributed to regional inequality (Wan, 2007; Chen, 2005). However, income from rural industry does not contribute to the rise in local inequality because wages from rural industry, mostly labor intensive sectors, were equalizing. Growing spatial inequality can also be attributed to uneven opportunities represented by the uneven development of TVEs and other markets (Guo, 2007).

How does rural financial development influence income inequality? Theoretical predictions on the finance-inequality nexus are inconclusive and mixed, including an inverted U-shaped relationship (Greenwood and Jovanovic, 1990) and a negative linear relationship (Banerjee and Newman, 1993), both from provincial panel data (Liang, 2006) and household panel data (Wan and Zhou, 2005).

China's current fiscal system is largely decentralized compared to her centralized governance structure. Due to large differences in initial economic structures and revenue bases, the implicit tax rate and fiscal burden to support the functioning of local government vary significantly across jurisdictions. The regressive nature of the rural taxation system explains why the fiscal decentralization exacerbates the rural-urban gap and gaps among rural areas, and it has been confirmed by studies using China County Public Finance Statistical Yearbook (CCPFSY) (Zhang, 2009) and rural household data (Khan and Riskin, 1998; Benjamin et al., 2006).

Does grassroots democracy help mitigate income inequality in rural China? Shen and Yao (2008) utilize village and household level RCRE to find that village

elections reduce inequality, and their role is not played through more income redistribution, but through more pro-poor public investment.

Political power and connections captured by party membership, presence of a past or present cadre, or the class labels given to families in the late 1940s and early 1950s are found to facilitate access to uneven opportunities and the resulting rural inequality (Morduch and Sicular, 2002).

1.4.1.2 Rising Inequality and Household Welfare

Rising income inequality might offset welfare gains in the economic reform. The relationship holds controlling for own resources in the household level specification, which casts doubt on the effect of an imperfect credit market. At the village level, Benjamin et al. (2006) explore growth and its potential linkage to various initial conditions. First, low inequality enhances growth in non-farm incomes and tilts the village away from agriculture; second, higher inequality is associated with higher overall tax rates and more regressive taxes, lower levels of revenue and expenditures, insufficient provision of public goods, and poorly developed factor markets.

Asset and consumption inequality are sometimes employed to complement the measure of income inequality. Ravallion (1998) finds a significant harmful effect of asset inequality on consumption growth. However, the effect is lost in an aggregate growth regression. At the provincial level, rising income inequality is identified to be an obstacle to a steady-state level consumption. Wan (2005) finds slow conditional convergences for total grain, fine grain, edible oil, poultry, aquatic product, and sugar, and divergences for animal fat and red meat. Testing nonlinear dynamics of household incomes and expenditures simultaneously over time shows negative effect of inequality, especially on mean income (Ravallion and Jalan, 2001).

Absolute poverty has fallen dramatically in China in the past 30 years' reform, and rural areas account for the bulk of the decline in poverty. However, rising

inequality within the rural sector greatly slows poverty reduction (Yao et al., 2004; Ravallion and Chen, 2007). Yao et al. (2004) provide a poverty reduction simulation under different inequality scenarios and growth rates. It shows that even under the most optimistic scenario, China will still have a large number of rural poor until 2015, but even under the pessimistic assumption of income and inequality growth, China can still manage to cut its impoverished population. However, Yao's combined data (the RCRE and CHIPS) are from different households. Employing the RSESS-NBS Data, Huang et al. (2008) find that changes in the incidence of poverty are not only related to overall economic growth, but also depend on the sources and distribution of income growth.

1.4.2 Spatial Inequality and Decompositions

Many key policy issues on inequality and income distribution show themselves in a disaggregated fashion, and the individualistic tendency in the inequality measurement is reinforced by the use of decomposable inequality measures (Kanbur, 2000). Spatial inequality and decomposition reflects one of the major concerns. Spatial inequality is often defined at regional, provincial, and county level. Some papers cover a single level, others two or three. Relevant studies use proxy variables such as per capita income, GDP per capita, gross value of industrial and agricultural output or one of its components, consumption, collective income, or even grain output as indicators of living standard. Most of the studies in this field limit their analyses to a snapshot, without a time profile (e.g. Cheng, 1996; Gustafsson and Li, 1998; Hussain et al., 1994; Knight and Song, 1993; Lee, 2000; Tsui, 1993; Griffin and Zhao, 1993; Hu, 1997; Wu, 2000), however, it is rarely seen after 2000.

Among those applying panel data, most of them use provincial level data to decompose spatial inequality. The results include greater consumption equality

between 1952 and 1987 (Lyons, 1991), U-shaped inter-provincial income inequality between 1978 (or 1985) and 1993 (or 1994) (Duncan and Tian, 1999; Fujita and Hu, 2001), and increasing inter-regional inequality but decreasing intra-regional inequality between 1985 and 1994 (Fujita and Hu, 2001). Concerning the contribution of inter-regional inequality to provincial inequality, the results show 14–35 percent between 1978 and 1993 (Jian et al., 1996; Kanbur and Zhang, 1999), 38–41 percent between 1986 and 1992, and 50-60 percent between the mid-1980s and 1996 (Wan, 2007).

Fewer studies employ county or village level panel data. Howes and Hussain (1994) and Peng (1999) use county data between 1985 and 1991 to find that inter-county inequality increased by 37 percent and 20–26 percent respectively. Rozelle (1994) employs one-province village panel data between 1983 and 1988 and concludes an increase in inequalities among villages, towns, and counties.

Meanwhile, even fewer studies (Tsui, 1998a; Gustafsson and Li, 2002; Gustafsson et al., 2007; Ravallion and Chen, 1999; Chen, 2005; Benjamin et al., 2005b; Morduch and Sicular, 2002; Wan and Zhou, 2005; Guo, 2007) explore spatial inequality in China with household panel data. According to Gustafsson and Li (2002), only 4 in 16 papers summarized use household data, let alone household panel data.

Tsui (1998a) finds that inter-provincial inequality only accounts for 6–12 percent of total rural inequality between 1985 and 1990. Guo (2007) further finds that the major part of inequality has changed from inter- to intra-village level from 1986 to 2000. Benjamin et al. (2005b) confirm that the province and village respectively only explain 10 percent and 30-40 percent of rural inequality. Most inequality in rural China is *within* villages.

Overall, only a few studies use household panel data that cover most provinces in China over time, and no study summarized above simultaneously uses data at county level, provincial level, and regional level. As a special case, Gustafsson and Li (2002) provide a comprehensive study between 1988 and 1995. They show that in rural China inter-county inequality increased from 43 percent to 47 percent of total inequality. Among inter-county inequality, intra-provincial inequality stayed at 18 percent of total inequality, while inter-provincial inequality changed from 25 percent to 29 percent. Among inter-provincial inequality, intra-regional inequality dropped from 13 percent to 6 percent of total inequality, while inter-regional inequality increased greatly from 12 percent to 23 percent. While income inequality within rural counties increased from 1988 to 1995, the uneven income increase across counties was also important for the growth of rural inequality. However, in Gustafsson and Li (2002) the particular counties are not identical, which poses some problems for interpretation.

Two other points should be noted. First, robustness of decomposition should be addressed. Morduch and Sicular (2002) demonstrate how sharply different conclusions can emerge for different decomposition rules. Second, it is dangerous to use data of limited coverage to project the magnitude and change of income inequality in rural China as a whole (Gustafsson and Li, 2002) as income has grown at noticeably different rates in different parts of rural China during the economic reform.

1.4.3 Income Inequality and Other Dimensions

1.4.3.1 Income Inequality and Mobility

If a society is characterized by a great deal of income mobility, income inequality derived from the comparison of income in a single year may be misleading

as an indicator of longer run income inequality. Studies on income mobility are crucial complements to the measure of income inequality, as more and more rural residents are moving from west to east and from inland to coastal regions. Even if people stay where they are, institutional transformation may still bring a drastic change to their relative positions.

There are two categories of income mobility: macro mobility answers how much income mobility exists in the economy and how has it changed over time;[9] micro mobility defines which individual or group experiences movements, of what magnitudes, and what these movements are correlated with.[10]

Very few studies are on the macro mobility in rural China. Wang (2005) and Ying et al. (2006) both find that major income mobility indicators (e.g. time independence, positional movement and income mobility as equalizers of longer-term incomes) fall over time in rural China. However, income mobility helped equalize longer-term incomes relative to initial incomes in rural China in the 1990s (Wang, 2005). Nee (1994) finds that positional movement in rural China was higher in 1983-1989 than in 1978-1983, which he explains by "institutional change resulted in a dramatic shake-up of the rural stratification order."

The only study on micro mobility in rural China we are aware of is Zhang et al. (2006). Using the RCRE in rural China from 1987 to 2002, Zhang et al. (2006) finds the possibility for the poorest 25 percent to climb up to higher income status increased. However, the upward mobility of those of the middle-income has gradually become stagnant. The richest five percent and 10 percent are the biggest winners

[9] Six concepts are quantified to measure macro income mobility: time-independence, positional movement, share movement, non-directional income movement, directional income movement, and income mobility as an equalizer of longer-term incomes (Fields, 2007).

[10] Two types of micro mobility studies have been conducted. Unconditional micro mobility examines individual correlates of income change as one of the correlates is controlled at a time. Conditional micro mobility gauges the effect of one correlate controlling for the role of others.

during the process. Zhang et al. (2006) also breakdown the change of income inequality between the wealthy and the poor into two parts: the income change of those remaining in the wealthy group and the poor group persistently, and the change due to the shift of income status of those who move upward to the wealthy group or downward to the poor group, the latter of which was accompanied by an increasing contribution of income mobility to inequality. To identify factors which may influence the probability of moving upward, downward, or holding position, they find that the household dependent population ratio, human capital endowment, land rental market participation, and party membership have significant effects on income mobility in rural China.

1.4.3.2 Inequality and Polarization

While inequality measures are conceived to assess the expected divergence or disparity among incomes, polarization measures are sensitive to the level of identification of individuals by their income levels. Intuitively, a higher level of between-group inequality is related to the polarization phenomenon. This gives additional information that inequality measures fail to capture.

Concern over growing polarization has been prominent in policy discussions since the economic reform, when the rural-urban gap has been an important dimension in polarized China (Li, 1996). Utilizing rural and urban components from 1983 to 1995, Zhang and Kanbur (2001) test three typical polarization indices against two standard measures of inequality, which do not show distinct results. An alternative polarization index is also developed to offer more insight. It is found that rural-urban polarization is more serious in levels but modestly decreasing compared with a dramaticly increasing inland-coast polarization trend. Wan (2007) finds that the fast increase in regional inequality is accompanied by worsening polarization.

Araar (2008) breaks down the polarization index by population groups and income sources over the period 1986-2002. For policy purposes, those decompositions can help target the apparent poor groups of population and propose corrections on existing distributive policies. Araar's results show that even if inequality has increased sharply during the last two decades, the pure polarization component has remained constant or even decreased on average.

1.4.4 Income Inequality and Health

Public health studies find a relationship between income inequality and adult health outcomes in developed countries. Specifically, there seems to be a correlation between social hierarchy and mortality as well as a correlation between social hierarchy and morbidity. Existing evidence from China shows similar results.

Ling (2008) examines the role of relative income and income inequality on anthropometric health outcomes as well as health related behaviors. Reverse causation is dealt with by exogenously introducing statutory retirement age and employing retired samples. The elderly are rapidly aging and most vulnerable to the economic reform. Normally, the elderly in China have mainly relied on intergenerational transfers within families. Besides income shocks due to economic restructuring, the health outcome and status competition of the working people may reallocate resources from elderly dependents in households. In addition, the relative incomes of the elderly may be crucial in determining their health. The confluence of these trends and the Elderly Dependency Ratio (EDR) is found to affect their health outcomes such as high waist circumference, overweight or obese, and underweight. Meanwhile, it leads to unhealthy behavior, such as smoking cigarettes or pipes in the past, possibly to cope with stress.

Ling (2007) also conducts a separate study on the relationship between relative deprivation and anthropometric health outcomes for infants and children and still finds strong and consistent evidence of the effects of relative deprivation on health.

Both Ling (2007) and Ling (2008) predict that relative deprivation and unequal growth affect the "social gradient of health" in China by potentially increasing the prevalence of obesity among the rich, while concurrently being unable to reduce the prevalence of underweight among the poor.

Li and Zhu (2006) find an "inverted-U" relationship between Self-Reported Health Status (SRHS)[11] and community level income inequality. They also confirm that high inequality increases the probability of health-compromising behaviors such as smoking and alcohol consumption. Meanwhile, Li and Zhu (2006) find that relative status has a strong positive effect on self-reported health status, but its protective effect decreases with inequality and is finally offset by extremely high inequality.

Summarizing health outcome indicators utilized, Ling (2007, 2008) attempts to circumvent biases and errors in the SRHS in Li and Zhu (2006) by anthropometric measures including self-reported dietary intake and other objective indicators. Errors in self-reported responses lead to imprecise measures. Li and Zhou (2006) adopt objective health measures such as Physical Functions (PF) and Activities of Daily Living (ADL). Their PF measures include indicators such as heart, lungs, and stomach conditions, and blood pressure. The ADL, only available for individuals over fifty, measures whether the individual is physically restricted or unable to perform daily activities, such as taking a bath, eating and drinking alone, or putting on clothes. To capture health behavior, Ling (2008) uses self-reported measures of past and

[11] The SRHS is a subjective measure of individual health, which suffers from measurement errors. However, studies show that the SRHS is highly correlated with subsequent mortality, even when more objective health measures are controlled (Deaton and Paxson, 1998).

current smoking behavior, while Li and Zhou (2008) use current drinker and drinking frequency as well as past and current smoking behavior.

1.5 Areas for Further Research

The research on inequality and well-being starts the early 21st century in a vibrant state, with the new conditions raising new questions, and old questions anew. We will put forward important areas with existing panel data that are underdeveloped. A new data set is highlighted followed by a promising direction for future research.

1.5.1 New Research Areas with Existing Panel Data Sets

1.5.1.1 Factors Influencing Rural Inequality

Is geography one of the most important factors for rural inequality? Existing provincial level panel studies find this to be true, especially when weather, infrastructure, and other natural resources are encompassed. However, studies utilizing household survey data rule out geography as the most important factor and conclude that the prevailing inequality is within village. If within-village inequality is crucial, we should turn our attention to determinants of within-village inequality, such as village-level institutions, village produce and labor market development, rural industrialization, informal mutual insurance, and distribution of household endowments. One important avenue for future research is to assess causal linkages between village growth and inequality considering a comprehensive set of factors.

How does financial development influence income inequality? Theoretical predictions on the finance-inequality nexus are inconclusive. Empirical evidence with provincial panel data shows a negative role. However, if we believe that the financial market is not neutral to every rural resident, as poor residents own low amounts and types of collateral, the relationship between rural finance and inequality might be

nonlinear. Meanwhile, there has been no household level empirical test in rural China, the relationship is still undecided and awaits further exploration.

Education distribution is likely to improve at a slower pace than market institutions and opportunities, which might disproportionately benefit the better educated. Is education unequally distributed among generations (cohorts), or is there considerable inequality of education within age groups? The answers to these questions have crucial implications for how education and income distribution evolve.

1.5.1.2 Rural Inequality Decomposition

Most studies do not net out spatial dimensions of income composition other than confirming the significant contribution of non-farm income to inequality. For example, wage income from local and non-local sources are usually lumped together, while total wage income is sometimes combined with income from family-run businesses. Grouping imperfectly correlated incomes together conceals important aspects of emerging inequality and their links to household attributes and the external economic environment with which these households interact.

1.5.1.3 Effects of Inequality on Growth

In studying the link between inequality and growth, household level estimation has been conducted and a set of instruments have been used to address measurement error. Explanations ruled out include imperfect credit market, artificial relationship due to the means to aggregate data, and measurement error . Although we observe a negative impact of higher village inequality on household economic growth, we cannot rule out the existence of an unobserved third factor correlated with both initial inequality and subsequent growth. Further, we do not know whether the link between inequality and growth is in the short run or long run.

1.5.1.4 Income Inequality and Mobility

Is more mobility always better than less mobility, no matter to what extent? As we know, rural China is now experiencing a rapid transformation with incomplete social security. Too much mobility may reduce welfare through making rural residents feel more at risk given their insufficient ability to smooth income and consumption.

To better understand macro income mobility in rural China, future studies might be directed to answering two questions: how much income mobility is there with different mobility measures, and how does macro mobility change over time for each of these measures? In parallel, to improve our knowledge of micro income mobility, further discussions are on two aspects. First, how do changes in income differ from changes in log-income and position concerning unconditional micro mobility? How has income mobility profile changed over time in the course of China's rapid economic growth? Second, what are the conditional determinants of income change and how do these determinants change over time?

1.5.1.5 Inequality and Health

Studies have identified the impacts of income inequality on health outcomes and health related behaviors among older adults in rural China. Although reverse causation is dealt with by exogenously introducing statutory retirement age in urban China and employing sampled population above the statutory retirement age, scholars are still concerned about reverse causation in urban China, and that unhealthy behavior may cause subsequently lower socio-economic status.

1.5.2 New Research Areas with New Panel Data Set

Can popular community level inequality indices capture the large picture of rural inequality? A second thought on how to bridge the gap between inequality and the inequality spectrum will reveal an untouched area with far reaching implications.

1.5.2.1 Neoclassical Utility and Relative Concern

A longstanding assumption in economics is that an agent's utility depends solely on the absolute level of well-being.[12] However, Smith implicitly put forward the idea in *The Wealth of Nations* in 1776 that people should be endowed with the ability to appear in public without shame**.** Since Veblen's seminal work in 1899, a few people started to argue that utility or happiness depends in part on the comparison of one's own consumption to that of others, and it was first formally modeled by Duesenberry (1949) in his relative income hypothesis. Since the 1970's, compelling evidence on relative concern has been accumulated (Easterlin, 1974; Sen, 1983; Frank, 1985; Van de Stadt et al., 1985).

Most people have a highly localized reference group with which they compare themselves, and people tend to make comparisons with others similar to themselves but above them (Runciman, 1966; Frank and Levine, 2008). Among others, the comparisons are more saliently based on relative consumption as well as relative income.

Evidence from designer-label goods consumption in Bolivia (Kempen, 2003), festivals' budgets in India (Banerjee and Duflo, 2007), "splendid" funerals in Ghana (*The Economist*, 2007), relative deprivation and migration in Mexico (Stark and Taylor, 1991), bride-prices and dowries in south Asia and Africa (Rao, 1993; Dekker and Hoogeveen 2002), marriage payments in Bangladesh (Anderson, 2007), and community level consumption in Nepal (Fafchamps and Shilpi, 2008) show strong support for relative concern over consumption.

Relative income in the reference group also matters. Relative income is of greater importance in determining an individual's access to local resources are scarce in a backward community. Moreover, unequal income distribution in a society may

[12] The permanent income hypothesis and the life cycle hypothesis are two typical examples.

lead to instability in social capital,[13] poor health outcomes as well as health-compromising behaviors through rising mistrust and stress or declining social cohesion (Knack and Keefer, 1997; Wilkinson 1997; Li and Zhu, 2006; Ling, 2009). Deaton (2001) even argues that relative deprivation defined in terms of the relative weight of all incomes of people within the reference group who are better off can be positively linked to mortality. Relative deprivation over the income dimension much better predicts the US states mortality rates than either the income or Gini coefficient.[14] The ordinary inequality measures do not explicitly distinguish idiosyncratic deprivation each agent perceives and inequality in a society, leaving out rich implications drawn from the agent level (Chen et. al., 2010).

While Heffetz (2007) argues that relative concern over conspicuous spending is only relevant for the richest half of the U.S. population, the evidence above has clearly shown that it also matters in developing countries. Fafchamps and Shilpi (2008) further notice that isolation from market, typical for developing countries, is associated with a significant increase in relative concern. However, the empirical studies of an impoverished context, particularly in developing countries, are inadequate.

1.5.2.2 Relative Concern in Rural China and the Proposed Research Data

Rural western China is an ideal region to observe relative concern, because the dense population guarantees close social contacts among local residents and facilitates a sound definition of reference group. Vast mountainous landscapes and thousands of years of rural culture lead to isolation from the market. Meanwhile, status seeking and face-saving have been centerpieces throughout Chinese history.

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[13] Kawachi et al (1997) summarize plausible mechanisms linking income inequality and outcomes, which include erosion of social capital and stressful social comparisons.

[14] However, the analysis is based on the state level and needs to be improved.

Recently, drastic socioeconomic transformation from a rural society to an industrialized one has spurred a great divergence in social classes, high-income mobility, and competitions for status. It becomes difficult to define clearly Chinese farmers' social reference groups, since they are now more and more divided by their diversified occupations as well as income sources, social networks, and entitlements.

The escalation in conspicuous consumption is particularly reflected in housing, gift exchange, and household ceremonies, but there are no salient increases in productive investment that would secure durable increases in welfare (Brauw and Rozelle, 2008; Brauw and Giles, 2008). Incomes allocated to gift giving, dowry, bride price, and funerals are thought of as vehicles for social prestige that might challenge social status (Yan, 1996; Liu, 2000). Such spending also facilitates social networks, which may be relied upon for mutual assistance, personal financing, or other forms of help.

On the other hand, the welfare consequences of "positional externalities" associated with status seeking are severe for Chinese households living close to subsistence. The highly ritualized practices of gift giving compel villagers to offer gifts to avoid isolation from local networks. Since farm income is limited and grows slowly and nonfarm income is highly unequal and favorable to the rich, for poor residents large portions of income facilitating gift exchange cannot be compensated with limited labor resources. For example, field records show oral evidence that inflows of remittances to some households set in motion status contests with adverse consequences to others through their engagement in blood sales over the long term (Brown et al., 2010). Worse still, more severe isolation from outside, combined with more unequal market access, usually lead to more pervasive status seeking activities.

Studies on the effect of relative deprivation need detailed information on household social spending in major events and other interested behaviors that

previous data sets do not have. More importantly, social network information that helps identify reference groups is missing in the literature. In addition, most of the data sets do not have accurate factor market information, such as wage rate, interest rate, bride price, and land rental rate.

Further, household panel data is needed to capture dynamic behaviors of status competitors. Panel data might also alleviate the simultaneity issue and omitted variable bias that may arise in a cross-section. Considering the panel data sets available, only a small portion of households in each village are interviewed. Among the interviewed, households in the tails of income distribution are tended to be overlooked. Although such datasets are helpful for measuring overall rural inequality, they are less useful for discerning inequality in a village. More importantly, despite its high costs and the resulting limited coverage, conducting a census-type panel survey provides a feasible way through which we acquire a complete picture of relative deprivation without relying on sampling. An ideal dataset further requires relative isolation from the outside market.

Therefore, an extensive in-depth panel dataset for only a few communities complements and improves upon the previous panel data. The IFPRI-CAAS is an example that satisfies the aforementioned major requirements: (1) three waves of census-type panel survey; (2) detailed information on social network, social status, and social behavior; (3) a geographically isolated region; (4) a large share of ethnic minorities that diversify social norms under study. These data features help us go beyond the immediate explanations of many important behaviors that are labeled with poverty, as poverty cannot really answer why not all poor people engage in these behaviors. Facilitating identification of social interactions, these features aid in understanding the heterogeneous patterns in behaviors that might improve policy targeting.

Applying the first two waves of the IFPRI-CAAS, Chen and Zhang (2009) explore the causality between social norm, status seeking, and blood donation behavior. First, they find preliminary evidence that social status seeking, intensified through positional spending and relative deprivation, drives more blood donation. Relative deprivation complements the measure of income inequality. Second, social norms matter through social pressure and imitation in networks. Further, contrary to the well-received idea, shocks do not consistently induce blood donation, suggesting the link between blood income and other needs that deserves further research.

Following the first two waves (2005 and 2007) of the IFPRI-CAAS, we conducted the 2010 wave in which extensive data collection on long-term gift exchange and social network was also implemented. Employing two identification strategies, i.e. instrumental variable and network-based identification, to control for the effect of social interactions on stigma behavior, Chen et al. (2010) estimate the impact of concern for relative income using all three waves of the IFPRI-CAAS. Apart from the income effect, Chen et al. (2010) find that social influences and relative concern are two key determining factors. First, the poor are faced with more pressure to raise social status, thereby donating blood. The pressure to donate blood is especially salient for households with more unmarried sons, suggesting tightening tension in the unbalanced marriage market. Second, the disutility associated with blood donation drops as more people in a reference group participate. A person's preference on stigmatized behavior is largely shaped by the behavior of peers.

1.6 Conclusions

China's rapid economic growth over the last thirty years has equipped her with the world's second largest economy. China has also witnessed a huge increase in average living standards. However, resource distribution is getting more and more

unequal between urban and rural, east and west, coastal and inland China. There are mounting concerns that the growing inequality might hinder sharing of the fruits of economic development, and the resulting social unrest may slow down economic transition.

However, it is firstly a miracle in human history that China has succeeded in sustaining fast growth and declining poverty for the last three decades. Meanwhile, it is also a miracle that China could successfully manage a stable society and smooth development when the Gini coefficient has already hit the widely accepted critical point in the early period. The study of income distribution and well-being in this fast transforming society is vital to understand this success, which might pave the way for improved policy-making and more harmonious growth, and substantially contribute to economics.

According to China's official statistics, the rural population of China still accounts for more than half of the total population. With unequal access to education, health care, the rural financial system, and non-farm opportunities, combined with low returns to agriculture, focusing on rural inequality and social class divergence are of utmost importance in maintaining economic growth and social stability in contemporary China.

Most previous studies of rural inequality and well-being in rural China use cross-sectional data, focusing on their levels, trends, and sources of inequality. The primary analyses have been built on macro data up until late 1990s. The last decade has witnessed a second wave of inequality studies dominated by micro panel datasets.

This chapter serves as one of the first comprehensive reviews of studies on those critical issues that use available longitudinal datasets from rural China. Most importantly, the fast but unequal economic growth suggests that relative concern based on resource distribution matters greatly to well-being for people of different

backgrounds, albeit largely neglected in the current policy discourse and academia. Highlighting it as an urgent direction to be explored, our unique dataset and research project may initiate the third wave of upgraded studies on distribution and well-being.

Table 1.1 Major Panel Datasets for Income Distribution Studies in Rural China

Data Source	Category	household	Village	Province	Sample Period	Main Characteristics	Literature
				Micro Level Panel Data			
RCRE	Planned panels	24,000	360	31	1986-present (except 1992, 1994)	diary book + visiting; nationally representative; 1/3 sample attrition over the period 1986-1999; collected on an annual basis; from fixed rural survey sites	Benjamin et al. (2005a, 2006); Wan and Zhou (2005); Araar (2008); Brauw et al. (2008); Zhang et al. (2006)
RHS-NBS	Planned panels	68,190	7,100	31	1981-present (annually)	sample rotation on a 5-year basis; diary book + visiting; detailed household income and consumption; nationally representative; micro data publicly unavailable; collected on an annual basis; the only data source covering a reasonably long time period	Ravallion (1998) Chen and Ravallion (1996)
CHNS	Planned panels	1920 / 2160	96/108	9	1989, 1991, 1993, 1997, 2000, 2004, 2006	a 3-day observations in each survey on detailed nutrition and health information; poor income and expenditure information; rural and urban samples; county names not revealed	Benjamin et al. (2002, 2005b); Ling (2008); Li et al. (2006); Wang (2005)
CHIPS	Retrospective panels	4178 / 7888 / 9200	-	18/22	1988, 1995, 2002	no linkage at household (but village) level among waves; recall data for income in years between nearest waves; detailed information on household income components; include a subsample of rural migrants; combine rural and urban samples	Khan and Riskin (1998); Yao et al. (2004); Chen (2005); Khor and Pencavel (2006); Ying et al. (2006); Brauw and Rozelle (2008); Brauw and Giles (2008)

CAPM	planned panels	7,950	130 / 138	25	1983, 1989	detailed information on nutrition, health, and medical research	Nee (1994)
MORDUCH	Planned panels	259	16	1	1990-1993	Special attention to consistent definitions of income	Morduch and Sicular (2002)
IFPRI-CAAS	Planned panels	805 / 834 / 872	3	1	2004, 2006, 2009	census-type household survey; detailed information on social spending, stigmatized behavior and health outcomes; 3-day observation on food and nutrition intake; 10-year spontaneous gift-exchange records for all households in three natural villages; geographically isolated; multi-ethnic populated	Brown et al. (2010); Chen et al. (2010)
Macro Level Panel Data							
RSESS-NBS	Macro Panels	-	-	28	1985–2002	provincial level panel data	Huang et al. (2008)
IFPRI	Macro Panels	-	-	29	1952-2001	longer provincial level panel data	Fan et al. (2005)
RHS Statistic	Macro Panels	-	-	28	1982-1998	provincial level panel data; detailed sub-categories of food consumption	Wan (2005)
CCPFSY	Macro Panels	1860 counties			1993-2000	detailed information on public sector at the county level	Zhang (2009)

Note: There are no inadvertent or pseudo panels other than planned panels and retrospective panels. Only rural samples in each wave of the CHIPS are included.

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CHAPTER 2

GIFT AND SOCIAL NETWORK STRUCTURE IN RURAL CHINA

2.1 Introduction

Written record for gift exchanges has been kept in many Asian countries, such as Thailand, Vietnam, China and Korea. The purpose is to record gifts one receives from hosting social events and pay back accordingly when fellow residents hold social events in the future. Across Asian countries, major social events vary but commonly involve wedding, funeral, childbirth and so on.

Widely spread gift record-keeping tradition offers researchers a means to collect valuable datasets for development studies and social network analysis (SNA) in sociology. More importantly, this type of data has a number of unique features lacking in previous network datasets. However, to our knowledge, long-term spontaneous gift record has not been utilized in economics studies. This paper attempts to draw researchers' attention to this underutilized data source.

The analysis is ordered into three parts: advantages of gift record data over previous dataset; gift spending patterns in major social events in rural China; gift network pattern and determinants.

I begin with discussion on how the dyadic gift record better fits studies at different level and of different purposes: household level network engagement and well-being as well as link formation. Unique features of gift record that address five critical issues in the literature are laid

out.

I then describe the IFPRI-CAAS project entitled *Relative Concern, Social Networks and Well-being*, a three-wave census-type household survey conducted in 18 remote villages in rural western China between 2004 and 2009 and a ten-year household gift exchange data we collected during the third wave in early 2010. One of the primary aims of the project was to gather quantitative data on the evolution of social networks and to understand how concern for relative standing and social network structure affect well-being.

The overall trend of household ceremonies is documented and major ceremonies are compared, emphasizing lavish spending on social events and its recent escalation. Our initial evidence rules out social exclusion hypothesis and points to status seeking and marriage market pressure. Moreover, though risk-sharing, such as mutual assistance in labor, information, production tools and informal credit, might not be the cause of gift escalation, it should play an important role in maintaining gift exchanges in the long run.

Gift network structure is evolved over long-term gift exchanges. I further explore its demographic and socioeconomic determinants. Blood relatives' network size, economic status, age structure, marriage market pressure, ethnicity and economic inequality are found to affect major network structure indicators.

Though only patterns of gift network and its associations with other social behavior are documented, this paper may help improve our initial understanding of networks. Our insights on unique features of gift record data can hardly be general enough for others to follow, but the proposal of gift record collection in this paper might help future studies to overcome some of the important issues.

The paper is organized as follows: in Section II I discuss the unique features of gift record data, in Section III I describe the gift data collection process as well the corresponding census survey, in Section IV household ceremonies in rural China are documented, in Section V, VI and VII I respectively analyze the recent gift spending pattern, its association with informal insurance and determinants of network structure, and in Section VIII I conclude.

2.2 Unique Features for Gift-Exchange Record Data

The standard economics literature has been resorting to approaches founded on the principle of centralized human interaction in the market, anonymous agents, and uniform prices through which individuals coordinate (Goyal, 2009). For instance, the literature quantifying welfare impact of social embeddedness (see a review by Durlauf and Fafchamps, 2005) measures social networks through membership in communities, ethnicity, gender, and geographic neighborhood and so on (Narayan and Pritchett, 1999). However, the differences in connections among heterogeneous agents (i.e. sizes, intensities, distributions and locations) through which social interactions flow, rather than memberships themselves, have an essential bearing on behavior (Murgai et al., 2000; Genicot and Ray, 2000).

Social network research calls for a new dataset that considers the following key issues: First, the reflection problem in identifying peer effects (Manski, 1993); Second, economists still largely ignore the role of indirect social ties.[15] The studies of dyad relationships had dominated economics for a long time before allowing triad relationships, which in turn has brought in many interesting social concepts within the bounds of economic models (Akerlof, 1976; Basu, 1986). However, empirical studies incorporating indirect ties are scant; Third, the snapshot feature of

[15] As H. L. Mencken put, a wealthy man is one who earns $200 a year more than his wife's sister's husband, which challenged the only pattern of direct ties.

most network data studied determines that the dynamic evolution of links and networks are not well explored (Jackson, 2007; Fafchamps and Gubert, 2007); Finally, agent and link sampling biases as well as measurement errors further hinder us from studying network impacts.

Fortunately, a census dataset on spontaneous gift-receiving records during major social occasions can aid us in understanding the mechanism of social interactions via taking care of the abovementioned key issues. Meanwhile, gift exchanges are widely seen in ceremonies linking households economically and socially but rarely studied in the literature.

2.2.1 Features for Studies at Different Levels

2.2.1.1 Household Network Engagement and Well-being

Conventional economics has been studying household decision making. To explore household behavior in social networks, the most straightforward way is to sample households, from where information on social links is collected. In the literature, sampling individuals are seen in three types: (1) census type survey of all individuals (also known as *sociometric network*)[16]; (2) random sampling (also known as *egocentric network*); (3) quasi-random sampling (also called *Snowball sampling*)[17]. Only approaches (1) and (2) have been utilized in the economics literature. Though most studies follow (2) due to its much lower costs, random sampling suffers from significant loss of information on the network structure. As a result, much knowledge accumulated by sociologists in social network analyses (SNA) (e.g. Wasserman and Faust, 1994), cannot be directly applied to datasets in economics, substantially missing potentially interesting interdisciplinary questions.

[16] For instance, see De Weerdt (2004), Dekker (2004) and Goldstein and Udry (1999).

[17] It starts from a set of initial respondents, and surveyors enlarge the sample by adding in those individuals mentioned by previous respondents (Goodman, 1961). In this way, sampling of relationships and individuals are simultaneously done. However, individuals following the first one are not randomly selected, which affects population inference (Heckathorn, 2002).

If our goal is to understand the impact of network engagement, complete information on network connections is required. However, random household sampling cannot provide us information on network structure, total resources devoted to the network, and one's position in the network. This flaw can be obviated when we have census survey data and network data for all agents.

2.2.1.2 Link Formation

When studying formation of social ties, sampling links is the immediate step following sampling individuals. Most studies include all the links (they could collect) among individuals in the sample (known as *matching within sample*), while a few randomly sample relationships (known as *random matching*). Santos and Barrett (2008a) questions the reliability of using *matching within sample* to infer network formation, but they also find that *random matching* performs poorly under certain conditions.[18] In other words, it is not apparent that one strategy is always superior to the other.

From the perspective of preserving network information, *matching within sample* is desirable. However, this sampling strategy is only preferred when sampling ratio is high, which does not fit usual network datasets. Fortunately, our gift record dataset in rural Guizhou obviates this flaw due to its census feature, which guarantees the coexistence of best possible features: high sampling ratio, unrestricted network size, and much information on network structure.

Studies usually survey links at one point of time. The snapshot feature of the network data determines that the dynamic evolutions of links and networks cannot be well explored (Jackson, 2007; Fafchamps and Gubert, 2007). For instance, our long-term gift-exchanges in three typical villages spread between isolation and openness amid the fast growing Chinese economy enable

[18] Santos and Barrett (2008a) finds that matching within sample is much less efficient than random matching when sampling ratio is low or when links are formed uninterestingly random. However, *random matching* also performs poorly when there is no restriction on the size of networks.

us to explore the dynamic evolution of social networks.[19]

A common econometric issue when studying dyadic link formation is non-independent observations, due to the presence of node-specific characteristics common to all links containing that node. Conventional OLS estimation generates consistent coefficient but inconsistent standard errors. Specifically, standard errors can be much underestimated.

Fortunately, two major approaches have been developed to deal with the issue. One way is to correct standard errors or p values, such as using the Quadratic Assignment Procedure (QAP) to adjust p-values (Simpson, 2001), adjusting dyadic standard errors (Fafchamps and Gubert, 2007) or multi-way clustering (Cameron et al., 2006). To release the assumption that the error terms of two dyads containing no mutual members are uncorrelated, Chen et al. (2012a) cluster the observations according to time periods. A second method uses node fixed effect to purge out the unobserved attributes (De Weerdt, 2004). A detailed review of these methods can be found in Chen et al. (2012a).

2.2.2 Tackling Measurement Errors

2.2.2.1 Missing Relations Linking Outside

In the literature, link sampling process is usually accompanied by missing ties with outside agents (De Weerdt, 2004; Fafchamps and Gubert, 2007), since these agents are usually not included in the sample.[20] Therefore, inference from sample to population might be with error when significant non-random differences between identified links and missing links exist. This is

[19] Specifically, the inflating social spending for higher social status and extended network motivates people to follow, while the rapid economic development drives people to the market and rely less on informal social insurance. However, unequal market access (e.g. remittance, job opportunities and windfall income) exacerbates inflating social spending.

[20] In De Weerdt (2004), one third of links, mostly formed with agents outside, are lost, while in Fafchamps and Gubert (2007) nearly 80% of the network members are not in the sample and lost.

probable, as there is large literature on lower covariance in shocks and the motive of cross-village insurance. Meanwhile, seemingly isolated agents might actually be linked to others out of sample. In all these situations, misleading results can be expected (Udry and Conley, 2005).

In our study, however, cross-village links between the sampled villages with gift record data and the other surveyed villages nearby are captured. In other words, all these gift senders and receivers are matched using information from three-wave household survey.

2.2.2.2 Implicitly Ranking Relationships

When limiting the maximum links to be identified by each respondent (e.g. Fafchamps and Gubert, 2007), there is a risk of implicitly ranking relationships. Sometimes the "maximum number" strategy is difficult to be implemented when respondents refused to rank people they regard as equivalently close to them. Meanwhile it is possible that names listed do not reflect their importance without respondents' thinking twice. Therefore, outcomes highly depend on specific contexts of the different surveys and might be unable to replicate. Even if we survey for complete relationships, stronger ties usually have higher probability of being identified, while weaker ties are usually left out. It can be a problem when we explore information networks than informal insurance networks, since *weak ties* matter more in the former case (Granovetter, 1974).

In our gift data, there is no limit for household gift links, and strength of relations can be precisely reflected in terms of money. Gift spending is mainly recognized as an informal insurance against lumpy ceremony expenditures incurred.

2.2.2.3 Real or Potential Links

Depending on different contexts, real links (Dekker, 2004, Krishnan and Sciubba, 2005 Conley and Udry, 2010; Udry and Conley, 2005) and potential links (De Weerdt, 2004;

Fafchamps and Gubert, 2007; Santos and Barrett, 2008b) have been the target of attention.[21] The "real" relationships in the literature were largely recalled by respondents themselves, while there are no spontaneous records in their daily life that are referred to. However, in the gift record data there normally is no recall error. According to the Chinese custom, all gifts are recorded on the day of ceremonies with at least two people on site counting and checking them.

2.2.2.4 Ambiguities between Sending and Receiving

The literature on social network usually does not explicitly distinguish resources received from resources provided in survey questions. For instance, Fafchamps and Gubert (2007) measures ties in Philippines by asking respondents in a one-question framework who they could rely on in case of need or to whom they provide help when called upon to do so. Similarly, De Weerdt (2004) asked "Can you give a list of people, who you can personally rely on for help and/or that can rely on you for help in cash, kind or labor" in a Tanzanian sample. These questions do not separate giving help from receiving help. Santos and Barrett (2008b) use data from Ethiopia where a link is measured asking people who they could rely on to ask for cattle as a gift. It is still difficult to separate relationships which involve only receiving from those involving both giving and receiving.

In contrast, our gift exchange data clearly distinguishes gift senders and gift receivers. Besides, the feature of ten-year gift record can further separate agents who have been only receiving or sending gifts from agents who have been involving in both gift giving and receiving.

2.2.2.5 Projection Bias in Self-Reporting and Proxy-Reporting

Given biases on respondents' self-reporting, some studies instead rely on proxy-reporting. However, proxy-reported peer behavior is often correlated with respondents' behavior due to

[21] Real links are preferred when we explore past decision-making, while potential links are more suitable when we study forward-looking behavior.

projection bias. In an informal insurance network, respondents may have more precise information on their closer fellow residents in the network, while projection bias can be large for more distant residents. In an information network, such as technology adoption network, innovative technology adopters tend to over-report the incidence of adoption in their social network.

Confirming that proxy-reporting errors are correlated with respondent attributes, Hogset and Barrett (2010) finds that self-reporting and proxy-reporting generate different regression results on peer behaviors, questioning the use of proxy-reporting. However, throughout the paper they assume that self-reporting reflects the truth, which may not be necessarily applied to other cases. For example, when we survey a household's gift spending, self-reporting may suffer from multiple biases due to respondents' strategic actions. Specifically, the poor might over-report gift expenditure to complain their huge social burden, while the rich may tend to hide their real income by under-reporting gift expenditure. The opposite may also be true when the poor treat enumerators as officials, thus under-report gift spending to compete for subsidies. The rich may prefer to over-report to show status.

Nonetheless, in our gift record data all written records are based on gifts people received, which simultaneously avoid subjective aspects of both self-reporting and proxy-reporting.

2.3 Data Collection for IFPRI-CAAS Project

2.3.1 Three-Wave Census Survey

The household information for this study comes from three waves of census-type household survey conducted by us in 18 natural villages in rural Western China.[22] Located in the central

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

part of the poorest Guizhou province, the 18 natural villages on average is at the median level in Guizhou. It is both geographically and ethnically diversified. Due to its isolation from outside, local residents know each other well. Most residents' kinship networks are confined in these natural 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.

801, 833 and 872 households were respectively surveyed in 2005, 2007 and 2010. All three waves include detailed information on villages, household demographics, income, consumption, transfers, expenditures and incomes related to gift-giving, ceremony organizations and blood donation. Most information was collected for each household member, including those who were working outside the county at the time of survey. In the follow-up survey in 2010, major health indicators were collected for all family members in the 18 natural villages. Among them, a 3-day on-site observation on food and nutrition intake was implemented for all family members from 9 out of 18 natural villages.

2.3.2 Gift-Exchange Records Collection

Gift-receiving records are usually kept for a long time in order to pay back accordingly when celebrations in other families are held (Yan, 1996).[23] Upon verifying the availability and ruling out significant selection of gift record book during our pilot survey in August 2009, during 2010 survey gift-receiving records for major social occasions (i.e. male members' wedding, female members' wedding, funeral, coming-of-age ceremony, child birth ceremony, and house-moving ceremony) occurred in the last decade were collected from all households in three out of eighteen villages that we conducted the three-wave census survey (Table 2.1).

[23] 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."

The unique Karst landform keeps the three villages isolated from the outside society. Among them, village 1 is the remotest (10 kilometers away from the county seat with poor road access), and the local custom is well preserved. In contrast, 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.[24] Since the surveyed villages are populated with Han group and ethnic minorities, we are able to explore social connections between ethnic groups.

We identified 335 households composed of 160 households from the three villages and 175 households from the other fifteen villages covered by our large scale survey. In total, 8074 gift links during 2000-2009 are identified, and 4611 cross-county / township gift links were recorded. Nearly all households' gift-receiving records for the ceremonies between 2005 and 2009 were included in this study, since less than 5 percent households reported gift book loss or damage to us.[25] Meanwhile, we collected gift-receiving records for some ceremonies between 1994 and 2004 to analyze its trend.

The centerpiece is gift link identification. Instead of embedding many enumerators in survey villages, the field work can be achieved by very few enumerators but continuous efforts for an extended period of time. Gift record collection requires repeated household visit to identify names and other information.

[24] A major difference in this aspect between public celebrations in India and household ceremonies in China can be found in Rao (2001) and Chen (2011b).

[25] We consulted major ceremonies with village leader and local residents to verify before going to individual families. Meanwhile, this prior information helped each household recall and find gift books for us.

If all family members are illiterates, a group of two or three educated relatives usually help record and check 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 brought the whole list of names for the 18 villages to each household to help identify and check the names on the records.[26] We also joined local public gatherings to identify some hard nicknames.

Information on kinship and relatedness among villagers was also collected and matched to each gift link. As many other traditional rural communities, the three villages are all organized by long-term coordination of major clans. Taking one of the three villages as an example (Figure 2.1), households in the same clan usually live closer to each other (due to the land owned by their common predecessor) with more intense gift exchanges.

2.4 Household Ceremonies in Rural China

2.4.1 The Overall Trend

Our paper presents a typical case in rural China where diversified traditional household ceremonies are preserved and gift connections maintained. The overall network centralities for both gift-sending and gift-receiving have been decreasing (Figure 2.2(a)), since local residents have been more widely involved in gift exchanges and ceremony hosting. However, average household centrality has been rapidly increasing (Figure 2.2(b)) due to the fact that households are more intensely exchange gifts in ceremonies. Meanwhile, the increasing Freeman/Flow betweenness Centrality in Figure 2.2(c) show that people tend to send gifts to more active households in the network, as they locate between more pairs of households and therefore are more powerful in mobilizing resources in the rural community.

[26] 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.

Exchanging in-kind gifts during ceremonies has been a long- term tradition. In wedding ceremonies, apart from the usual large expenses on cash gift, people send dumplings, pork, wool, woolen blankets, bed sheets, quilts, kitchen supplies, candles, wine, basins and pillows to the new couple to symbolize a sweet life or to help purchase necessities. During funeral ceremonies, people send less cash but more in-kind gifts and non-cash help. The in-kind gifts include corn, lamb, pork, woolen blankets, quilts, edible oil, wine as well as other sacrificial offerings. In celebrating come-of-age occasion, people send rice and children's wear, while in child birth ceremonies people additionally give wool, eggs and fruits. When friends and relatives move their houses, furniture, stoves and curtain are usually sent as gifts.

In-kind gifts are more widely seen in the following conditions: one, in impoverished villages residents need in-kind gift to compensate cash shortage; two, in some household celebrations that are saliently featured by reciprocal assistance, such as funeral and house-moving, people send in-kind gift to show their closeness to hosts in addition to large amount of cash gift; three, poor market access in remote regions make in-kind goods scarce and relatively more attractive.

However, in recent years cash gift has become more and more intense relative to in-kind gifts (Figure 2.3). While evidence from the western culture demonstrates that sending cash to friends is associated with stigma (Waldfogel, 2002), it is quite interesting that our observation in rural China is the opposite, i.e., people tend to measure closeness according cash gift. The pressure from social network may drive people to follow others in sending cash, which has been replacing in-kind goods to measure closeness among fellow residents. Meanwhile, significant differences are found in both likelihood and intensity between in-kind and cash gifts (Table 2.2). The contrasting pattern for cash and in-kind gift is more salient for the more open villages.

Different ethnicities demonstrate different network intensity for cash gifts but not for in-kind gifts. For instance, during 1994-2009 the Catholic village has witnessed both fewer and less intense cash ties among residents than other Han villages. Nonetheless, the patterns are not saliently different for in-kind gift network in Han villages versus minority villages.

2.4.2 Major Ceremonies

Based on resemblance for each pair of ceremonies, three comparisons are conducted.

Firstly, male weddings are one of the most publicly participated social occasions during which hosts invite as many guests as possible. The size of wedding ceremonies signals how rich one family is to the fellow residents. However, when females get married only closest relatives, friends and neighbors are invited. Brides' families have little motive to show how rich they are. The contrasting pattern between female wedding network (Panel (a) in Figure 2.4) and male wedding network (Panel (b) in Figure 2.4) illustrates this point. Figure 2.5a shows that the out-degree and in-degree centralities for male wedding network is smaller than female wedding, meaning that people more widely exchange gifts during male weddings. Only two female weddings were held in the past ten years, though many girls were married out. One major reason is that unbalanced sex ratio triggers asymmetric marriage market competition from grooms' families. Another important point is that the patrilineal society with son preference makes wedding ceremony mainly an event for grooms' families in the purpose of extending network and achieving higher social status.

Second, childbirth is more of a private ceremony, in which the closest relatives and friends are invited. The extremely poor households may combine it[27] with wedding ceremony due to the fact that organizations of such events are extremely costly for them, and gifts they receive will be

[27] People usually do not celebrate birthday in rural China except for the elderly.

a huge burden to pay back later. Compared to childbirth, come-of-age, a ceremony solely for sons, is more formally and widely held in the community. The contrasting pattern between childbirth network (Panel (c) in Figure 2.4) and come-of-age network (Panel (d) in Figure 2.4) demonstrates this point. Figure 2.5b presents that the out-degree and in-degree centralities for come-of-age ceremony is smaller, suggesting wider participation. One reason is that a family faces higher pressure in the marriage market when a son grows up. Taoists are invited to host a ritual followed by a large banquet, signaling the growing up of a son to the fellow residents as well as the potential matchmaker.

A third comparison is between house-moving and funeral. It is quite often that only closest friends, relatives and neighbors are invited to a house-moving ceremony. No much assistance in its preparation is needed. However, a funeral lasts for at least three days and requires much assistance. A more fundamental difference between the two occasions might be that funeral serves as a status signal for both dead and alive, while house-moving only sends status signal for this generation. The contrasting pattern is verified by a comparison of network map between the two occasions (Panel (e) & (f) in Figure 2.4). Figure 2.5c further suggests that funerals are more and widely participated, since both its in-degree and out-degree centralities are significantly smaller than house-moving.

Comparing six major occasions over recent years, funerals and male weddings have been the most widely held, while female weddings and child births ceremonies have been the least widely held. Meanwhile, people most widely exchange gifts in come-of-age ceremonies and male weddings, while they have sent gifts the least widely during female weddings, house moving and child birth ceremonies. The gift-sending network centralities decline for nearly all

ceremonies, especially for female weddings and funerals, while gift-receiving network centralities decline the most for funerals and childbirths.

2.5 The Recent Gift Spending Escalation

Though believed to facilitate informal insurance, increasingly large proportion of resources devoted to gifts and festivals spending, especially in impoverished areas, may have negative impact on well-being (Chen, 2012b). Thus, we are interested in understanding why so many resources have been spent on gifts and festivals and why the expenditure has been escalating in recent years. Fortunately, the rich gift record data, combined with panel household information, provide us with a chance to explore the mechanism.

First, three indicators, relative centrality in the network (also known as network activeness or social visibility in the literature), household gift expenditure for major occasions and share of gift expenditure, embody network engagement of different aspects: centrality focuses more on the density of links; gift expenditure addresses strength of the links; share of gift expenditure further adjusts for income size and measures gift-exchange burden across households.

As discussed in the overall trend of household ceremonies in rural China, network centralities for both gift-sending and gift-receiving have been decreasing. Consistently, the average household centrality has been rapidly increasing. The trends of both household and network centralities suggest more frequent and evenly distributed gift exchanges overtime.

Utilizing gift record data, Table 2.3 presents rapid growing gift expenditure per occasion as well as inflating sizes of major social events in terms of number of households attending. In the three-wave survey, respondents were also asked to recall their average gifts to direct relatives, friends, and neighbors during major ceremonies between 2001 and 2006. After adjusting for

inflation, the median gift per occasion jumped from 42 RMB to 67 RMB for direct relatives and from 21 RMB to 35 RMB for friends and neighbors. The gift expenditure per occasion increased more dramatically for villages closer to the county seat. All major ceremonies demonstrate booms in the number of guests. Combining both dimensions, it suggests that total household gift expenditure has increased quickly in recent years. From organizers' perspective, total expenditures in major ceremonies amount to several times of their per capita income, especially weddings for grooms' families (Table 2.4).

Next only reciprocal ties are used to acquire a closer view of gift escalation. Reciprocal ties are defined as gift exchanges in both directions between a pair of households during 2000-2009. If we further understand reciprocal ties as reciprocal financial assistance within each category of ceremony, it might provide us with more accurate and comparable account of gift escalation. In the gift record, reciprocal ties are usually confined to within two years, while they are scant for time duration longer than six years.

Figure 2.6a presents inflation rates for reciprocal ties. In terms of mean gift inflation per year (RMB), male wedding ranks the highest, followed by house-moving and funeral. Meanwhile, in terms of annualized gift inflation rate, funeral ranks the highest, followed by male wedding. Concerning the relationship between time gap (gift repaying - gift receiving) and gift inflation, Generally, gift inflation (in terms of RMB and inflation rate) is the highest when a gift is repaid shortly afterwards, while it lowers as time gap increases. Figure 2.6b decomposes gift inflation into major social occasions. Funeral has the highest immidiate inflation rate of 300% if it is paid back in the same year, followed by an immediate inflation of 70% for male wedding. The annualized gift inflation vanishes faster for funerals and male weddings than other

ceremonies. However, we should be cautious in interpreting this result, since the figures can be driven by extreme values when divided into small categories.

Figure 2.7 presents share of gift expenditure categorized by four income quartiles and year. The poorer a household is, the higher share of income is devoted to social spending, and the higher growth rate of gift expenditure share is between 2004 and 2009. Using the first two waves of our survey, Brown et al. (2011) show that gift spending far exceeds annualized growth in per capita income and other consumption in recent years, also suggesting a rapid increase in the share of gift expenditure.

Why has gift spending escalated? One hypothesis is social exclusion, meaning that gift giving may serve as an exclusion strategy. On the one hand, the larger the risk sharing network, the better the group can diversify their income risks; on the other hand, if the group includes too many households with persistently low income, the relatively high income households would rather not share risks with them but exclude them. However, the transition matrixes based on the three-wave survey data (Table 2.5a and Table 2.5b) do not reflect much rigidity in the three natural villages. Meanwhile, Table 2.6a and Table 2.6b respectively summarize changes in network participation and activeness. Much fewer households drop out of gift exchange activity or become less active, while their inactive counterparts significantly join or become more active in the network. In other words, there is no convincing evidence on social exclusion.

An alternative hypothesis is the concern for relative standing, which can be motivated by income inequality as well as social pressure. Unequal income distribution is widely seen in contemporary China where the Gini coefficient has been far surpassing 0.4 (Chen, 2011a), while in our surveyed communities it is even larger than 0.5 (Table 2.1). The enlarging income gap motives people to climb social ladders. Social pressure can be originated from tightening

marriage market with unblanced sex ratios. The pressure to compete in the marriage market motivates households with unmarried son to actively engage in social events, which signals to matchmakers and brides' families (Brown et al., 2011; Wei and Zhang, 2011).

Windfall & non-earned income are suspected to trigger more gift spending, and their growth rates coincide with the gift growth rate (Figure 2.8). It has been well recognized that windfall income is often spent differently compared to regular income. In rural China, Chen et al. (2012a) find that the recent growth in gift spending is enhanced due to more opoortunities to get access to lumpy windfall income, such as resettlement subsidy (targeting dilapidated houses and vulnerable habitats) and land acquisitions subsidy (targeting villages close to the county seat affected by urbanization development program). Households with these windfall incomes are found to spend more on gift exchange while spillover to other households in the networks.

Moreover, remittance from family members working in developed regions may intensify gift spending. Table 2.3 shows booming gift spending in ceremonies after 2005, and Table 2.4 shows that ceremony organization has become more costly since 2004-2005. This trend coincides with the research finding that China passed the Lewis turning point of unlimited labor supply after 2003 (Zhang et. al., 2010). The passage of the turning point means significant rising wages in the labor market and potentially higher remittance.

Apart from remittance and large windfall income, the smaller sized official subsidies have been more and more widely seen over the past five years. For instance, direct grain subsidy was implemented since 2005, and it targets grain growing area rather than yield. The subsidy, influencing household decisions in our 2nd and 3rd wave, may be disproportionally spent on gift and festival spending. Overall, the decisions to distribute windfall income and subsidies are made by officials and affect household gift expenditure.

2.6 Gift Exchange and Informal Insurance

Gift exchanges and the resulting social networks might be associated with the concern for risk-pooling, including labor exchanges and informal credit. Though in this paper we do not attempt to explore the complex causality between social events engagement and risk-sharing, an initial analysis of correlations is also informative.

Table 2.7a summarizes major forms of mutual assistance. In the local rural community, labor exchanges during busy seasons and house building, though irrelevant for half of the families, are more often than other forms of resources exchange. During the period of assistance, hosts normally spend much money in providing delicious meals. Nowadays, people are prone to hire relatives / friends / neighbors with cash wage during harvest time and house building period, rather than exchanging labor with each other, which is especially prevalent in villages with easier market access. Nonetheless, Table 2.7b shows a significant correlation between centrality in a network and frequency of labor exchange, job information exchange and assisting elderly/kids care. Meanwhile, households with higher share of gift expenditure (usually the poor households) have poorer access to these informal resources exchanges.

Table 2.8a shows that more than half of the rural residents surveyed are in debt, and people generally rely on relatives when faced with cash shortage. Most loans do not carry an interest, especially those offered by relatives and neighbors. Households of higher centrality and those spend more on gifts are associated with more debt accumulation, and significant loans have been granted by relatives. Meanwhile, they are more likely to ask relatives / friends / neighbors for help when faced with cash shortage. Surprisingly, households more central to the network significantly resort to donating blood when faced with cash shortage (Table 2.8b). This suggests

that blood donation might be complementary to other means in coping with cash shortage, or high network centrality may be achieved at the cost of more social spending and higher chance of blood donation. The latter possibility is further explored in Xing et al. (2009).

2.7 How is Gift Network Structure Determined?

The Network structure depicted in Figures 2.1-2.4 has been built upon all gift exchanges. Each group member plays a role in its formation. Having discussed social norms, risk-sharing motives, status concern, windfall income that may affect gift expenditure, one step further we are curious about whether anything can be said about the demographic and socioeconomic determinants of the long-term gift network structure. In order to do so, we introduce some key network concepts and measures. *Bonacich Centrality* is a function of the (direct and indirect) connections of the actors in one's neighborhood. The more connections the actors in one's neighborhood have, the more central one is. *Popularity* measures links that one receives from peers, while *influence* measures links that one sends out to peers. *Closeness* gauges distance of the respondent to all others in the network, utilizing both direct and indirect links. The four measures embody network information from four dimensions, and altogether they are most often used in describing important network features. A detailed review of these measures is included in the Appendix.

Estimation results from treating all years' gift exchanges as one network are presented in Table 2.9a. First, Households with larger blood relatives' network attend more ceremonies and thus have higher centrality and influence, but they do not have higher closeness, since their blood relatives may not be at the center of networks. However, richer households perform more actively in gift networks in all four dimensions, one difference is that the latter can choose to

whom they send gifts; second, concerning demographic characteristics, it is salient that households with older head have higher influence over neighbors. However, households with (more) senior member(s) tend to be inactive in sending gift. Consistently with our marriage market argument, households with (more) unmarried son(s) are often pushed to be active in gift exchanges; third, ethnic minorities exert less influence in gift spending, and they are away from the heart of the networks; fourth, households once organized events are more popular and tend to reciprocate; fifth, unequal communities tend to motivate their members to be more central, more influential and closer to the networks, which is consistent with our status seeking argument.

In Table 2.9b, within estimations are conducted treating each year's gift exchanges as a network. Time-invariant characteristics are dropped out. Given that, we still confirm the roles income inequality, blood relatives' network size and demographic structure play in shaping the four network dimensions. However, age structure seems to work on closeness, rather than influence.

2.8 Conclusions

The tradition of celebrating household social events and keeping gift record in many Asian countries offers researchers a great potential to collect valuable datasets for development and social network study. More importantly, this type of data has a number of unique features compared with previous network datasets. However, to our knowledge, spontaneous long-term gift record has not been utilized in economics studies.

This paper attempts to draw researchers' attention to this widely available but under-explored dataset. I begin with a discussion on how the dyadic gift record can be better fitted into studies at different level and of different purposes: household level network engagement and

well-being as well as link formation. Unique features of gift record that address five critical issues in the literature are then laid out.

Based on the discussion, the data collection process for the IFPRI-CAAS Project is introduced, which incorporates a census-type in-house panel survey and a corresponding long-term gift record collection. The overall trend of household ceremonies in rural China is documented and major ceremonies are compared using the gift record data. I emphasize lavish spending on social events and its recent escalation. Based on an analysis of income distribution and long-term mobility, the social exclusion hypothesis is ruled out. Further, the evidence points to potential status seeking and social pressure. Mutual assistance in labor, information, production tools and informal credit is found associated with intense gift spending. Though risk-sharing might not be the cause of gift escalation, it should play an important role in promoting gift exchanges in the long run.

Gift network structure is evolved over long-term gift exchanges. One step further, I explore its demographic and socioeconomic determinants. Blood relatives' network size, economic status, age structure, marriage market pressure, ethnicity and economic inequality are found to affect major network structure indicators.

Our insights on unique features of gift record data can hardly be general enough to follow, as they are based on the experience of only one project. Nevertheless, it is hoped that the proposal of gift record collection in this paper helps future studies to overcome some of the potential issues. Moreover, though only patterns of gift network and its associations with other social behavior are documented, this paper may help improve our initial understanding of networks, especially in underdeveloped regions. Future research projects are underway, which involves deriving spatial instruments from the gift network structure to identify other social

behaviors, exploring causality of gift spending escalation, and evaluating its impact on basic well-being.

APPENDIX

Measures of Network Structure

In this appendix, we summarize a series of comprehensive social structure measures, including in-degree centrality, out-degree centrality, closeness centrality, betweenness centrality and Bonacich centrality. The centrality of an individual in a network captures the idea of power and prominence in a certain social structure (Freeman, 1979; Bonacich, 1987).

In the following measures, we assume the network g has n individuals.

Degree centrality The individual level degree centrality $\eta_i(g)$ is each individual's number of direct links $\eta_i(g) = \sum_{j=1}^{n} g_{ij}$. There are two types of degree centrality that convey quite different information, namely in-degree centrality and out-degree centrality. In-degree centrality measures number of links one receives from peers, so it captures one's popularity. Out-degree centrality measures number of links one send to peers, and it describes one's influence. To compare networks of different sizes, the normalized degree centrality of an individual i in network g is defined as the degree of the individual divided by the maximum possible friends individual i can have, i.e. $C_d(i;g) = \frac{\eta_i(g)}{n-1}$. It ranges from 0 to 1. Higher degree centrality corresponds to more ties, more dominance of the resources in the network, and hence lower dependence on other individuals. Degree centrality for the entire network g is defined relative to the maximum attainable centrality,

$$C_d(g) = \frac{\sum_{i=1}^{n}[C_d(i^*;g) - C_d(i;g)]}{\max_{g' \in G}[\sum_{i=1}^{n}[C_d(i^*;g') - C_d(i;g')]]} = \frac{\sum_{i=1}^{n}[C_d(i^*;g) - C_d(i;g)]}{n-2}$$

where i^* is the node that achieves the highest degree centrality in network g.

Closeness centrality Closeness centrality is calculated based on proximity. $d(i,j;g)$ is the geodestic distance (i.e. length of the shortest path) between individual i and j in network g. $\sum_{j \neq i} d(i,j;g)$ denotes the geodesic distance from node i to all other n-1 individuals in network g. The individual level closeness centrality is given by the inverse of the sum of geodesic distance $\frac{1}{\sum_{j \neq i} d(i,j;g)}$. To compare different networks, the normalized closeness centrality for

individual i is defined as $C_c(i;g) = \frac{n-1}{\sum_{j \neq i} d(i,j;g)}$, where n-1 is the maximum possible distance between two individuals in network g and the minimum possible geodesic distance from individual i to all other n-1 individuals. The normalized measure ranges from 0 to 1, and it equals one when individual i is directly connected to all other n-1 individuals in the network. The higher total geodesic distance, the lower closeness centrality it would be. Closeness centrality for the entire network g is defined relative to the maximum attainable differences between closeness centrality for node i^* and the others.

$$C_c(g) = \frac{\sum_{i=1}^{n}[C_c(i^*;g) - C_c(i;g)]}{\max_{g' \in G}[\sum_{i=1}^{n}[C_c(i^*;g') - C_c(i;g')]]} = \frac{\sum_{i=1}^{n}[C_c(i^*;g) - C_c(i;g)]}{(n-1)(n-2)/(2n-3)}$$

where i^* is the node that achieves the highest closeness centrality in network g.

Betweenness centrality The standard individual betweenness centrality is measured as

$$C_{bt}(i;g) = \sum_{j<l} \frac{\#\, shortest\ paths\ between\ j\ and\ l\ through\ i}{\#\, shortest\ paths\ between\ j\ and\ l}$$

where j and l denote two given individuals in network g. Betweenness centrality measures how advantaged an individual is in a network because of locating between other pairs of individuals. Higher betweenness centrality gives an individual the capacity to broker contacts among other pairs. To compare between different networks, Normalized betweenness centrality is defined as

$$C_{nbt}(g) = \frac{C_{bt}(i;g)}{(n-1)(n-2)/2}$$

Bonacich centrality Bonacich centrality is mainly based on the adjacency matrix G of network g, in which an entry in a square corresponding to a pair {i, j} denotes whether there exists a link from i to j. In adjacency matrix G, entries in the main diagonal is set to be 0. G^k denotes the k-th power of the matrix, where $G^0 = I$. In G^k, an entry g_{ij}^k measures the amount of walks of length k that exist between players i and j in network g.

Define a matrix $M(g, \alpha\sigma)$, which is well-defined when $\alpha\sigma$ is sufficiently small. Its entry $m_{ij}(g, \alpha\sigma) = \sum_{k=0}^{\infty} (\alpha\sigma)^k g_{ij}^k$ measures the total amount of walks in g from i to j where walks of length k are weighted by $(\alpha\sigma)^k$.

$$M(g,\alpha\sigma) = [1-\alpha\sigma G]^{-1} = \sum_{k=0}^{\infty} (\alpha\sigma)^k G^k$$

Given parameter $\alpha\sigma$, Bonacich centrality vector is defined as $C_b(g,\alpha\sigma) = [1-\alpha\sigma G]^{-1} J$, where Bonacich centrality of node i $C_b(i;g,\alpha\sigma) = \sum_{j=1}^{n} m_{ij}(g,\alpha\sigma)$. It is straightforward to observe that Bonacich centrality is no smaller than 1.

$$C_b(i;g,\alpha\sigma) = m_{ii}(g,\alpha\sigma) + \sum_{j\neq i}^{n} m_{ij}(g,\alpha\sigma) = \begin{cases} >1 \ \ if \ \alpha\sigma > 0 \\ =1 \ \ if \ \alpha\sigma = 0 \end{cases}$$

In our analysis, Bonacich centrality with positive attenuation factors generated by the UCINET software are adopted, as we accept the idea that being connected to neighbors with more connections makes one powerful. However, in some sociology literature negative attenuation factors are used since they argues that neighbors without many connections to others make ego more powerful. The two results differ, especially for households whose ties are mostly with households of high degree.

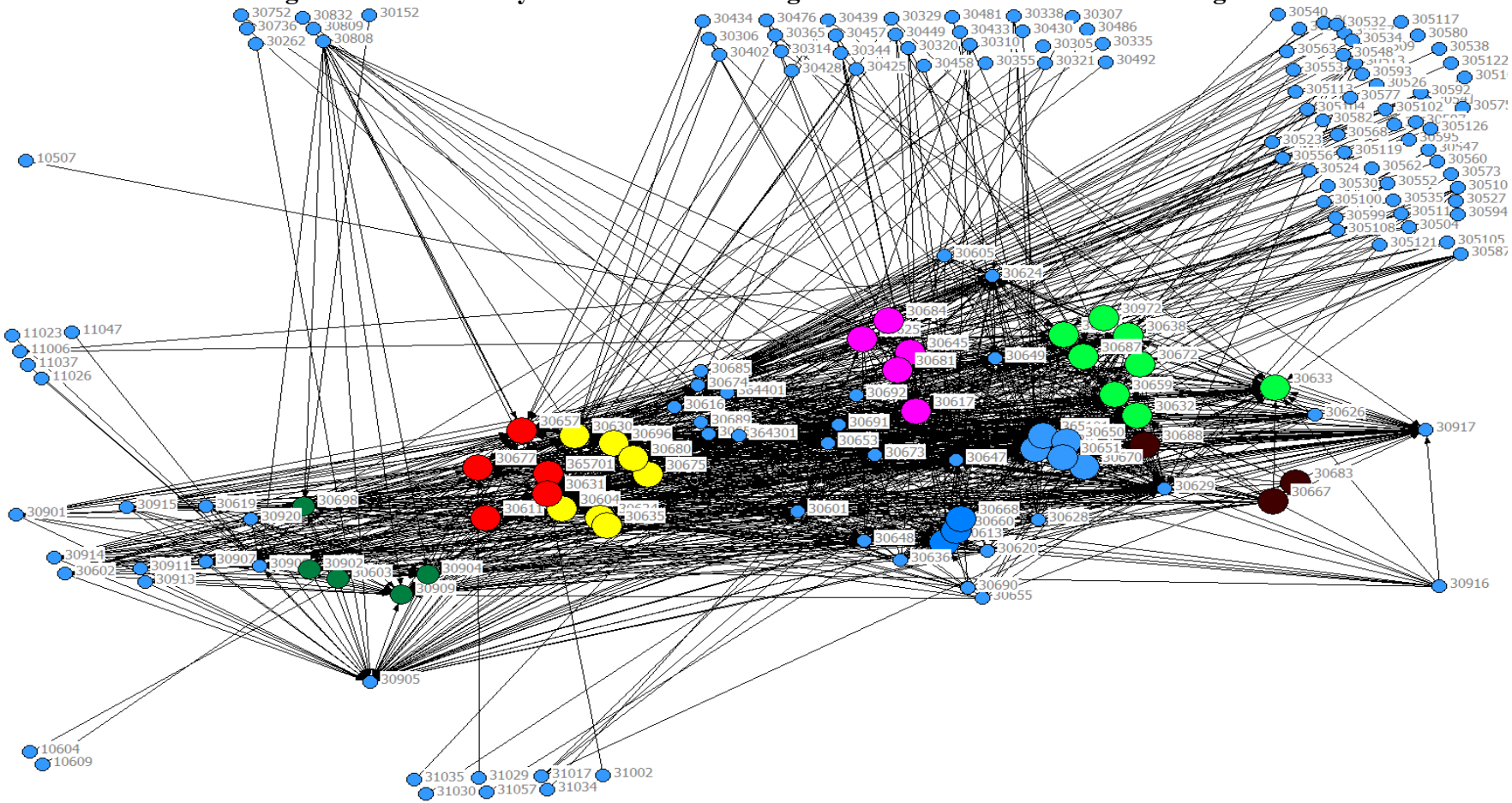
Comparison Among Network Structure Measures The degree centrality and closeness centrality are equal for two extreme cases, star network and cycle network, while they are valued differently in this range. The major shortcoming for the two centrality measures is that it excludes the case when actions of a person influence actions of their neighbors which in turn feedback on the initiator. The degree centrality only takes into account the immediate ties each node has. An individual might be centrally tied to a large number of others, but those others are disconnected from the network as a whole. The closeness centrality solely depends on the length of the shortest paths between nodes in network, while it is possible that ties are not perfectly reliable and other paths of different lengths may take effects. Fortunately, the direct and indirect influences in a network are captured by Bonacich centrality. Moreover, all these centrality measures except Bonacich centrality are parameter-free (Calvó-Armengol et al., 2009). Finally, Bonacich centrality has behavior foundation that is derived from Nash equilibrium of a non-cooperative game, while other centrality measures are mainly geometric in nature (Ballester et al., 2006).

APPENDIX TABLE

Definition and Measures of Network Structure (Engagement)

Indicators	Definition	Calculation
Popularity (Intensity)	also called in-degree, measures number (intensity) of links the respondent receives from peers	Known as in-degree centrality, g_{ij} is a binary (continuous) variable denoting (intensity of) the link from j to i. $C_d(i;g) = \sum_{j=1}^{n} g_{ij} /(n-1)$
Influence (Intensity)	also called out-degree, measures number (intensity) of links the respondent sends out to peers	Known as out-degree centrality, g_{ij} is a binary (continuous) variable denoting (intensity of) the link from i to j $C_d(i;g) = \sum_{j=1}^{n} g_{ij} /(n-1)$
Closeness	distance of the respondent to all others in the network	$\sum_{j \neq i} d(i,j;g)$ denotes the geodesic distance from i to all other n-1 individuals in network g. $C_c(i;g) = \frac{n-1}{\sum_{j \neq i} d(i,j;g)}$
Betweenness	how advantaged an individual is in a network because of locating between other pairs of individuals	$C_{bt}(i;g) = (\sum_{j<l} \frac{\#\, shortest\ paths\ between\ j\ and\ l\ through\ i}{\#\, shortest\ paths\ between\ j\ and\ l})\frac{2}{(n-1)(n-2)}$
Centrality (Bonacich)	Respondent's centrality, weighted by the centrality of those to whom he or she sends ties	g_{ij}^k is the amount of walks of length k that exist between i and j in network g. $\alpha\sigma$ is decaying parameter for indirect ties $C_b(i;g,\alpha\sigma) = \sum_{j=1}^{n}\sum_{k=0}^{\infty}(\alpha\sigma)^k g_{ij}^k$

Figure 2.1 The Clan System and Gift Exchange Network in one of the Three Villages

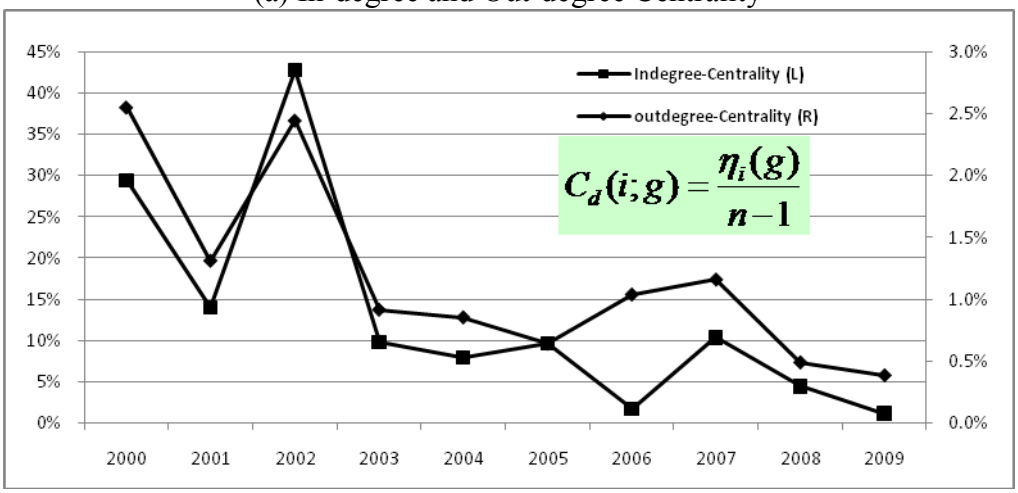


Source: Authors' social network data.

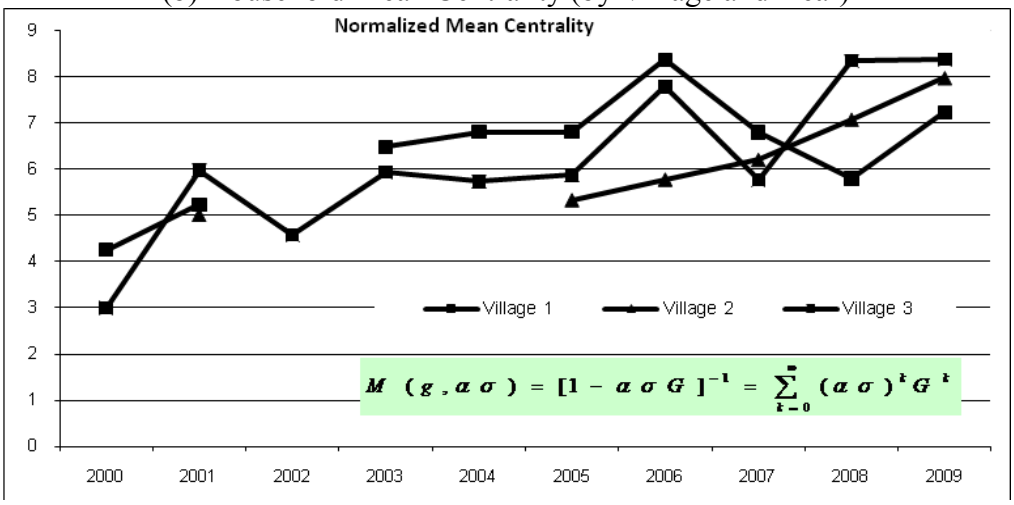
Notes: Those bigger dots of the same color show households in the same clan. Dots to the boundaries show households from other villages. The dots (households) are based on actual geographic locations.

Figure 2.2 Gift Network Centrality

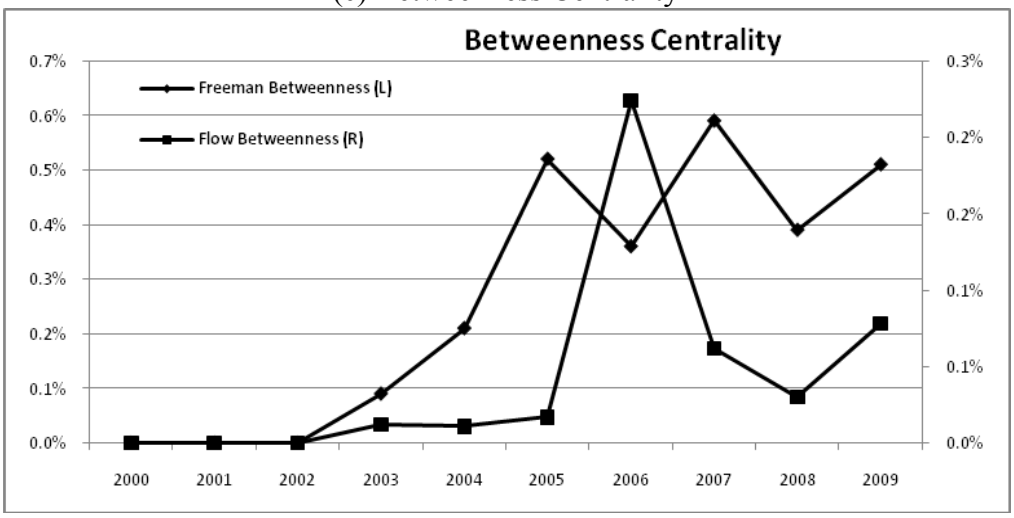
(a) In-degree and Out-degree Centrality



(b) Household Mean Centrality (by Village and Year)



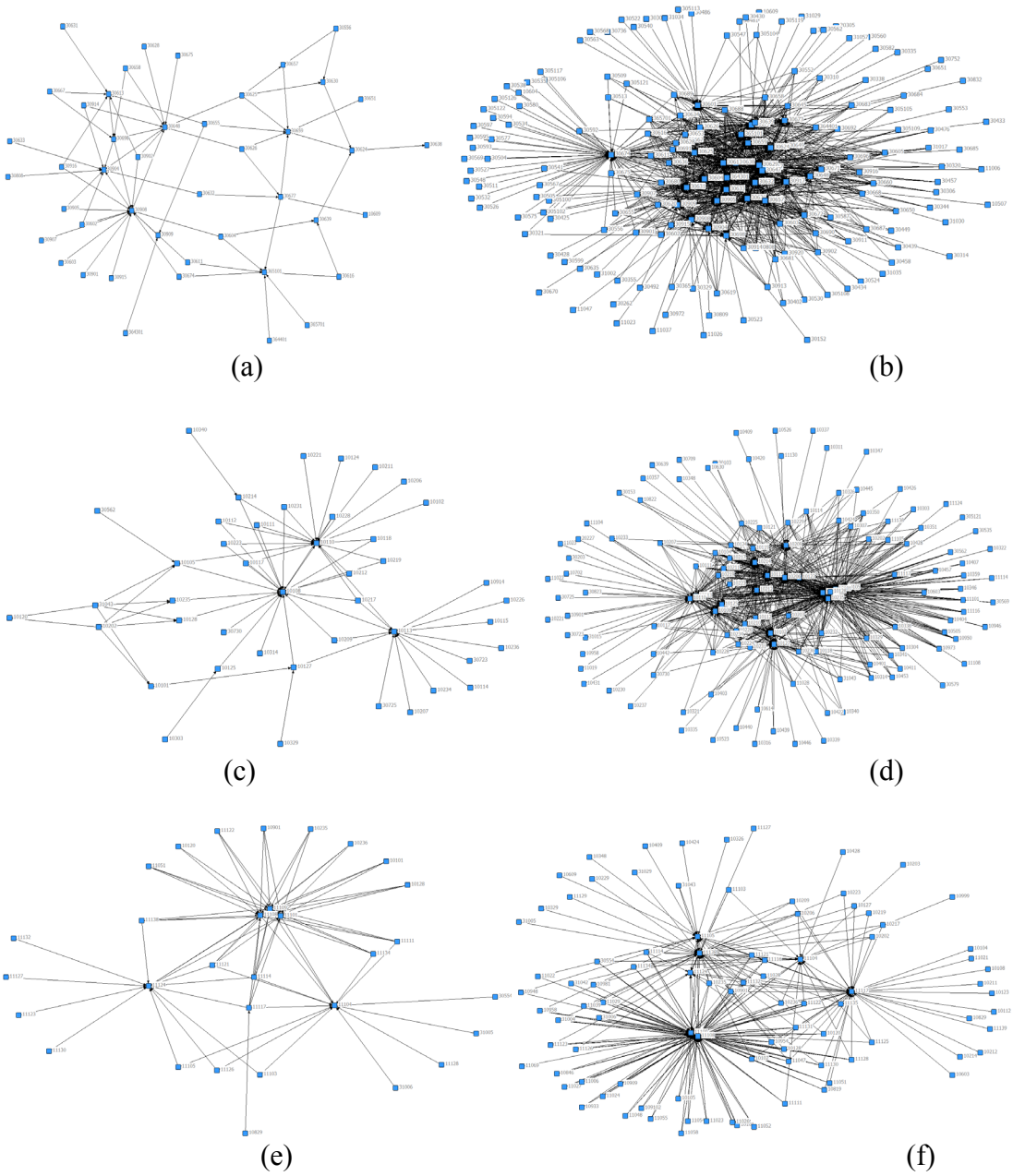
(c) Betweenness Centrality



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

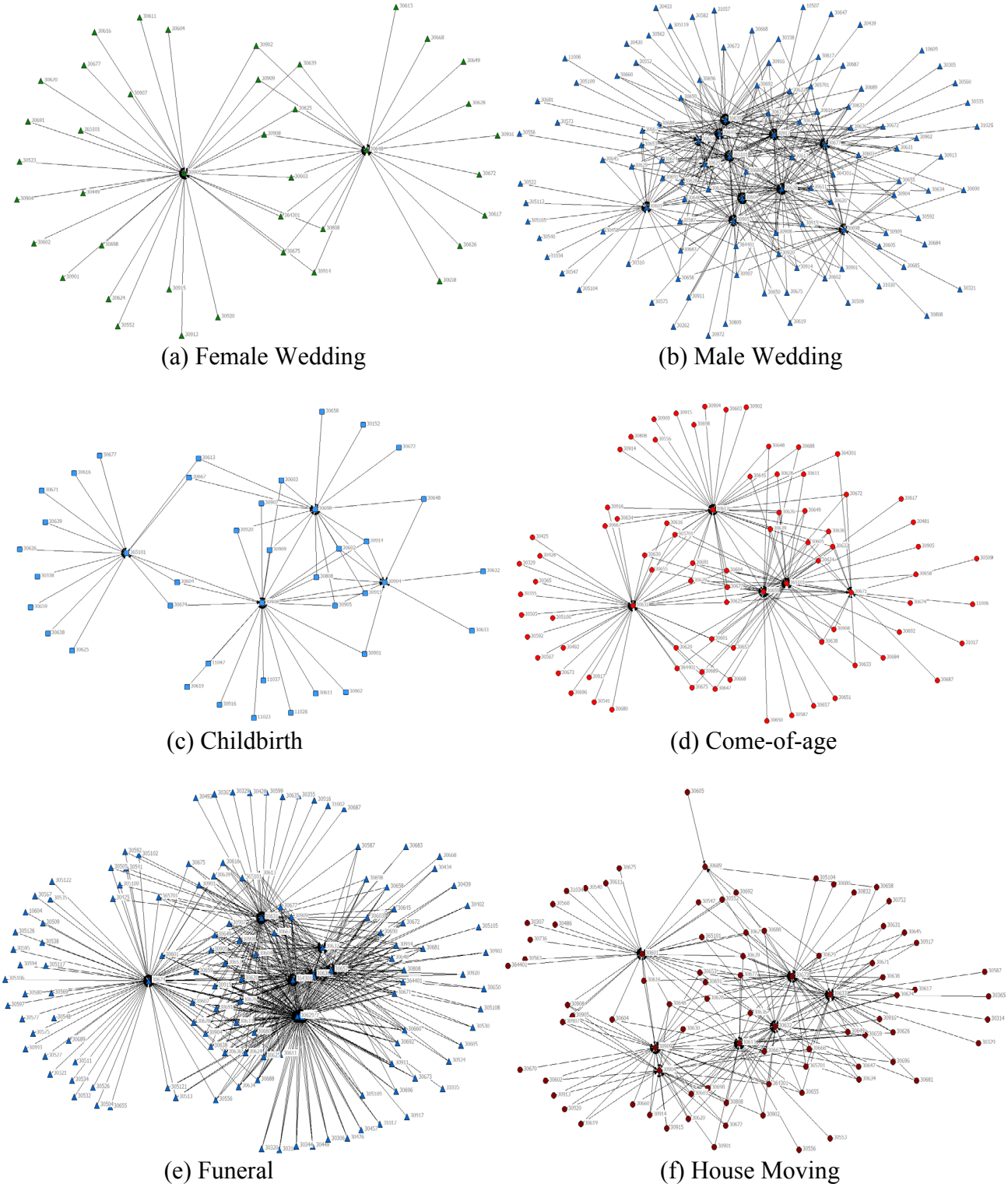
Notes: Network centrality is also known as network activeness or social visibility in the literature. Centrality measures are calculated using UCINET 6.

Figure 2.3 In-kind and Cash Gift Network in Three Villages



Note: (a), (c) and (e) show in-kind gift network, while (b), (d) and (f) show cash gift network. From the top to the bottom shows gift-giving network in Village 3 ((a) and (b)), Village 1 ((c) and (d)), and Village 2 ((e) and (f)).

Figure 2.4 Gift Networks for Social Occasions in One of the Three Villages



(a) Female Wedding

(b) Male Wedding

(c) Childbirth

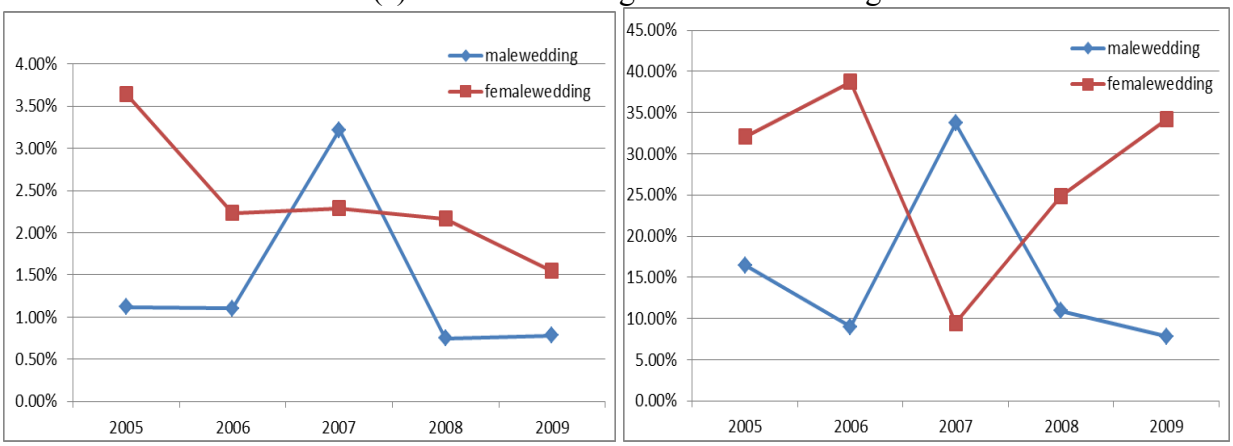
(d) Come-of-age

(e) Funeral

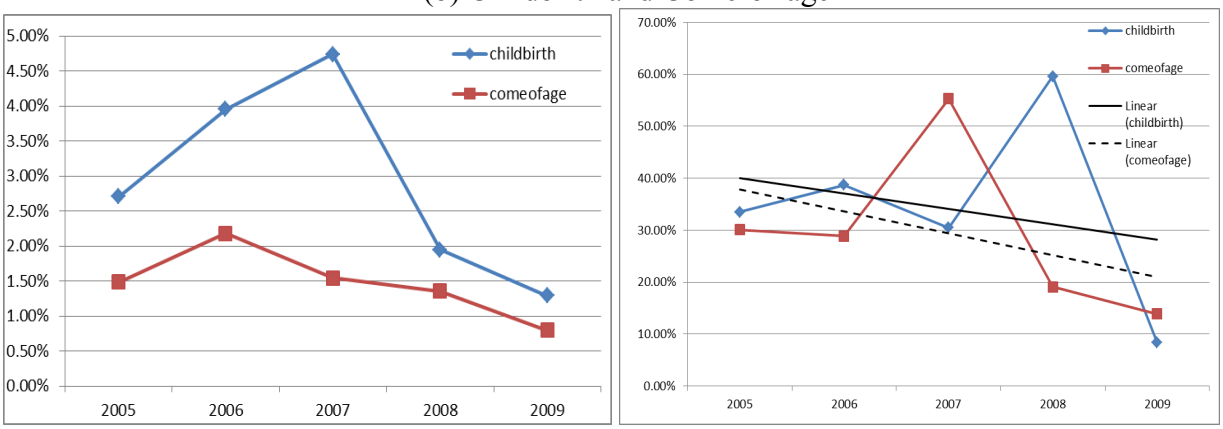
(f) House Moving

Figure 2.5 Gift Network Centrality by Occasion

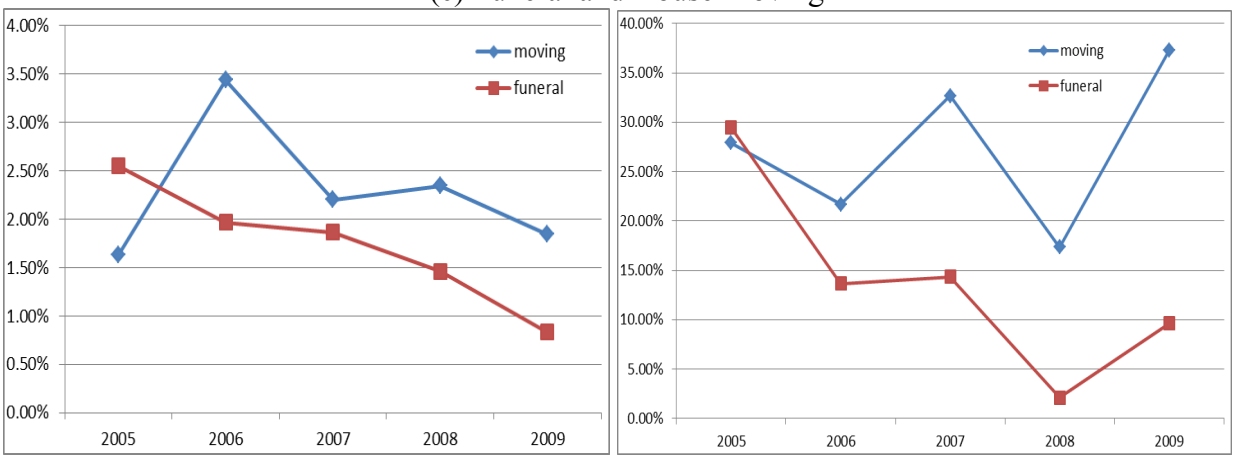
(a) Female Wedding and Male wedding



(b) Childbirth and Come-of-age

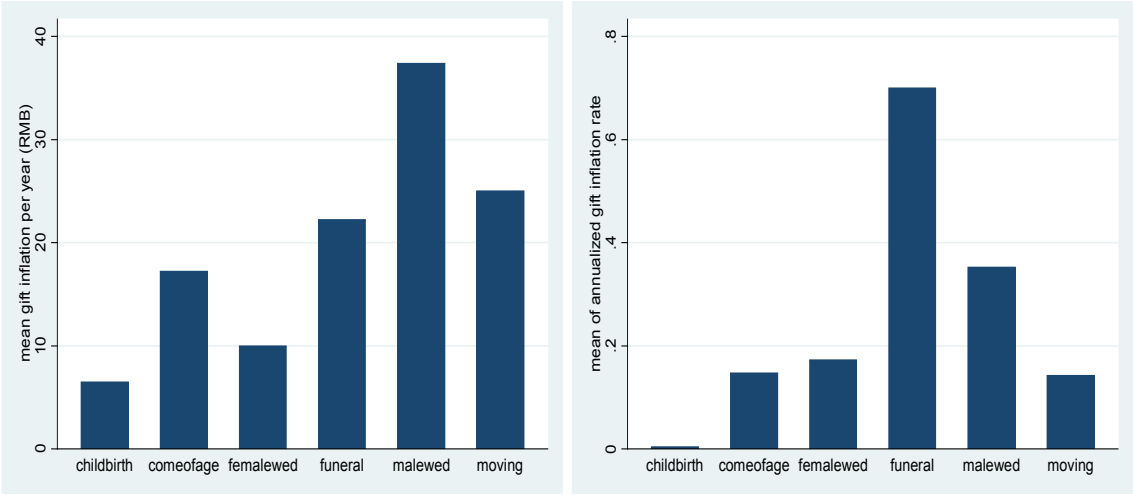


(c) Funeral and House Moving



Notes: Left Figures show out-degree centrality (influence), while right Figures show in-degree centrality (popularity).

Figure 2.6a Annualized Mean Gift Exchange Inflation (RMB) and Inflation Rate (100%) for Reciprocal Households (2000-2009)



Source: Authors' gift exchange data from three natural villages.
Notes: [1] All gifts have been adjusted for inflation based on *China Statistic Year Book* published by NBS.
[2] The left figure is **i**n terms of mean gift inflation per year (RMB), while the right figure is in terms of annualized gift inflation rate (100%).

Figure 2.6b Annualized Gift Inflation Rate and Time Gap by Occasion

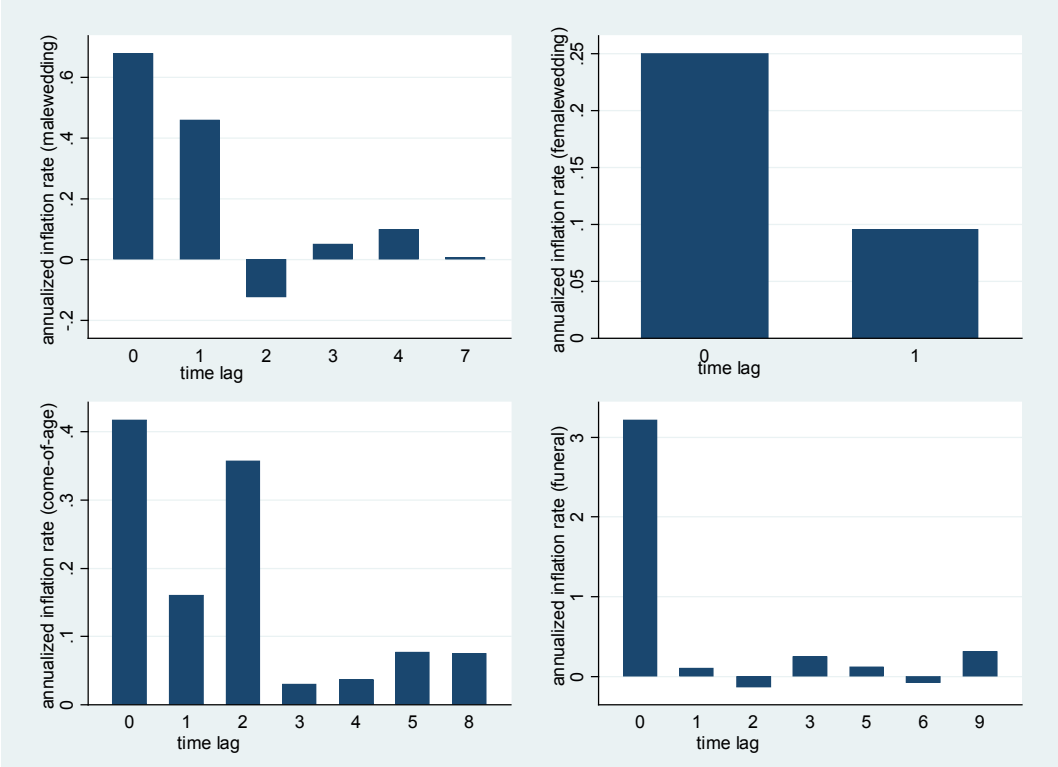
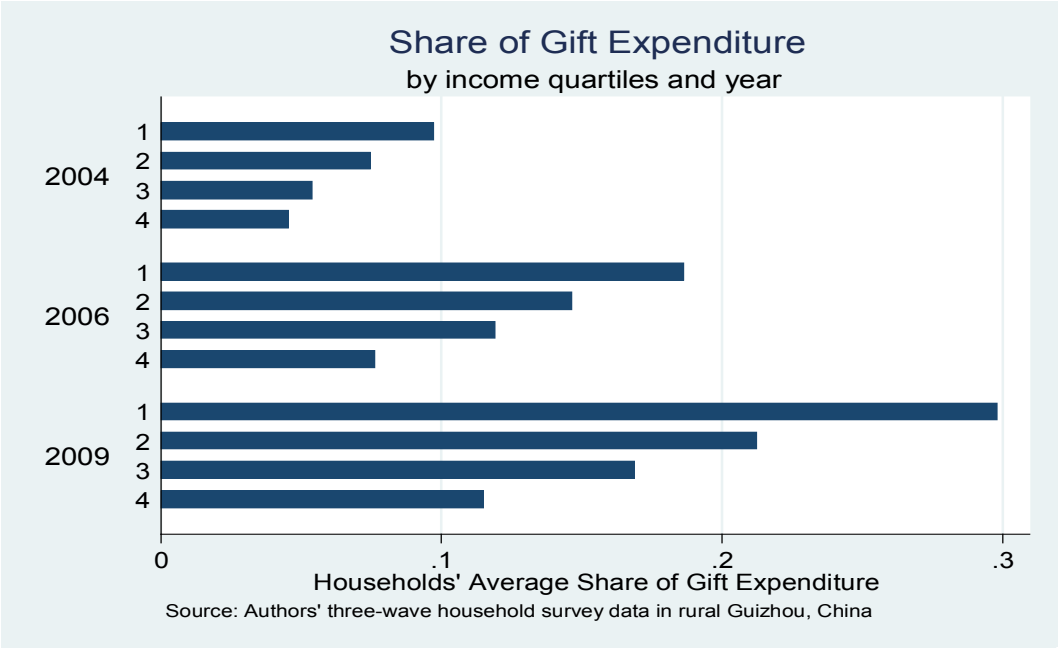


Figure 2.7 Share of Gift Expenditure Relative to Income



Source: Authors' survey data.
Notes: 1: live with less than $1 per day; 2: live with less than $2 per day; 3: live with $2-$4 per day; 4: live with $6-$10 per day. The poverty lines are adjusted according to 2005 PPP rate from http://iresearch.worldbank.org/PovcalNet/jsp/index.jsp.

Figure 2.8 Windfall Incomes, Remittance and Gift Expenditure (Per capita RMB, 2004-2009)

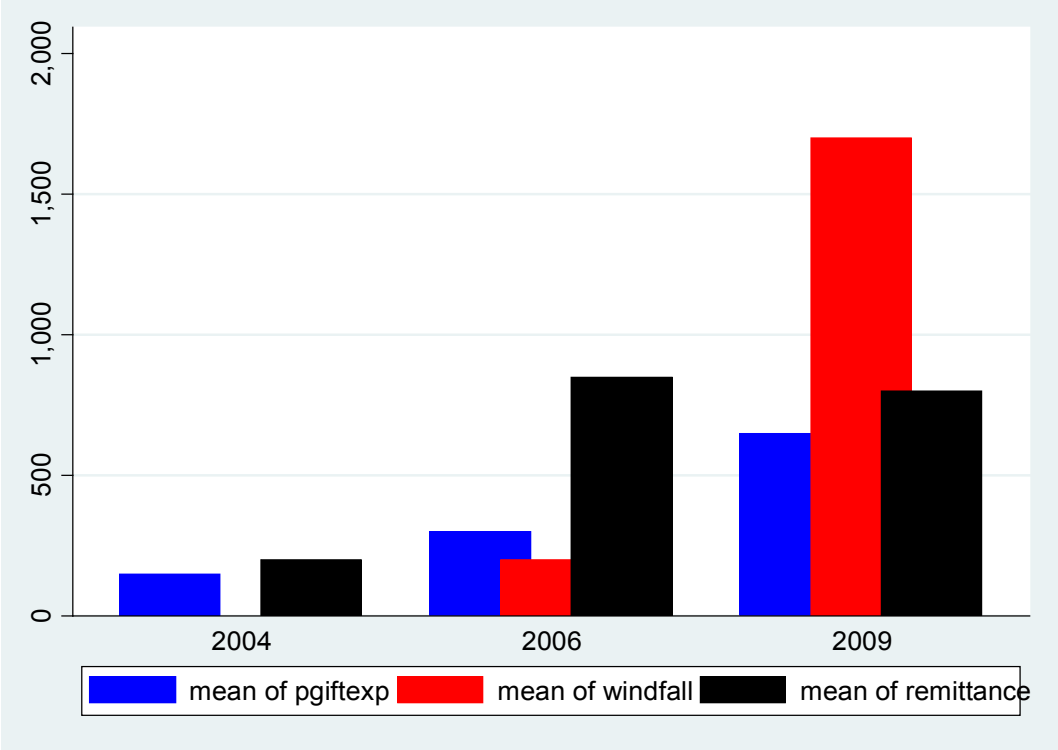


Table 2.1 Summary Statistics by Natural Village (2009)

	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
Income inequality in 2004 (Gini)	43.7	41.9	41.6	44.2
Income inequality in 2006 (Gini)	46.3	52.9	42.7	48.9
Income inequality in 2009 (Gini)	46.5	61.7	50.9	55.2

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

Table 2.2 Testing for Differences between In-kind and Cash Gift-giving (1994-2009)

Year	Differences in the Probability of Ties			Differences in the Intensity of Ties		
	Village 3	Village 1	Village 2	Village 3	Village 1	Village 2
1994-2009				2.934 / 0.144 [0.000]***	2.255 / 0.184 [0.010]***	1.284 / 0.142 [0.020]**
1994-2000	0.048 / 0.040 [0.009]***	0.067 / 0.039 [0.012]**	0.040 / 0.078 [0.121]	1.202 / 0.463 [0.123]	0.602 / 0.118 [0.157]	-
2001-2005				1.948 / 0.083 [0.028]**	0.990 / 0.050 [0.030]**	0.874 / 0.046 [0.072]*
2006-2009				2.608 / 0.121 [0.000]***	2.178 / 0.189 [0.020]**	1.301 / 0.160 [0.037]**

Notes: Values in the square brackets denote p-value. The standard errors are adjusted by Bootstrap SE for the difference (paired samples), which constructs more conservative t-tests. When our measure of tie-strength is binary, the mean is the Probability of all ties that are present. When our measure of tie-intensity is valued, the mean is indicated by the average intensity of the tie across all the relations (Hanneman and Riddle, 2005).

Table 2.3 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	31.1	31	41.6	31.1	22	23.5	17.2	31
2005	25.1	12.3	34	45.9	36.1	38	-	-	-	28.7	17.4	49
2006	27.6	8.0	41	55.4	49.2	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	44.1	26.3	-	-	-
2008	-	-	-	53.6	34.8	35.5	59.7	29.2	36	85.4	80.7	56
2009	73.3	51.6	51.5	90.6	61.3	37.3	68.4	39.7	45	37.9	33.2	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 2.4 Median Funeral Expenditures (RMB) in Major Ceremonies (1996 – 2009)

year	Come-of-age	Wedding (Groom's Family)	Wedding Ceremony (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: Using Recall data from the 2007 survey and 2009 survey.
[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 per capita income.

Table 2.5a Transition Matrix (2004 – 2006)

t \ t+1	Lowest 20%	Lower 20%	Mid 20%	Higher 20%	Highest 20%
Lowest 20%	0.27	0.24	0.26	0.13	0.11
Lower 20%	0.21	0.27	0.19	0.20	0.13
Mid 20%	0.22	0.24	0.18	0.21	0.16
Higher 20%	0.17	0.18	0.23	0.22	0.20
Highest 20%	0.13	0.11	0.14	0.20	0.42

Source: Authors' survey data.
Notes: Shorrocks' MET - the Prais index: **0.913** (SE: .02064661; CI: [0.872 , 0.953])
Atkinson et al. Mobility Ratio: **0.389** (SE: .02293795; CI: [0.344 , 0.434])
The rows denote income quartiles in the initial period, while the columns denote income quartiles in the later period.

Table 2.5b Transition Matrix (2006 – 2009)

t \ t+1	Lowest 20%	Lower 20%	Mid 20%	Higher 20%	Highest 20%
Lowest 20%	0.35	0.21	0.24	0.13	0.07
Lower 20%	0.18	0.35	0.21	0.16	0.10
Mid 20%	0.17	0.15	0.34	0.23	0.11
Higher 20%	0.11	0.14	0.23	0.27	0.25
Highest 20%	0.10	0.16	0.14	0.20	0.40

Source: Authors' survey data
Notes: Shorrocks' MET - the Prais index: **0.823** (SE: .02649932; CI: [0.771 , 0.875])
Atkinson et al. Mobility Ratio: **0.326** (SE: .0276683; CI: [0.272 , 0.380])
The rows denote income quartiles in the initial period, while the columns denote income quartiles in the later period.

Table 2.6a Numbers of Households Join / Drop Out of the Gift-Exchange Network

Panels	hhs (base year)	Active hhs (base year)	Among them: Active hhs (end year)	inactive hhs (base year)	Among them: inactive hhs (end year)
Definition for "Active": centrality>0					
04-06	222	80	70	142	67
06-09	233	150	119	83	23
04-09	221	80	71	141	40
Definition for "Active": centrality>0 (hhs from outside villages excluded)					
04-06	124	61	58	63	27
06-09	123	94	91	29	12
04-09	123	61	60	62	14
Definition for "Active": per capita gift expenditure(RMB)>0					
04-06	222	189	179	66	15
06-09	233	221	210	28	7
04-09	221	188	176	66	13

Source: Authors' gift exchange data from three natural villages.
Notes: The centrality measure is normalized in UCINET 6.

Table 2.6b Households Being Very Active (or not) in the Gift-Exchange Network

Panels	hhs (base year)	Very active hhs (base year)	Among them: very active hhs (end year)	Not very active hhs (base year)	Among them: not very active hhs (end year)
Definition for "Very Active": household centrality>mean(centrality) in the base year					
04-06	222	66	57	156	70
06-09	233	148	109	85	24
04-09	221	66	54	155	46
Definition for "Very Active": household centrality>mean(centrality) in the base year (hhs from outside villages excluded)					
04-06	124	48	45	76	29
06-09	123	92	81	31	13
04-09	123	48	43	75	19

Source: Authors' gift exchange data from three natural villages.
Notes: The centrality measure is normalized in UCINET 6.

Table 2.7a Labor/Information/Production Tool Exchange among Neighbor/Friends/Relatives

Categories		Labor exchange (busy season)	Labor exchange (house building)	Job info exchange	Production tool exchange	Elderly/kids care
Most often		5.9%	6.2%	3.9%	4.7%	1.8%
Very often		14.8%	19.5%	11.2%	13.9%	11.2%
Somewhat often		12.1%	15.4%	11.9%	14.7%	12.9%
Not at all often		12.4%	11.5%	11.3%	12.4%	15.9%
Rare or never		54.8%	47.5%	61.7%	54.4%	58.3%
Total (days)	Median	0	0	-	-	-
	p75	5	5	-	-	-
	Mean	3.62	4.86	-	-	-
	Std. Dev.	7.4	15.6	-	-	-

Source: Authors' survey data

Table 2.7b Correlation between Network Engagement and Resources Exchange

Resources Exchange / Network Engagement	Labor exchange (busy season)	Labor exchange (house building)	Job info exchange	Production tool exchange	Elderly/kids care
HH total gift expenditure	0.050	-0.030	-0.070	0.050	0.002
	(0.43)	(0.65)	(0.23)	(0.43)	(0.98)
Centrality	-0.127**	-0.158***	-0.116**	0.007	-0.121**
	(0.04)	(0.01)	(0.05)	(0.91)	(0.05)
Share of gift expenditure	0.108*	0.161***	0.113*	-0.052	0.195***
	(0.06)	(0.01)	(0.05)	(0.37)	(0.00)

Source: calculation based on Authors' survey data.
Notes: [1] p-values are presented in the parentheses. The first row in each cell presents pairwise correlation coefficients. [2] All five columns indicating resources exchange set the possible values into five categories: 1=most often, 2=very often, 3=somewhat often, 4=not at all often, 5=rare or never.

Table 2.8a Household Debt and Credit (end of 2009)

Percentage of families with debt (%)	57.1
Percentage of families grant a loan (%)	6.0
Percentage of families with debt & grant a loan (%)	3.1
The median amount of debt (RMB) when incurred	6,000
The median amount of loan (RMB) when granted	5,000
Major sources of debt (%)	
Relatives	70.9
Neighbors	4.0
Rural credit union	25.1
Usury	8.6
Others (e.g. non-local friends, fertilizer retailers)	1.8
When borrowing from relatives	
Percentage of zero interest	89.8
Median monthly interest rate (%) when charging interest	1.0
When borrowing from neighbors	
Percentage of zero interest	70.0
Median monthly interest rate (%) when charging interest	2.0
When borrowing from formal rural credit union	
Median monthly interest rate (%)	1.0
When borrowing from usury lenders	
Median monthly interest rate (%)	3.0
When borrowing from others	
Median monthly interest rate (%)	0.0
Major ways to deal with credit constraints in 2009 (%)	
Borrowing from relatives, neighbors and friends	45.3
Selling assets	40.6
Working out or receiving remittance	26.1
Applying for a loan	7.4
Borrowing from usury lenders	2.0

Source: Authors' survey data.
Notes: [1] "Major sources of debt (%)" categories stock value at the end of 2009, while "Major ways to deal with credit constraints" categories flow value during 2009. Meanwhile, the latter only includes households faced with credit constraints, which accounts for 90.1% of the surveyed households.

Table 2.8b Correlation between Network Engagement and Informal Credit

Credit Insurance / Network Engagement	Debt (end of 2009)	Debt from relatives	Debt from neighbors	Interest rate	Cash shortage coping: relatives / friends / neighbors	Cash shortage coping: blood sales
HH total gift exp	0.232***	0.143***	0.053	-0.038	0.115**	-0.088
	(0.00)	(0.01)	(0.36)	(0.61)	(0.05)	(0.13)
Centrality	0.132**	0.180***	0.110*	-0.112	0.122**	0.160***
	(0.03)	(0.00)	(0.07)	(0.15)	(0.04)	(0.01)
Share of gift exp	0.088	0.013	0.034	-0.029	0.053	-0.045
	(0.13)	(0.83)	(0.56)	(0.70)	(0.36)	(0.44)

Source: calculation based on Authors' survey data.
Notes: p-values are presented in the parentheses. First row in each cell presents pairwise correlation coefficients.

Table 2.9a Determinants of Network Structure (All Years' Gift Exchanges as A Network)

	R1	R2	R3	R4
	log Centrality	log Popularity	log Influence	log Closeness
Ceremony organizer	0.71	5.21***	0.53***	0.00
	(0.77)	(0.07)	(0.14)	(0.00)
Per capita income (log)	0.67***	0.06*	0.05**	0.00**
	(0.22)	(0.04)	(0.02)	(0.00)
Blood relatives' network size	0.12**	0.01	0.04***	0.00
	(0.05)	(0.01)	(0.01)	(0.00)
Marriage status	0.63	0.25	0.04	0.01
	(1.15)	(0.21)	(0.11)	(0.01)
sex	0.31	0.06	-0.12	-0.01
	(1.05)	(0.20)	(0.10)	(0.01)
edu	-0.07	0.01	0.01	0.00
	(0.10)	(0.02)	(0.01)	(0.00)
cadre	1.43	-0.04	0.15	0.00
	(0.99)	(0.18)	(0.10)	(0.01)
Share of youth	1.47	0.20	0.61***	-0.01
	(1.26)	(0.12)	(0.23)	(0.01)
Share of the elder	-0.05	-0.19	-0.49*	0.00
	(1.37)	(0.13)	(0.25)	(0.01)
age	0.01	0.01	0.02***	0.00
	(0.03)	(0.01)	(0.01)	(0.00)
Household size	0.32	0.02	0.08**	0.00
	(0.20)	(0.02)	(0.04)	(0.00)
Minority status	0.70	-0.05	-0.61***	-0.04***
	(0.73)	(0.13)	(0.07)	0.00
Gini coefficient	16.49***	1.50	2.64***	0.25***
	(6.09)	(1.13)	(0.59)	(0.03)
Machine (#)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Land size (mu)	0.04	0.02	0.01	0.00
	(0.10)	(0.02)	(0.01)	(0.00)
Cow (#)	-0.08	0.02	0.04	0.00
	(0.29)	(0.05)	(0.03)	(0.00)
Horse (#)	0.14	-0.21	0.12*	0.01***
	(0.73)	(0.14)	(0.07)	(0.00)
Cumulated large disease (lag)	-0.06	-0.07**	0.02	0.00
	(0.36)	(0.03)	(0.04)	(0.00)
Cumulated livestock death (lag)	-0.70*	0.02	-0.05	-0.01**
	(0.41)	(0.08)	(0.04)	(0.00)
r2	0.29	0.60	0.61	0.78
N	264	264	264	264

Notes: Pooled cross-sectional estimations. All network structure indicators as the dependent variables are normalized. Village fixed effect is controlled. All four columns treat gift exchanges over recent years as one network. For a detailed review of network structure measures used here, please refer to the Appendix.

Table 2.9b Determinants of Network Structure (Each Year's Gift Exchanges as a Network)

	R1	R2	R3	R4
	log Centrality	log Popularity	log Influence	log Closeness
Ceremony organizer	0.44	2.03***	0.09	-0.02
	(0.59)	(0.13)	(0.18)	(0.01)
Per capita income (log)	0.40**	0.06	0.01	0.01*
	(0.17)	(0.04)	(0.05)	(0.00)
Blood relatives' network size	6.64*	1.82**	1.00	0.02
	(3.85)	(0.82)	(1.19)	(0.01)
Marriage status	0.74***	0.02	0.01	0.01
	(0.26)	(0.11)	(0.11)	(0.01)
Share of youth	1.05	-0.06	-0.32	0.11***
	(0.83)	(0.18)	(0.26)	(0.02)
Share of the elder	0.72	-0.07	-0.07	-0.07***
	(0.92)	(0.20)	(0.29)	(0.02)
age	0.08*	0.00	0.00	0.00
	(0.04)	(0.01)	(0.01)	(0.00)
Household size	-0.04	0.00	-0.05	0.00
	(0.14)	(0.03)	(0.04)	(0.00)
Gini coefficient	15.80***	0.35	6.88***	0.04
	(2.99)	(0.64)	(0.93)	(0.06)
Machine (#)	-0.07	0.06	-0.66	-0.04
	(1.36)	(0.29)	(0.42)	(0.03)
Land size (mu)	0.04	0.00	0.05***	0.00
	(0.06)	(0.01)	(0.02)	(0.00)
Cow (#)	0.33	0.06	0.06	0.03***
	(0.25)	(0.05)	(0.08)	(0.01)
Horse (#)	0.22	-0.12	-0.37	0.06***
	(0.72)	(0.16)	(0.23)	(0.02)
Cumulated large disease (lag)	-0.63*	0.13	-0.28**	-0.05***
	(0.38)	(0.08)	(0.12)	(0.01)
Cumulated livestock death (lag)	0.16	0.10	-0.05	-0.04***
	(0.44)	(0.09)	(0.13)	(0.01)
r2	0.29	0.50	0.21	0.76
N	652	652	652	652

Notes: Household fixed effects estimations. All the dependent variables are normalized. Village fixed effect and year fixed effect are controlled. All four columns treat gift exchanges during each year as a complete network. For a detailed review of network structure measures used here, please refer to the Appendix.

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CHAPTER 3

PEER EFFECTS, RISK POOLING, AND STATUS SEEKING: WHAT EXPLAINS GIFT SPENDING ESCALATION IN RURAL CHINA?

3.1 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), extravagant bride-prices and dowries (Rao 1993; Brown 2009), and lavish festivals (Banerjee and Duflo 2007), at the expense of their basic nutrition intake (Subramanian and Deaton 1996; Thomas and Strauss 1997; Chen and Zhang 2010). Peer pressure, status concerns, and risk pooling are three notable explanations for this observed puzzle in the literature.

Many of the poor live in a closely knit community. Their behavior is deeply influenced by their peers in the reference group. Peer effects 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 therefore 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; Watson and McLanahan 2011; Brown, Bulte, and Zhang 2011) 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 human-made shocks, people have used gift giving as a means of smoothing shocks and mitigating risks. For example, funerals are very costly in many developing countries. It is hard for a family to come by the means to pay 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 that risk sharing represents another key motive for gift giving.

Previous studies have investigated the behavior of gift giving from different angles, such as risk sharing (Fafchamps and Gubert 2007) or status concern and peer pressure (Brown, Bulte, and Zhang 2011). 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. Meanwhile, we try to improve the empirical identification along all the three dimensions.

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. The large variation in guest composition across occasions circumvents the main identification problems. Fourth, the gift records advance the literature on network formation through gift values, since relationship intensities often matter more to behavior than the connections themselves.

As a preview of the main results, we find that 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, poor families with sons spend more on gift giving in proportion to their income than their rich counterparts in response 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 receive unexpected windfall income, for example, they start 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 the data; Section 4 lays out our basic analytical framework; Section 5 discusses the main issues in peer effect identification and its relevance to our strategy; Section 6 specifies the empirical model; Section 7 presents the main results on the determinants for gift spending and its escalation; finally, Section 8 concludes with further discussion.

3.2 Gift Giving in Rural China

Gift exchange is commonly practiced in developing countries but rarely documented in the economics literature. 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 3.1). Table 3.2 presents gift expenditure per occasion and the number of guests in coming-of-age ceremonies, weddings (bride's family and groom's family), and funerals over time. The average gift size has increased steadily for all the four occasions, as has the number of guests participating. However, the rising gift size is not sufficient to cover the total expenditures on these events. As shown in Table 3.3 on the total expenditures for the four types of events, the median expenditure for a coming-of-age ceremony is more than 8,000 Chinese yuan renminbi (CNY), while on average the host of such an event receives only CNY 3,782. In other words, the host has to cover more than 54 percent of the expenses out of his own pocket. The gap is even larger for wedding ceremonies among groom families: The amount of gifts received accounted for only 20 percent of total expenditure in 2009.

Figure 3.1 presents the share of gift expenditure by income quartile over our three-wave survey 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 the income quartiles. The poorer a household, the higher the share of consumption devoted to social spending, and the faster the growth in share of gift and festival expenditure between 2004 and 2009.

Figure 3.2 plots the annual growth rates of gift spending, consumption, and income over the period 2005–2009. Annual gift growth rates range from 18 percent to 45 percent in three villages, much higher than the 10 percent 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 percent to 17 percent. Apparently, gift spending escalation is an acute phenomenon in this impoverished region.

3.3 Data Collection

3.3.1 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.[28] They are both geographically isolated and ethnically diversified. Local residents know each other well. Most residents' kinship networks are confined to these villages. More than 20 ethnic groups are living in the area, including Han, Miao, Buyi, Gelao, and Yi. In total, ethnic minorities make up about 20 percent 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. Since our analysis uses gift-exchange records from 3 of the 18 villages, only households involved in the social occasions surrounding the recorded gifts are relevant for this study.

3.3.2 Gift-Exchange Records Collection

Rural households usually keep the records of gifts received on major occasions for a long period because they have to pay back accordingly when the gift givers hold a social event (Yan

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

1996).[29] In the survey area in Guizhou, we find that all the households keep a gift book. In early 2010, we used a digital camera to capture the gifts recorded in the books for major occasions (male family member's wedding, female family member's wedding, funeral, coming-of-age ceremony, child birth ceremony, and house-moving ceremony) during the period 2000–2009 for all the households in 3 natural villages. The 3 natural villages were selected from the 18 natural villages (3 administrative villages) where the three-wave census survey was conducted (Table 3.1). In each administrative village, we selected the natural village with mirroring the average development level of the whole administrative village..

A unique Karst landform keeps the 3 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 local customs are well preserved. On the other hand, 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 by the Buyi ethnic minority, who preserve the Catholic culture and ceremony tradition different from that of the major Han villages (such as villages 1 and 3). In major public ceremonies in village 2, people generally participate in the events (such as Halloween and Christmas) without bearing a huge burden of gift exchange.[30] 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 three-wave household surveys in 18 natural villages, we identify 335 households in gift record books, including 160 households from the 3 natural villages where the

[29] Yan 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" (1996, page 49).

[30] 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).

gift records were collected and 175 households from the other 15 natural villages covered by our large-scale household survey.[31] Once having joined in gift exchanges, most people remain active. A great proportion of previously inactive households become active at the end of each period.

Figure 3.3 shows a map of the gift network in 1 of the 3 villages. In total, 8,074 gift links during the period 2000–2009 are identified. The potential links include all households in the hosts' local villages and the identified links between local villages and the other 15 surveyed villages, whether or not there was a gift given. The assumption is that all households in the same village know each other and are aware of the dates of ceremonies. Given the geographic and local social environment, this is very likely to be the case. Meanwhile, 4,611 cross–township/county gift links among 4,924 potential links were recorded. These potential cross–township/county links included all the recorded cross–township/county links and zero-gift-flow links between the hosts and their bride's-side blood relatives recalled by each household. Every effort was made to identify these potential but nonexistent gifts to circumvent sample attrition and sorting problems during our records collection process. Nearly all households' gift-receiving records for the ceremonies were included in this study, since less than 5 percent of households reported gift book loss or damage.[32]

If all family members are illiterate, a group of two or three educated relatives usually helps record gift giving on the celebration days. However, names on the records are usually nicknames, which might not offer precise identification of the individual involved. To solve this problem, we showed a name list to each household to facilitate their identifying the people

[31] Our census-type survey determines that all households in the eighteen villages, who had presented any gifts to people residing in the three villages in recent years, are identified. Other names, such as those from out of the three administrative villages, are not included in our analysis.

[32] We consulted on major ceremonies with village leaders and local residents to verify before going to individual families. Meanwhile, this prior information helped households recall and find gift books for us.

represented on the records. We also consulted many local people to help identify the people recorded by their nicknames.

Information on kinship and relatedness among villagers was also collected and matched to each gift link. The information was verified with the help of village leaders, the elderly, and local elites. As do many other rural communities, each of the 3 surveyed villages has several major clans. Taking village 3 in Figure 3.3 as an example, households in the same clan usually live closer to each other for historical reasons. Gift exchanges are more prevalent within a clan than across clans.

3.4 Risk Pooling and Network Formation: An Analytical Framework

In the literature, most studies tie pairwise link formation to individual decisions. Separability of the utility function is imposed with the assumption that the utility derived from the network is equal to the sum of the utilities brought by each link and that these link-specific utilities are not affected by the structure of the network. Following the conventional setting (De Weerdt 2004; Udry and Conley 2005; Fafchamps and Gubert 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,

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

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 are the shocks, and the more there might be monitoring and enforcement difficulties. Therefore, both the benefit and the cost of link formation should increase with social

distance d_{ij}, leading to a trade-off between the scope and ability of mutual insurance in the networks. Thus, the effect of multidimensional social distance on link formation is an empirical question.

First, income pooling should be more effective between households engaged in different activities or occupations, such as, in our context, between farmers and nonfarm migrant workers. A farmer's income is determined by such factors as weather conditions and pest infestation, while the income of a nonfarm migrant worker depends on economic prosperity, which is expected to be uncorrelated with farm income. However, households with different occupations usually have less common ground to socialize with each other.

Second, taking care of children and elderly is a form of risk sharing that differs from income pooling. Young households with children are faced with different health risks than those faced by the elderly; moreover, younger households are more capable of helping each other than are the elderly. Therefore, households with a 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 the latter than to the former. Likewise, the poor may have stronger motivation to link with the rich than vice versa. On the other hand, rich households might be willing to help poor households who are not able to bear large expenses resulting from shocks and ceremonies. Since link formation is directional and the incentives behind it are asymmetrical, social distance should capture this factor.

Kinship may strengthen link formation inasmuch as it reflects history, norms, and trust in a community. Given a certain geographic closeness, blood relationships facilitate in punishing

uncooperative behavior. From a Darwinist's perspective, helping family members is a way to expand the gene pool.

A *level effect* should also be included in framework (1) to explore whether households with certain common characteristics tend to form links. For instance, it is expected that wealthier and better-educated people tend to link to each other, and households with a higher share of elderly or children are less likely to link to each other. The wealth effect is captured by per capita income. Because networks affect the ability to generate income, income is endogenous to the network and thus should be instrumented in the first-stage estimation.[33]

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

Furthermore, the framework does not clearly consider the role of status. Unlike information networks, networks of gift giving on social occasions help in 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.

[33] Since one's social network affects the capability of income generation, income is potentially endogenous to the network formation process. Households with better networks may earn higher incomes. Therefore, we instrument per capita income with variables that predate the formation of gift links, including education of the head, size of the head's lineal family, major family productive assets (such as a cow, a 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 (Table A.1). 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 this context, where a great proportion of family assets is composed of dated housing.

3.5 Peer Effect Identification

Although peer effect has been studied for decades, no consensus has been reached on its significance and magnitude due to criticisms related to identification (Manski 1993; Moffitt 2001; Brock and Durlauf 2001). Even less is known about the mechanisms through which it operates. Three challenges confront peer effect identification: first, the real group within which people interact with each other is a priori unknown; second, correlated effects confound the identification because people usually endogenously form peer groups or are affected by common group characteristics (for example, common shocks in the development literature and teacher effects in studies of education) and thus behave similarly; third, the reflection problem persists because people influence each other in a group, which hinders any judgment on whether a person's action is the cause or the effect of peers' actions.

3.5.1 Reference Groups

The definitions of reference groups vary substantially in the literature, from the most comprehensive, a national population, to the very restrictive, such as a grade cohort. The large variation in the scope of reference groups reflects how hard it is to establish who influences whom a priori.

Most studies do not have that information due to limitations on their data, on their understanding of the specific context and social mechanism, or both. Instead, they assume individuals in the population as potential peers and define peer influence based on average intragroup externality that affects group members identically.[34] However, different time and social constraints among agents suggest that the set of potential partners has large variation, whether or not the population is partitioned.

[34] Another strategy is to pick at random many sets of potential peers to build a simulated likelihood (Mihaly 2007).

In our study, identifying the effects of both peer pressure and status seeking on gift giving during social events requires an appropriate definition of the reference group. Peer pressure in sending gifts is most likely to work through information sharing among guests attending social events.[35] Therefore, the main reference group for gift spending is defined according to gift presenters on each occasion. We also define reference groups for gift spending based on gift receivers to whom one presents gifts in any given year. A comparison of estimates from the two peer group definitions, fellow gift presenters and gift receivers, informs us of the relative intensity of peer pressure in extending gifts.

Relative status is measured according to the geographic reference group.[36] According to a recent study (Mangyo and Park 2011), geographic reference groups, often at the village level, are salient for rural residents living in close proximity. In rural China, a natural village is evolved over generations. Due further to the local Karst landform that isolates the natural villages in this study from the outside, a natural village is particularly suitable to be treated as a unit for social comparison. As a result, we define the reference group as the natural village for purposes of measuring yearly household-specific social status.

3.5.2 Correlated Effects

Correlated effects may come from two sources: unobservable common shocks and endogenous group formation. To separate correlated effects that confound peer effect identification, some studies use randomly assigned peers (Sacerdote 2001; Zimmerman 2003),

[35] Rural residents send gifts to their local events, and information on the gift price is shared. On the day of a ceremony, an educated person is often responsible for keeping the record of gifts received. As a result, the market information on gifts given is largely common knowledge within a village. As shown by comparing kernel density estimates among social events, gift spending at each event tends to cluster.

[36] Ideally, the identification of relative status should follow that of peer effect. However, multiple relative status values appear for a household that gives gifts more than once a year, if fellow gift presenters per event are defined as peers. If gift receivers are defined as peers, missing values appear for a household that sends no gifts in a year.

some use conditional variance restrictions that disentangle excess variance due to peer effect from that due to group-level sorting (Graham 2008), and others use composition variations of adjacent cohorts within schools to identify peer effect (Hoxby 2000; Gibbons and Telhaj 2008; Ammermueller and Pischke 2009). Similar to the methodology of these latter studies, we identify peer effect through the large variation in the size and composition of guests attending each social event.

To tackle the issue of common unobservable shocks, lagged all peers' median gift per occasion is instrumented with lagged new peers' median gift per occasion from brides' out-of-township blood relatives.[37] The longitudinal structure of the data allows us to track each household's previous peers and distinguish between new peers and old peers. On the one hand, the large distance between villages in the mountainous region limits the spread of common shocks and the sharing of information, which mitigates the concern for common unobserved factors. Information sharing is further restricted by the patrilineal culture, whereby fellow villagers attending a male-side ceremony have little connection with the external relatives of the bride. On the other hand, new peers' median gift per occasion is highly correlated with that of all peers by construction. These two relevant features of out-of-township new peers result in a good instrument.

To mitigate the concern for self-selection into gift groups, all fellow villagers and brides' out-of-township blood relatives, whether they present gifts or not, are included in the analysis, since all households in each village know each other well and know about social events due to close local connections spanning generations. Moreover, correlated effects arising from unobserved individual and group effects are taken care of in our fixed-effect estimations. We

[37] The traditional patrilineal culture and land allocation system in rural China determine that most males stay in birth villages, while most females migrate out upon marriage. Since local geographic condition restricts social connections with the outside, most out-of-township new peers are brides' blood relatives.

further control guests' group characteristics to test whether individuals sort themselves into groups according to certain unobservable characteristics or abilities (Broeck and Dercon 2007).

3.5.3 The Reflection Problem

The reflection problem arises when the endogenous effect and exogenous effects are entangled in the identification of peer effect. Since only the endogenous effect can generate a social multiplier with policy implications, studies never give up finding effective solutions. Methods utilized to isolate the two effects include these: instrumenting peers' current behavior with their lagged behavior (Hanushek et al. 2003) or the lagged treatment they received (Boozer and Cacciola 2001), specifying a nonlinear setting (Manski 1993; Brock and Durlauf 2001), designing a partial-population experiment setting that directly affects the behavior of some but not all group members (Bobonis and Finan 2009), and utilizing network information or partially overlapping groups (De Giorgi, Pellizzari, and Redaelli 2010).

In principle, the identification of endogenous effect from contextual effect is made possible when an appropriate exclusion restriction is found whereby an influencing factor of individual outcomes does not directly affect peers' outcomes (Manski 1993). While it is difficult to distinguish a factor's impacts on an individual from its impacts on peers using a standard dataset with perfectly overlapping peer groups, partially overlapping peer groups create direct as well as indirect connection. Ideally, rich information on social networks makes possible a clear identification (Calvó-Armengol, Patacchini, and Zenou 2009; De Giorgi, Pellizzari, and Redaelli 2010; Lin 2010), but our outcome variable—individual gift spending per occasion—raises the concern for duplicated usage of gift information. Therefore, this strategy cannot be applied here.

Nonetheless, the partially overlapping peer groups across social events separate new peers from old peers and out-of-township peers from local peers. As discussed above, gifts from brides' out-of-township blood relatives generally have no direct effect on gift spending from local residents, thereby satisfying the exclusion assumption. In line with the literature, we also take lagged median gifts from fellow gift presenters to break down the reflective influence.

3.6 Empirical Strategy

3.6.1 Model Specification

Our main empirical estimations are dyadic regressions. In network analysis, a dyad is a pair of agents. Dyadic data contain 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 are normally transformed into level effect ($z_i + z_j$), social distance ($z_i - z_j$), and link attributes w_{ij} to best preserve information.[38] Since gift exchanges are directional, the outcome variable y need not satisfy $y_{ij} = y_{ji}$ for any i and j. Following Fafchamps and Gubert (2007), let

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

where -*i* denotes peers of household *i*; $y_{i,j,c,t}$ is the actual gift guest i presents to the host j on occasion c at time t; $w_{i,j,t}$ denotes link attributes between *i* and *j* at time t, such as cross-village or not and blood relations; and $z_{i,t}$ and $z_{j,t}$, respectively, denote attributes of households *i* and *j* at time *t*.

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

Peer effect α_1 is identified via an instrumental variable (IV) approach. Reference groups for gift spending are defined according to fellow gift presenters per occasion in the main estimations and gift receivers to whom one presents gifts per year in the robustness check. Compared with the methodology of Brown, Bulte, and Zhang (2011), which restricts peer groups at the village boundary, our novel definition of peer group enables us to eliminate correlated effects and contextual effects that would confound peer effect identification.

In the main estimations, lagged median gift spending per occasion from brides' out-of-township blood relatives, whether they sent a gift or not, instruments lagged all peers' median gift to j per occasion c, that is, $m[y_{-i,j,c,t-1}]$. Adopting a nonlinear peer influence setting, that is, lagged median behavior among peers, partially overlapping guests across occasions creates exclusion restrictions that mitigate the reflection problem.

Out-of-township peers circumvent the concern for correlated effects that arises from common unobservable shocks. All fellow residents within the village boundaries and brides' out-of-township blood relatives, whether they present gifts or not, are included in the peer group to mitigate concern for self-selection into gift groups.

To test the risk-pooling motive, we combine α_2 and α_3: α_2 identifies social distance effect while α_3 identifies level effect. The two effects are controlled to eliminate the concern that apparent sorting by gift given could be due solely to the similarities in preferences that come from closeness. A set of household factors is included to construct social distance and level effect indicators, including head characteristics (gender, marital status, education, age, and ethnicity), family characteristics (share of youth and elderly, cadre, household size, land size, family assets, number of farm workers, and number of nonfarm workers), and major household shocks (natural disaster, livestock death, and family member death).

However, the link formation framework used by Fafchamps and Gubert (2007) (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 extent one can rely on networks when needed, rather than what the mere existence of links could do. Therefore, we substitute the actual gift one presents on an occasion for the existence of a link as the dependent variable.

From the econometric identification perspective, the Fafchamps and Gubert (2007) framework illustrates that low-degree variation hinders the effort to reliably identify determinants of more links, that is, the level effect α_3, since the degree for a directional link from i to j is either 0 or 1. 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. However, link intensity based on gift amounts provides much larger variation. Therefore, a linear dyadic model of gift spending per occasion is estimated to circumvent the issue of indecomposable dependent dyadic observation likelihoods.

Relative status $RD_{i,t}$ is measured via defining natural villages as peer groups. It 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. Its value lies between 0 and 1. The more relatively deprived, the higher the value.[39] The identified impact is denoted by α_4. This is an improvement over the method of Brown, Bulte, and Zhang (2011), which uses community-specific distributional indicators to measure status seeking.

[39] For a detailed review of a series of relative deprivation measures, see Chen and Zhang (2011).

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,[40] the pairwise difference model (3) investigates how the incremental gift spending can be interpreted as influenced by three major factors: risk sharing, *changes in* status, and *changes in* peer influence. The pairwise difference model removes the unobserved pair heterogeneity:

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

To check whether peer effect is robust to more IVs, we keep out-of-township peers' median gifts and additionally follow the strategy of De Weerdt and Dercon (2006), which uses changes in peers' windfall income and remittance to instrument changes in peers' median spending per occasion. Changes in peers' windfall income directly affect changes in peers' gift spending and exert only indirect impact on one's gift spending growth via peer influence.

3.6.2 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 nonindependence 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 ordinary least squares estimation generates consistent coefficient estimates but inconsistent standard errors. Monte Carlo simulations show that the corrected standard errors can be much larger, especially when the average links per nodes is large (Fafchamps and Gubert 2007).

Three general categories of approaches have been utilized to tackle the dependence of dyadic observations. The first category is to run the generalized least squares estimation while

[40] We restrict our analysis to dyadic links between households that once held social occasions.

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 has one dimension to be clustered, 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 multiway clustering method is developed to allow arbitrary heteroskedasticity and intragroup correlation in distinct non-nested categories (Cameron, Gelbach, and Miller 2011; Thompson 2009). Though applied in some settings 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 the cases when $E(\varepsilon_{i,j}, \varepsilon_{k,i}) \neq 0$ or $E(\varepsilon_{i,j}, \varepsilon_{j,k}) \neq 0$. 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 in this category, that of Fafchamps and Gubert (2007), corrects dyadic standard errors due to the cross-observation correlation in error terms involving certain individuals. It thereby 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, the fixed-effect model may not handle some forms of correlated errors (Thompson 2009). Another limitation with dyadic fixed effects is that they limit the set of covariates that can be included due to collinearity. Fortunately,

the long-term network records 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 relax this assumption in the robustness check through clustering the observations by time periods. Results, not shown here to save space, indicate that this affects only standard errors, not inference.

In this paper, we estimate dyadic regressions across all possible dyads using De Weerdt dyadic fixed-effect correction (De Weerdt 2004), Fafchamps-Gubert (FG) standard error correction (Fafchamps and Gubert 2007), and QAP (Simpson 2001). The absence of some dyadic observations is perfectly predicted by a household's never holding any ceremonies in the past few years, two households' not knowing each other across villages, or both. Therefore, there is no point including those pairs in the estimation. All estimations are based on an N x N square adjacency matrix composed of (potential) pairwise connections among event organizers. Through this survey design, square adjacent matrices are built.[41]

To implement the De Weerdt dyadic fixed-effect correction, a set of dummy variables is introduced, one for each household in the sample indicating whether that household is involved in a pair. Every row of the data contains two dummies equal 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 the 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

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

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 an *N* x *N* square adjacency matrix.

$$Var(\hat{\beta}) = \frac{1}{N-K}(X'X)^{-1}(\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N}\frac{m_{ijkl}}{2N}X_{ij}u_{ij}u_{kl}'X_{kl})(X'X)^{-1}. \quad (4)$$

To implement QAP, the dependent variable is permuted and merged back with the independent variables. During repeated permutations, values sharing a row or column in the original data will share a row or column in the permuted data. Therefore, we preserve any dependence among elements of the same row or column but eliminate any relationship between the dependent variable and the independent variables. Then we run the estimation with the new merged dataset 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.

3.7 Empirical Results

3.7.1 Determinants for Gift Spending per Occasion

We first attempt to explore factors for gift exchanges. In Table 3.4, three standard error corrections are adopted in the dyadic estimation of determinants for gift spending. Regression 1 adjusts for dyadic standard errors according to FG, regression 2 reports QAP adjusted p-value, and regression 3 presents results from the De Weerdt dyadic fixed-effect estimations.

We find incomplete risk pooling. The estimation in regression 1 shows that households do not purposefully insure along occupation or education, but they do significantly insure each other along income profile and against shocks. Younger families send more gifts to households with

senior members.[42] Level effects show more intense gifts between cadres and richer households. Families with unmarried sons are motivated to link to each other in exchange for insurance against large expenses on future weddings. Gift giving is more intense between lineal relatives. Given a 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 with risk pooling.[43, 44] Regressions 2 and 3 present similar results on risk sharing. The differences lie in insignificant insurance against shocks.

Peer influence is salient. Regressions 1–3 show that a 1 percent increase in peers' gift spending leads to an increase in gift giving per occasion by 0.26 percent, 0.26 percent, and 0.46 percent, respectively. The FG and QAP methods demonstrate very similar results that are consistent with the experience of Fafchamps and Gubert (2007) and of Santos and Barrett (2010).

Status seeking weakly determines more intense gift spending for the lower tail of the distribution. For regressions 1–3, the lowest-ranked households spend 13.5 percent, 56.7 percent, and 25.7 percent more, respectively, on gift giving per occasion than do top households.

3.7.2 Determinants for Changes in Gift Spending per Occasion

Having presented the determinants for gift spending on an occasion, we now explore the main issue—driving forces behind the recent escalation in gift spending. The estimation methods

[42] Unlike other studies using household head age, our family demographic structure indicators in terms of share of elderly and share of unmarried sons are controlled. Our structure more directly captures potential complements in taking care of the elderly and insuring against lump-sum wedding expenditure for an unmarried son, respectively.
[43] Our estimation of geographic proximity might be more reliable than that of Fafchamps and Gubert (2007), since variations in geographic distance are larger in our dataset, capturing numbers of cross-village links, while this type of link is absent in Fafchamps and Gubert.
[44] There is a concern that households may self-select into a neighborhood. However, the historically evolved locality of farmland in rural China prevents endogenous household placement. See Figure 4.3 for the typical pattern of household geographic clustering based on inherited farmland in each clan.

in regressions 1–3 in Table 3.5 correspond to those of regressions 1–3 in Table 3.4, respectively.

Different from gift giving itself, the evidence for risk pooling through gift spending *escalation* is largely insignificant. We find risk sharing responding to shocks only in regression 1. Health and weather shock smoothing and income pooling are even of the opposite sign in regression 3, suggesting that poorer households suffering from more shocks purposefully connect with richer counterparts through rapidly growing gifts. Under regressions 1 and 3, gift spending among families with unmarried sons 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 percent growth in peers' gift spending increases own gift expenditure per occasion by 0.70 percent under FG correction, 0.72 percent under QAP, and 0.51 percent under De Weerdt correction.

Being more deprived in social ladders boosts gift spending growth. A 1-point increase in the Deaton relative deprivation index, that is, from the bottom to the top in the distribution, causes a 75 percent higher increase in gift spending per occasion under FG correction, an 85 percent higher increase under QAP estimation, and an 82 percent higher increase under De Weerdt correction. Compared with its weak impact on gift giving, the rapid increase in gifts is well explained by the motive to improve relative standing.

Following the IV strategy in De Weerdt and Dercon (2006), we further add changes in peers' windfall income and remittance to instrument changes in peers' median gift per occasion and conduct four robustness checks (Table 3.6). Windfall income in our context includes two exogenous sources: resettlement subsidy targeting dilapidated houses and vulnerable habitats,

and land acquisitions subsidy due to urbanized projects near the local county seat (Table A.2). Both sources of income survive the test of their association with observable family characteristics (Table A.3), which suggests that they are largely random to household characteristics. To mitigate endogeneity that drives the effect of remittance on gift giving, remittance is restricted to that sent from household members who migrated at least two years ago.

The F-statistic for the first-stage estimations demonstrates that the IVs have large predicting power, while the p-values for the Hansen j-statistic suggest that the instruments are not overindentified. All four estimations on changes in gift expenditure with these IVs confirm peer effect and status seeking.

First, pairwise difference models are estimated with these IVs. The identified marginal peer effects are 0.75 under FG correction, 0.78 under QAP, and 0.55 under De Weerdt correction. The identified status-seeking effects are 0.75 under FG correction, 0.84 under QAP, and 0.76 under De Weerdt correction. All identified peer effects 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.[45] We conclude that peer pressure in extending gifts comes from both fellow ceremony guests and event organizers, the former dominating the latter with regard to the marginal effect. The identified peer effect is 0.36, closer to that of the De Weerdt scenario. The status-seeking effect is 0.47, which is smaller than that of any of the three pairwise dyadic regressions.

In the first-stage estimations for both pairwise dyadic regression and household fixed-effect

[45] The median values are taken for a set of own gift-sending links per year (the left-hand side) and a set of all peers' gift-sending links per year (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 spending per occasion within each year on median peers' gift spending per occasion. This model eliminates the household unobserved factor(s) that may result in inconsistent estimation of peer effect.

regression, changes in peers' median windfall income significantly predict changes in peers' median gift per occasion, while remittance demonstrates significant impact in the household fixed-effect model. There is no windfall income-sharing mechanism in the 18 villages. Therefore, changes in peers' windfall income should exert only indirect impact on own gift growth via peers' gift expenditure and its influence over own gift spending, generating a 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 wages in recent years may be increasing remittance. If these incomes are unevenly distributed, it is very likely that gift expense escalation spills over within communities, exerting a disproportionate impact on the poor.

3.8 Concluding Remarks

Lavish household social spending has been widely observed in rural China. This paper studies an impoverished context wherein 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 foundations of the behavior—how own gift spending for an event responds to relative status, peer influence, and risk sharing. We present estimates for the separate effects of each of these factors on gift giving.

Our results confirm the prevalence of peer influence and status-seeking motivation in shaping gift spending escalation. The two effects persist upon applying different dyadic standard error corrections, adopting alternative IVs, 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.

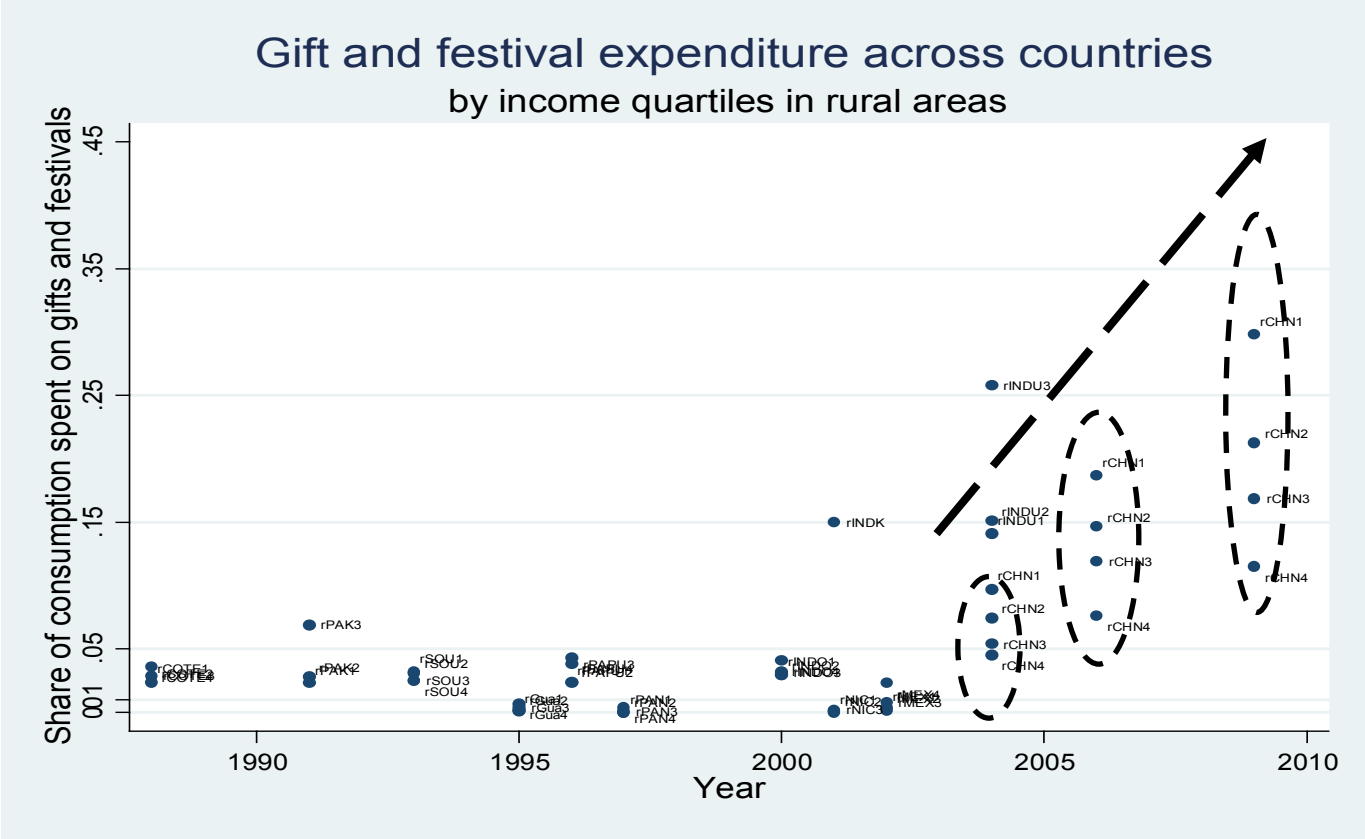
The risk-sharing effect on gift giving is consistently observed only via income pooling, but it is not evident via occupation diversification, education, shock smoothing, and so on. Moreover, none of the above social distances accounts for the recent gift escalation. One standard interpretation is that network maintenance cost in some dimensions is too high to sustain.

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 sons tend to extend more gifts. Considering the finding that part of the effect is captured by the status-seeking factor (Watson and McLanahan 2011), the evidence becomes more salient. This is hardly surprising when the marriage market in China is tightening and favorable to girls. The pressure to build bigger houses, bid up bride-prices, and throw larger wedding banquets to improve their sons' likelihood of marriage drives households with sons to invest early in the market.

The capability and motive for gift giving is amplified by massive windfall income and other opportunities amid the rapid development in China. Though received by only some households, their effects spill over to peers and contribute to the escalation in gift expenditure. For instance, the passing of the Lewis turning point means significantly rising wages in the labor market (Zhang, Yang, and Wang 2011), 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 a lumpy land acquisitions subsidy due to the accelerating urbanization process in rural China. The challenge is to minimize the negative externalities

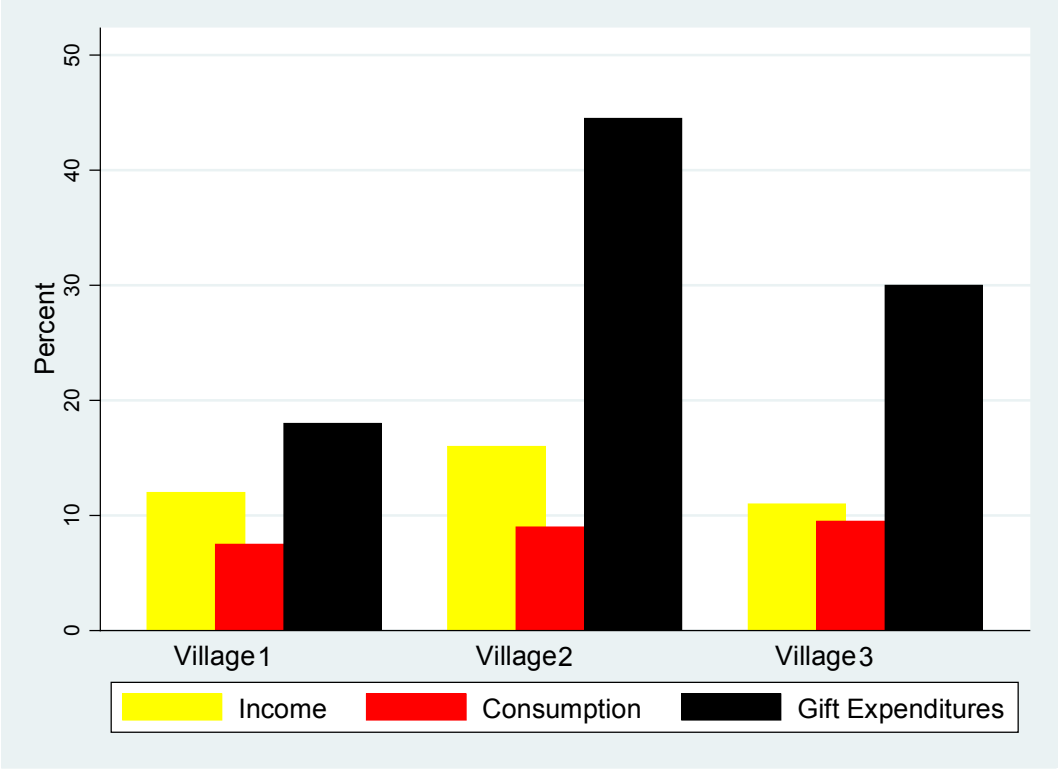
caused by peer influence over gift giving and to promote more effective risk pooling for the poor on social occasions.

Figure 3.1 Cross-country comparison of the share of household social spending (rural)



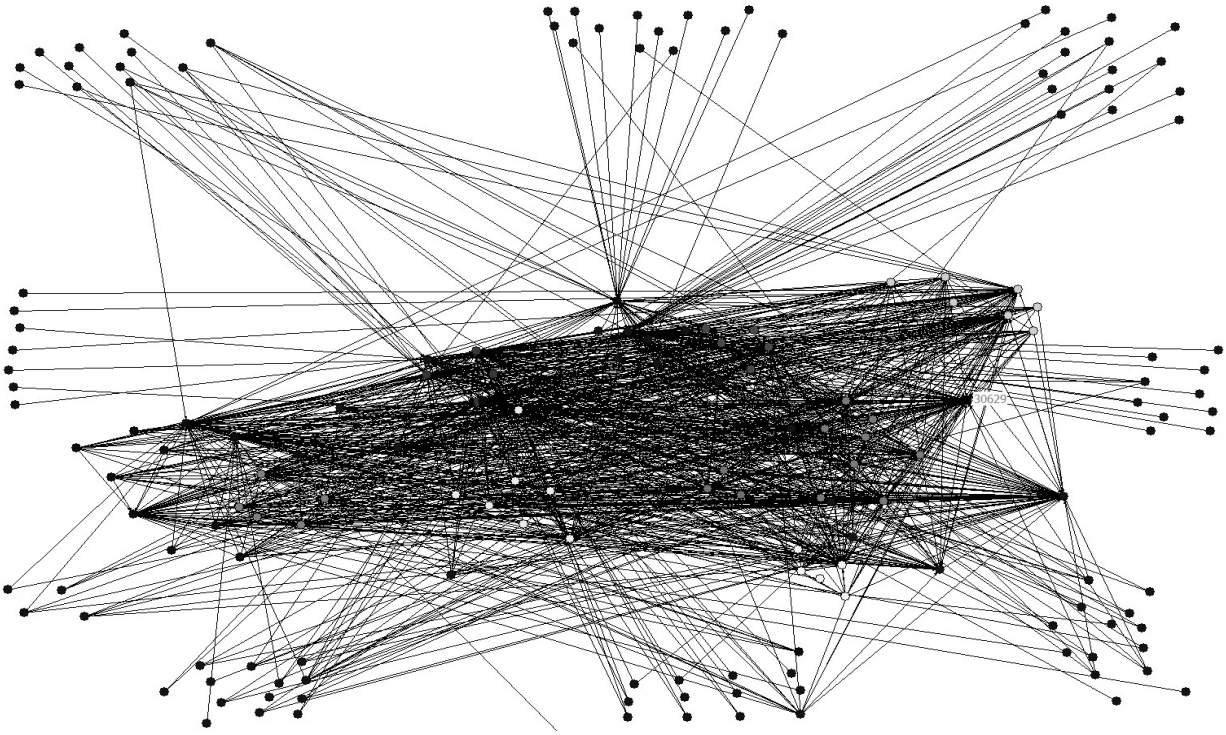
Sources: Banerjee and Duflo 2007; authors' three-wave census data in rural Guizhou; Rao 2001.
Notes: 1. The categorization for rural China (rCHN1, rCHN2, rCHN3, rCHN4) is based on the same four quartiles as other datasets (dollar amounts in U.S. dollars): less than $1 per day (denoted as "1"), $1–$2 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 purchasing power parity (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, Côte 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 3.2 Annualized growth of (per capita) income, consumption, and gift spending



Source: Gift records data (2005–2009) and three-wave survey data.
Notes: Annualized growth rates have been adjusted for inflation based on *China Statistical Yearbook* issued by the National Bureau of Statistics (NBS) of China, various issues.

Figure 3.3 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 3.1—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 (Yes=1; No=0)	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 (Yes=1; No=0)	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 the three natural villages where we collected gift records.

Table 3.2—Gift spending and sizes of ceremonies (2000–2009, per occasion)

Year	Coming-of-age			Male wedding			Female wedding			Funeral		
	Mean gift (CNY)	Gift SD	Mean # guests	Mean gift (CNY)	Gift SD	Mean # guests	Mean gift (CNY)	Gift SD	Mean # guests	Mean gift (CNY)	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 gift values have been adjusted for inflation based on the appropriate year's *China Statistical Yearbook* published by the National Bureau of Statistics (NBS) of China, various issues. "-" means no ceremony occurred during that year.

Table 3.3 Median expenditures (CNY) in organizing major ceremonies (1996–2009)

Year	Coming-of-age	Wedding (groom's family)	Wedding (bride's family)	Funeral
1996	-	4,500 (**3.00**)	3,157 (**2.10**)	2,688 (**1.79**)
1997	-	3,852 (**2.84**)	3,100 (**2.29**)	3,471 (**2.56**)
1998	-	5,211 (**3.85**)	3,025 (**2.23**)	3,170 (**2.34**)
1999	-	3,634 (**2.64**)	3,829 (**2.79**)	4,328 (**3.15**)
2000	-	6,250 (**4.85**)	2,929 (**2.27**)	4,393 (**3.41**)
2001	-	7,371 (**5.81**)	5,644 (**4.45**)	3,388 (**2.67**)
2002	-	7,347 (**5.20**)	4,536 (**3.21**)	3,402 (**2.41**)
2003	-	7,891 (**6.22**)	5,143 (**4.05**)	4,655 (**3.67**)
2004	-	10,423 (**8.24**)	4,243 (**3.35**)	6,150 (**4.86**)
2005	3,208 (**1.95**)	9,486 (**5.76**)	7,633 (**4.63**)	5,156 (**3.13**)
2006	3,387 (**2.62**)	11,805 (**9.14**)	7,502 (**5.81**)	6,175 (**4.78**)
2007	4,284 (**2.75**)	8,569 (**5.50**)	4,927 (**3.16**)	8,096 (**5.20**)
2008	8,046 (**5.50**)	13,983 (**9.56**)	5,833 (**3.99**)	7,561 (**5.17**)
2009	8,154 (**5.51**)	15,066 (**10.18**)	7,766 (**5.25**)	7,151 (**4.83**)

Source: Authors' survey data.

Notes: 1. All expenditure amounts have been adjusted for inflation based on the appropriate year's *China Statistical Yearbook* published by the National Bureau of Statistics (NBS) of China, various issues. All values are in CNY. 2. Recall data for coming-of-age ceremonies were collected only since 2005. 3. Numbers in parentheses denote expenditure as proportion of average per capita income in the 18 villages.

Table 3.4 Dyadic regression on gift expenditure per occasion

	R1		R2		R3	
	FG SE correction		Quadratic Assignment Procedure (p-value)		De Weerdt SE correction	
Social distances (def(Zi , Zj))						
Cumulated shocks	-0.079**	(0.04)	-0.076	(0.13)	-0.130	(0.09)
Head minority status	-0.061	(0.06)	-0.022	(0.43)	2.026**	(1.01)
Household size	0.022	(0.02)	0.012	(0.36)	-0.063	(0.09)
Number of farm workers	0.047	(0.04)	0.031	(0.25)	0.081	(0.17)
Number of nonfarm workers	0.007	(0.02)	0.018	(0.34)	-0.026	(0.08)
Head education	-0.005	(0.01)	-0.008	(0.33)	-0.043	(0.03)
Head gender	0.019	(0.08)	0.053	(0.41)	1.823	(1.37)
Cadre	-0.055	(0.08)	-0.021	(0.43)	-0.237	(0.23)
Head marital status	0.147*	(0.08)	0.113	(0.24)	-0.062	(0.32)
Head age	0.016***	(0.00)	0.015***	(0.00)	0.071*	(0.04)
Share of elderly	-0.315***	(0.11)	-0.294	(0.12)	-1.082**	(0.47)
Share of unmarried sons	-0.097	(0.08)	-0.081	(0.29)	-0.130	(0.31)
Per capita income (predicted, log)	0.248***	(0.04)	0.260***	(0.00)	0.246***	(0.04)
Level effect (sum(Zi , Zj))						
Cumulated shocks	-0.040	(0.03)	-0.050	(0.28)	0.089	(0.07)
Head minority status	0.014	(0.06)	0.030	(0.44)	-0.453	(0.86)
Household size	0.099***	(0.02)	0.093***	(0.01)	0.100	(0.08)
Number of farm workers	0.067*	(0.04)	0.037	(0.24)	0.021	(0.06)
Number of nonfarm workers	0.009	(0.02)	0.029	(0.32)	-0.125*	(0.08)
Head education	0.011	(0.01)	0.016	(0.23)	0.051	(0.03)
Head gender	-0.077	(0.08)	-0.071	(0.36)	-2.276	(1.39)
Cadre	0.321***	(0.08)	0.334**	(0.02)	0.293	(0.23)
Head marital status	-0.075	(0.08)	-0.110	(0.27)	-0.630**	(0.31)
Head age	-0.005*	(0.00)	-0.005	(0.18)	-0.047	(0.04)
Share of elderly	0.494***	(0.11)	0.489**	(0.03)	0.420	(0.49)
Share of unmarried sons	0.215***	(0.07)	0.212	(0.13)	0.309	(0.30)
Per capita income (predicted, log)	0.495***	(0.06)	0.470***	(0.00)	0.804***	(0.11)
Link attributes						
Lineal relatives or not	1.578***	(0.12)	1.706***	(0.00)	1.566***	(0.13)
Across villages or not	-1.938***	(0.10)	-1.814***	(0.00)	-1.761***	(0.11)
Peer influence						
Peers' median gift (per occasion, lag, log)	0.262**	(0.12)	0.263**	(0.05)	0.455*	(0.27)
Status seeking						
Deaton relative deprivation	0.135	(0.13)	0.567**	(0.05)	0.257	(0.31)
R-square / N	0.44 / 3,136		0.47 / 3,136		0.55 / 3,136	

Source: Gift records data and three-wave survey data.
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 3.5 Pairwise dyadic regression on *changes in* gift expenditure per occasion

	R1		R2		R3	
	FG SE correction		Quadratic Assignment Procedure (*p-value*)		De Weerdt SE correction	
Social distances (def(Zi , Zj))						
Cumulated shocks	-0.146**	(0.07)	-0.060	(0.21)	0.604***	(0.20)
Head minority status	0.214***	(0.04)	0.119*	(0.05)	-1.992***	(0.64)
Household size	0.019	(0.02)	0.015	(0.25)	0.037	(0.06)
Number of farm workers	0.012	(0.01)	0.010	(0.32)	0.014	(0.02)
Number of nonfarm workers	0.002	(0.02)	0.003	(0.48)	0.084*	(0.05)
Head education	-0.006	(0.01)	-0.002	(0.44)	-0.026	(0.03)
Head gender	-0.021	(0.07)	-0.009	(0.47)	-4.901**	(1.88)
Cadre	0.248***	(0.09)	0.098	(0.14)	-0.115	(0.24)
Head marital status	0.091	(0.06)	0.039	(0.33)	0.045	(0.20)
Head age	0.003	(0.00)	0.001	(0.35)	-0.274***	(0.09)
Share of elderly	0.027	(0.11)	0.060	(0.32)	0.185	(0.59)
Share of unmarried sons	-0.182**	(0.08)	-0.093	(0.16)	-0.134	(0.35)
Per capita income (pred, log)	0.199	(0.15)	0.070	(0.31)	-1.137***	(0.37)
Level effect (sum(Zi , Zj))						
Cumulated shocks	-0.017	(0.03)	-0.002	(0.50)	0.038	(0.05)
Head minority status	-0.170***	(0.04)	-0.078	(0.11)	-4.304***	(1.57)
Household size	-0.052***	(0.02)	-0.024*	(0.08)	-0.016	(0.06)
Number of farm workers	0.031*	(0.02)	0.031	(0.23)	0.025	(0.02)
Number of nonfarm workers	-0.036**	(0.02)	-0.019	(0.17)	-0.072*	(0.04)
Head education	0.017**	(0.01)	0.011*	(0.08)	0.038	(0.03)
Head gender	-0.151**	(0.06)	-0.085	(0.15)	-4.213***	(1.20)
Cadre	-0.221***	(0.07)	-0.104*	(0.07)	0.112	(0.15)
Head marital status	0.079	(0.05)	0.045	(0.30)	-0.123	(0.23)
Head age	-0.001	(0.00)	-0.001	(0.46)	-0.040*	(0.02)
Share of elderly	0.208**	(0.10)	0.143	(0.14)	1.078**	(0.48)
Share of unmarried sons	0.162***	(0.06)	0.095	(0.12)	0.512**	(0.23)
Per capita income (pred, log)	0.010	(0.05)	-0.011	(0.36)	0.210***	(0.07)
Change in peer influence						
Peers' median gift (per occasion, lag, log)	0.698***	(0.15)	0.717***	(0.00)	0.506***	(0.14)
Change in status seeking						
Deaton relative deprivation	0.750***	(0.27)	0.845***	(0.00)	0.821***	(0.26)
R-square / N	0.18 / 3,136		0.11 / 3,136		0.24 / 3,136	

Source: Gift records data and three-wave survey data.
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 3.6 Pairwise dyadic regression on *changes in* gift expenditure with more IVs
(*Changes in* peers' windfall income, *changes in* remittance, and *changes in* out-of-township median gift per occasion 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)	0.749***	(0.15)
Δ Deaton relative deprivation	0.747***	(0.27)
2. Pairwise difference model (under Quadratic Assignment Procedure)		
Δ Peers' median gift (per occasion, lag, log)	0.778***	(0.00)
Δ Deaton relative deprivation	0.840***	(0.00)
3. Pairwise difference model (under De Weerdt standard error correction)		
Δ Peers' median gift (per occasion, lag, log)	0.548***	(0.14)
Δ Deaton relative deprivation	0.761***	(0.26)
Pairwise dyadic regression—first stage		
1st stage: Δ out-of-township median gift (per occasion, lag, log)	0.687***	(0.02)
Δ peers' windfall income (lag, log)	0.016**	(0.01)
Δ peers' remittance (lag, log)	0.007	(0.02)
F-statistic for joint significance	19.28	
p-value for Hansen j-statistic	-	
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)	0.363***	(0.09)
Δ Deaton relative deprivation	0.465**	(0.24)
Household fixed-effect regression—first stage		
Δ peers' windfall income (lag, log)	0.210***	(0.04)
Δ peers' remittance (lag, log)	0.361***	(0.07)
F-statistic for joint significance	14.90	
p-value for Hansen j-statistic	0.41	

Source: Gift records data and three-wave survey data.
Notes: 1. Scenarios 1 and 3 in the second stage report dyadic standard errors. Scenario 2 in the first stage reports QAP p-values. Scenario 4 reports robust standard errors. 2. * significant at 10%; ** significant at 5%; *** significant at 1%. 3. The previous IV—*changes in* out-of-township peers' median gift spending per occasion—is utilized. Meanwhile, two additional IVs are used, *changes in* peers' windfall income and *changes in* peers' remittance. The instrumental variables strategy follows De Weerdt and Dercon (2006). We adopt a more exogenous remittance definition that includes only family members who migrated at least two years ago. 4. The organization of the observations by household and year in the household fixed-effect estimation (scenario 4) prohibits us from identifying out-of-township peers' median gift spending pending per occasion. Therefore, it is dropped from the IV list.

APPENDIX TABLE

Appendix Table A.1 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)
Education (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 (# times)	-0.19***	-0.14***
	(0.01)	(0.04)
Year dummies	Y	Y
Village dummies	Y	Y
R-square	0.83	0.45
N	3,136	3,136

Source: Gift records data and three-wave survey data.
Notes: Dyadic standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table A.2 Summary statistics for windfall income and nonearned 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 who migrated at least 2 years ago)			
2004	1,385.588	980	686.47	34
2006	3,357.313	2,000	1,685.53	67
2009	3,635.147	3,000	2,656.85	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	10,000	5,548.74	5
2009	60,147.5	55,000	35,341.32	18

Source: Gift records data and three-wave survey data.

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

Appendix Table A.3 Windfall income and family characteristics

	1	2	3	4
	Resettlement subsidy (logit)		Land acquisitions subsidy (logit)	
Network size (# lineal relatives, log)	0.00	0.01	-0.09	-0.07
	(1.00)	(0.77)	(0.54)	(0.50)
Hhsize (# members)	0.02	0.02	0.40	0.40
	(0.93)	(0.90)	(0.45)	(0.31)
Share of migrants	-1.08	-0.76	1.81	3.62
	(0.45)	(0.58)	(0.52)	(0.24)
Sex (dummy)	-1.00	-0.91	-0.72	-0.65
	(0.18)	(0.21)	(0.49)	(0.23)
Minority (dummy)	-0.54	-0.21	-1.21	0.73
	(0.46)	(0.67)	(0.35)	(0.41)
Education (years)	-0.02	0.00	-0.07	0.26
	(0.84)	(0.95)	(0.82)	(0.17)
Cadre (dummy)	0.69	0.62	0.31	0.42
	(0.26)	(0.30)	(0.22)	(0.24)
Age (year)	0.04	0.03	0.22	0.15*
	(0.11)	(0.26)	(0.12)	(0.06)
Share of the elderly	-1.75	-0.50	-5.24	0.26
	(0.19)	(0.67)	(0.36)	(0.93)
Share of youth	0.54	2.22**	-0.03	0.76
	(0.61)	(0.02)	(0.99)	(0.81)
Land (mu)	-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 (# times)	-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 R-square	0.157	0.077	0.379	0.245
N	616	616	607	609

Source: Gift records data and three-wave survey data.

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

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CHAPTER 4

SPATIAL IDENTIFICATION OF STIGMA BEHAVIOR THROUGH SOCIAL NETWORKS: PEER EFFECTS ON PAID BLOOD DONATION

4.1 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 selling blood, signaling to people around that they are lazy and do not participate 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 selling blood. The question I am interested in is why blood sales still persist 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 blood sales persist in many regions with fruitful poverty alleviation efforts and in more developed Eastern China.

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 selling blood 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).

The understanding of stigma behavior may also revolve around the issue of status seeking. However, the literature on the effect of relative concern on well-being mainly refers to *keeping up with the Joneses* in the context of wealthy populations, while empirical evidence from poor contexts is much less and results are mixed (Banerjee and Duflo, 2007; Ravallion and Lokshin, 2010; Akay et al., 2011). An agent's relative economic standing may contribute to the observed stigmatized behavior as being at the lower end of the income distribution may set in motion status contests (Hopkins and Kornienko, 2004). Those at the bottom end of the economic

distribution may perceive both greater potential rewards and a smaller downside risk when engaging in risky but "profitable" activities (Hopkins, 2011). Meanwhile, for families with unmarried male members or regions with skewed sex ratios, relative social standing in unbalanced marriage market with many excess men may further push them to engage in those activities (Robson, 1996; Wei and Zhang, 2011b).

We collected two datasets to investigate peer effects and status seeking: a three-wave census-type household survey from 18 villages enables me to examine the evolving patterns and determinants of frequent plasma donations and capture relative socioeconomic status; and the collection of detailed gift exchange records from all households were designed in three out of the 18 villages over 2000-2009 to define reference groups, measure intensity of social interactions, and identify peer effects. 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 blood sales behavior. The main network fixed effect and household fixed effect estimations further get rid of unobserved factors varying at network and household level which simultaneously affect network formation and blood sales.

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 attempt 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. It is among the first empirical tests on relative status and risk-taking behavior.

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 information on amount of pairwise gifts, and it records complete friendship networks.

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 important in identifying peer effects; 3) peer effects are directional and appear to be partially driven by preference interactions that reduce stigma; 4) the less well-off in the

distribution appear to be more motivated to engage in stigmatized behavior; and 5) tightening pressure from the unbalanced marriage market in China further increases the behavior.

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 and income dispersion on plasma donation. In section 4, I describe the three-wave census type survey and gift-exchange network data, the identification of peer influence, the measures of relative status and the empirical framework. In section 5 I report estimation results, discuss the potential mechanism and present some initial evidence on health impacts. Finally, section 6 concludes.

4.2 Plasma Donation 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 4.1), 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 we collected data for this paper (see Figure 4.1). It is also the poorest province in China (Table 4.1).

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.[46] 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 2008. 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.

46 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.

4.3 Conceptual Model

A static model of stigmatized behavior in a social norm is developed in which peer pressure and relative social standing impact 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 [47], ranging from $\theta_{\min}$ to $\theta_{\max}$ with the cumulative 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),

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

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

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

[47] To simplify the analysis, in this static model labor quality is not a function of blood sales.

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., $U_S < 0$, $U_{SS} < 0$.

$\bar{h}$ 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.[48] The social stigma function $S(\cdot)$ satisfies $S_h > 0$, $S_{hh} > 0$, $S_{\bar{h}} < 0$, $S_{h\bar{h}} < 0$. Stigma is increasing in own engagement but decreasing in others' engagement in the group. The marginal stigma is 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 $S(0,\bar{h}) = 0$. Two major propositions follow. The corresponding derivations are provided in Appendix I.

Proposition 1: Individual engagement in stigmatized behavior is increasing in others' engagement in the reference group.

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

Proposition 2: Let $F(\theta_i, \xi)$ denote the cumulative distribution function of income excluding plasma donation compensation, where ξ is the mean-preserving spread parameter. As income distribution becomes more unequal ($\xi' > \xi$, $F(\theta_i, \xi)$ second-order stochastically dominates $F(\theta_i, \xi')$), the average plasma donation increases if $\partial F(\theta, \xi) / \partial \xi > 0 \;\; \forall \theta \in [\underline{\theta}, \bar{\theta}]$.

[48] 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.

$$\frac{\partial \bar{h}}{\partial \xi} = -\frac{\int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \theta} \frac{\partial F(\theta, \xi)}{\partial \xi} d\theta}{1 - \int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} dF(\theta, \xi)} \qquad (3)$$

$$sign(\frac{\partial \bar{h}}{\partial \xi}) = sign[-\int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \theta} \frac{\partial F(\theta, \xi)}{\partial \xi} d\theta] \qquad (4)$$

where $\partial h(\theta, \bar{h}, w) / \partial \theta < 0$ and $\partial F(\theta, \xi) / \partial \xi$ may vary over $[\underline{\theta}, \bar{\theta}]$. Nonetheless, a sufficient condition ensures an increase in the overall plasma donation intensity when income distribution becomes more unequal. Specifically, if $\partial F(\theta, \xi) / \partial \xi > 0 \ \ \forall \theta \in [\underline{\theta}, \bar{\theta}]$, plasma donation intensifies. Appendix I shows a special case when income distribution is subject to the uniform distribution.

This model is built on a general setting in which no status or rewards is explicitly introduced. I argue that even in this standard model the impact of changes in the distribution can be derived. In impoverished areas, frequent plasma donation is regarded as risky due to potential blood contamination, disease transmission and insufficient nutritional compensation. The dispersion of income motivates the disadvantaged in the distribution to engage in risky behavior when social rewards are sufficiently unequal. This result can be linked to a branch of rising literature on risk-taking behavior and inequality of rewards (e.g. Hopkins, 2011). Developing a framework of a status tournament, Hopkins (2011) finds that risk-taking behavior is increasing in the inequality of rewards. The poor become risk-loving if their lowest level of awarded status is sufficiently low. Status or rewards from a fair gamble are directly embodied in agents' preferences (Hopkins, 2011), and my result is confirmed.

4.4 Data and Empirical Strategy

4.4.1 Data Collection

As noted above, the dataset for this study comes from a three-wave census-type rural household survey conducted by the authors in 18 natural villages (from three administrative villages) in Puding County, Guizhou province in Western China.[49] While Guizhou province is the poorest province in China. Puding's per capita GDP is 6495RMB in 2009, which is close to the median level in Guizhou. It is both geographically and 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 first-wave census survey of 801 households at the beginning of 2005 on the recall data from 2004. It collected detailed information on public facilities, investment and institutions in the villages and demographic characteristics, incomes and consumption for households. Transfers and blood donations were collected on each family member, including those who were working outside the county at the time of survey. Given the sensitivity of collecting data on blood donations, we made great efforts to ensure the accuracy of these data, including extensive training of local survey numerators who were able to effectively interact with the residents in our sample villages. Moreover, the numerators were trained to identify, and probe into major discrepancies between income and expenditures, a strong indication that respondents concealed blood donations as an income source.

As documented earlier, blood banks in Guizhou were shutdown in early 2006 due to Hepatitis C contamination in some branches. Prior to the 2006 shut-down, donors received a cash "nutrition" subsidy valued at 80RMB for the plasma contained in 580 cc of blood. At that time,

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

31.2% households surveyed engaged in plasma donation, and the compensation accounted for 10.9% of total income (Table 4.2 and Table 4.4).

A follow-up survey of the same households was administered in early 2007 and 833 households was interviewed on recall data from 2006. After the shutdown of the local blood bank in early 2006, a few local residents were still able to continue donation through traveling to other counties nearby, since the timing of shutting down differs. Therefore, the number of donors, donation compensation and share of income from donation were all much smaller than 2004 and 2009 but were nonzero. In other words, the summary statistics for plasma donation in 2006 reflect some households' persistency in plasma donation through other means.

In early 2010, the third wave follow-up survey was conducted for all 872 households on their recall information from 2009. Further information on each of the family members donating plasma was collected. Since 2008 when all blood banks were reopened, they were commercialized and therefore have had no connection with the local government. Nutrition subsidies have nearly doubled to 142RMB (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 4.1% of total income, it was still much less than the 2004 year level (Table 4.2 and Table 4.4). It is also worth noting that while the payment is rather minimal to the rich, the amount of cash is still a strong incentive to donate blood for impoverished farmers. Over a longer term, i.e., 2004-2009, the villages where plasma donation has been pervasive are poorer as indicated by the FGT poverty measures (Table 4.3). Plasma donation is becoming a major source of income that helps lift households out of poverty (Figure 4.2). A donor typically earns around 3600 RMB from

continuous plasma donation per year, much more than from other local income generating activities.

Throughout our three-wave survey, 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 engaging in these two activities are higher than women. However, the ratios of women donors in different villages vary significantly, reflecting different labor market situations. For instance, Table 4.4 suggests that villages with more local odd job opportunities have higher proportion of female donors.

In addition to the census conducted in the 18 villages, I gathered a ten-year gift-exchange record book for each household in three natural villages.[50] Gift-exchange data were spontaneously recorded on the days of all social occasions when guests presented the gifts to hosts, including male members' weddings, female members' weddings, funerals, coming-of-age ceremonies, child birth ceremonies, and house-moving ceremonies. Close relatives are responsible for recording gifts on site when hosts are busy organizing events or when hosts 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 three villages and the other fifteen 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 4.3).

[50] Village 1 is the most remote (10 kilometers away from the county seat with poor road access). In contrast, Village 3 is only 2.5 kilometers away from the county seat. In between, Village 2 is populated with Buyi ethnic minority, who preserve the Catholic culture different from the major Han villages (e.g. Village 1 and Village 3).

4.4.2 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, 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 a recent study, Mangyo and Park (2011) suggest that village reference groups are salient for rural residents living in close proximity. Different from an administrative village that includes several natural villages and represents the lowest level bureaucratic entity in China, a natural village is spontaneously evolved. Households within each natural village know each other well. Therefore, reference groups for relative status measures and peer behavior are first defined at the natural village level when the whole sample is estimated. In our surveyed region, the special geographic condition, *Karst* landform, further isolates local villagers' daily connections with other natural villages.

Apart from the reference group confined by the natural village boundary, rich information on 10-year gift networks enables us to redefine reference groups according to each household's corresponding gift receivers (alters). This definition has advantage over the village-based one due to one's social interactions with multiple reference groups and overtime variation in peer group composition. Specifically, gift record between 2000 and 2004 is utilized to construct peer groups for the 2004 survey, 2000-2006 gift record is applied to reference groups for the 2006 survey, and 2000-2009 gift record corresponds to reference groups for the 2009 survey.[51]

[51] The estimation results in section 5 are robust to weighting reference group composition by a time decay factor. For example, corresponding to the 2006 survey, reference groups formed during 2000-2004 are discounted. Corresponding to the 2009 survey, reference groups formed during 2000-2006 are discounted.

Figure 4.3 illustrates the 10-year gift links for one of the three villages that I collected network data. Gift exchange networks are observed to be more intense within clans and natural 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 natural 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 4.4 shows the correlation between plasma donation decisions in the reference group and own donation decisions in all 18 surveyed villages, involving whether to donate and number of family members engage in, at the natural 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 natural village. The vertical axes are average own plasma donation decisions for each natural village. The positive correlation is salient for both donation decisions.

Unequal income distribution seems to drive people to engage in plasma donation. Comparing Gini coefficient with and without plasma compensation, plasma donation reduces inequality (Table 4.3). Furthermore, households at the lower end of the distribution tend to be more motivated to engage in plasma donation. Figure 4.5 plots the negative association between relative status and one's likelihood of plasma donation at the household level in all 18 surveyed villages. The reference group defined for this figure is the natural village boundaries. The higher the index (the horizontal axis), the more relative deprived a household is in the reference group.

The association can be explained by the evidence that inflows of remittances to some households set in motion status contests through plasma donation from others (Brown et al., 2011), and that a rise in the average income but more unequal distribution in the region (Table 4.3) is accompanied with more spending on non-productive investments, such as housing (De Brauw and Rozelle, 2008), dowry and bride price (Yan, 1996; Liu, 2000) and ceremonies (Chen and Zhang, 2011). Though they are vehicles for social prestige that might challenge social status, welfare consequences of "positional externalities" associated with status seeking are severe for households living at or near subsistence levels. The highly ritualized practices of social occasions compel them to engage in risky income generating activities to avoid isolation from local networks.

4.4.3 Conventional and Spatial 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:

$$y_i = \alpha + \beta \frac{\sum_{j \in P_i} y_j}{n_i} + \gamma x_i + \delta \frac{\sum_{j \in P_i} x_j}{n_i} + \varepsilon_i, \qquad \mathrm{E}[\varepsilon_i \mid X] = 0 \qquad (5)$$

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:

$$y = \alpha\iota + \beta G y + \gamma x + \delta G x + \varepsilon, \quad \mathrm{E}[\varepsilon_i \mid x] = 0 \qquad (6)$$

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

$$y = \alpha(I - \beta G)^{-1}\iota + (I - \beta G)^{-1}(\gamma I + \delta G)x + (I - \beta G)^{-1}\varepsilon \qquad (7)$$

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 $G^2 x$ and peers' peers peers characteristics $G^3 x$ 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 II 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.[52] 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

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

$$J = I - G = I - \frac{1}{n}\iota\iota'$$

and the structural model becomes,

$$Jy = \beta JGy + \gamma Jx + \delta JGx + J\varepsilon \qquad (8)$$

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:

$$Jy = J(I - \beta G)^{-1}(\gamma I + \delta G)x + J(I - \beta G)^{-1}\varepsilon \qquad (9)$$

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.

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 affect network formation and is captured by the error term. Fortunately, the gift networks 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. However, it is possible that, rather than pairwise influences, alters' overall activeness in networks exerts influences on egos. The third strategy addresses this possibility through reweighing average peer behavior using Bonacich centrality in the sociology literature (briefly introduced in Appendix III). The spatial identification is applied to instrument the weighted peer behavior. Unique to social network studies that explicitly track all peers of each node i, information on long-term gift structure facilitates the calculation of centrality, i.e., the activeness of each node in networks.

I would like to draw a cautious note on comparing magnitude of the results. First, having only extensive social network data for three out of eighteen villages surveyed, I have to use a sub-sample to spatially identify peer effects. However, the conventional instrument strategy cannot be adopted in the sub-sample estimations because the community level instruments do not have enough variation in the sub-sample belonging to a small number of communities.

Therefore, the magnitude of identified peer effects using the two strategies is not comparable. Moreover, the same sub-sample estimations that weight peers' behavior differently still yield incomparable peer effects, because the weights are in different magnitude. Nonetheless, the consistency of identifications can be judged by their significance.

4.4.4 Measures of Relative Concern

Since Smith (1776), Veblen (1899) and Duesenberry (1949), it has been well established that relative concern affects well-being.[53] Relative concern can originate from different dimensions, such as positional consumption and socioeconomic status. Unequal income and consumption distribution in a society may lead to social capital erosion and social comparisons (Kawachi and Kennedy, 1999), vulnerability to shocks, poor health outcomes and health-compromising behaviors (Knack and Keefer, 1997; Wilkinson, 1997; Deaton, 2001; Li and Zhu, 2006; Ling, 2009) through rising mistrust and stress or declining social cohesion.

While the literature on relative concern has mainly referred to *keeping up with the Joneses* in the context of wealthy populations,[54] empirical evidence from poor contexts has started to accumulate.[55] Living in an impoverished context, people may have strong incentives to compete

[53] Adam Smith implicitly put forward the idea in *The Wealth of Nations* in 1776, where he claimed that people should be endowed with the ability to appear in public without shame**.** Since Veblen's seminal work in 1899, a few people started to believe that utility or happiness depends in part on the comparison of one's own consumption to that of others, which was first formally modeled by Duesenberry (1949) in his relative income hypothesis. Since the 1970's, compelling evidence on relative concern has been accumulated (Easterlin, 1974; Sen, 1983; Frank, 1985; Van de Stadt et al., 1985).

[54] For example, in the US counties with high income inequality, intense competition for social status leads to higher median housing prices, higher personal bankruptcy rates, and a higher incidence of divorce. Meanwhile, relative concern explains the link between inequality and observed disparities in international savings rates, which were not predicted by traditional consumption theories (Frank, 1997; Levine et al., 2011). Bowles and Park (2002) find that total working hours were positively associated with higher inequality in OECD countries over time. Other evidence includes Clark and Oswald (1996), Solnick and Hemenway (1998), Neumark and Postlewaite (1998), Stutzer (2004), Luttmer (2005).

[55] Evidence from designer-label goods consumption in Bolivia (Kempen, 2003), festivals' budget in India (Banerjee and Duflo, 2007), "splendid" funerals in Ghana (*Economist*, 2007), relative deprivation and migration in Mexico (Stark et al., 1991), bride-prices and dowries in south Asia and Africa (Rao, 1993; Dekker and Hoogeveen 2002),

for a higher spot on the social ladder when the status reward is high (Hopkins and Kornienko, 2010). For instance, status may determine one's access to scarce resources in a backward community, such as informal credit (Fafchamps and Gubert, 2007) and potential brides in the marriage market (Wei and Zhang, 2011a). Being surpassed on the social ladder, the poor households are compelled to divert limited resources from productive investments. As I explore in this paper, one funding channel is to exchange plasma for cash. "Positional externalities" is thus a problem that is particularly acute for households living near subsistence levels.

While community-specific inequality measures may restrict my attention to the impact of overall inequality,[56] household-specific relative status measures have two immediate advantages over community-specific inequality measures. First, such status measures help to avoid making an inference about an individual household based on aggregate data. Second, a specific pathway implicated in the relationship between income inequality and the interested behavior can be empirically evaluated.

Previous studies use different measures of relative status. For instance, Gerdtham and Johannesson (2004) use mean and median income of a reference group as a proxy for relative status. Eibner and Evans (2005) apply measures of relative deprivation. Li and Zhu (2006) apply rank and an interactive term between rank and the Gini coefficient to capture relative status. Both the rank & Gini interaction measure and mean & median income capture income information for the entire distribution, while relative deprivation adopts the view that we only eye people richer than us. The view is consistent with the popular *expenditure cascade* hypothesis that every agent

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marriage payments in Bangladesh (Anderson, 2007), and community level consumption in Nepal (Fafchamps and Shilpi, 2008) show strong support for relative concern. Fafchamps and Shilpi (2008) further notice that isolation from market is associated with a significant increase in relative concern. However, empirical evidence from developing contexts is still mixed. Ravallion and Lokshin (2010) find that relative deprivation is not the dominant concern Akay et al. (2011) find very low positional concerns both for income *per se* and for income from aid projects in Ethiopia.

[56] See Kaplan et al. (1996), Putnam (2000) and Kawachi et al. (1997) for studies on its effect on other behaviors, including violent crime, education and health that have adverse impacts for rich and poor alike.

except the richest one judges own behavior according to others closest above them in an economy (Levine et al., 2011).

Relative deprivation was originally proposed by Runciman (1966), arguing that one is deprived if the others in the group possess something that one does not have. Easterlin (1974) proposes a simple model to incorporate consumption norms into the individual's utility maximization framework whereby utility of individual *i* depends on *i*'s consumption relative to a weighted average of other people's consumption. Yitzhaki (1979) develops the definition by viewing income as personal possessions and deriving the relationship between relative deprivation and income inequality. Chakravarty (1990) defines relative deprivation as "utility foregone" because of not possessing the economic variables under consideration. Similar to Easterlin (1974), Cooper et al. (2001) propose a model in which an individual's utility depends on the absolute quantity and the quality of a good consumed as well as the quantity and quality of a status good consumed relative to peers. Wildman (2003a, 2003b) shows the relationship between average health, health inequalities, absolute income and income inequalities, and he links absolute and relative status hypotheses in the production of health.

In Yitzhaki (1979) and Wildman (2003a), the level of deprivation experienced by an individual i with income y relative to another individual with income z is formulated as,

$$D(i;y) = z - y \quad \text{if } y < z \qquad (10)$$

$$D(i;y) = 0 \qquad \text{if } y \geq z$$

Based on this form, one would feel more deprived as the number of individuals in society with higher income z increases. Thus, an overall measure of deprivation for the individual i is given by summing the differences in income and weighting it with the proportion of people with

higher income than the individual i. Accordingly, Li and Zhu (2006) define relative deprivation of absolute income (RDA) as,

$$RDA_i = \frac{1}{N_i}\sum_j (y_j - y_i) \quad \forall y_j > y_i \qquad (11)$$

Through normalization by N_i, the total number of people in their reference groups, RDA adopts normalized total income of other group members who earn more than i does to measure the relative deprivation of person i with income y_i. One concern with RDA is that it does not take into account differences in the scale of the income distribution across reference groups. In other words, if everyone's income doubles, relative deprivation will double as well. This would be a problem as I am using a panel dataset to measure relative deprivation over time, and incomes are not adjusted for inflation. Even if people view within-reference group income differences in proportional terms, RDA still overstates relative deprivation of individuals in high-income reference groups. To improve upon it, relative deprivation over individual income (RDI) is defined as the ratio of RDA relative to person i's own income.

$$RDI_i = RDA_i / y_i \qquad (12)$$

Intuitively following the measure of Gini coefficient, Wildman (2003b) proposes a measure of relative deprivation for an individual with income y at the provincial level and stratifies it by urban and rural regions as follows:

$$d_y(F) = \mu[1 - F_1(y)] - y[1 - F(y)] \qquad (13)$$

where μ denotes mean income and the population is ranked by income. $F_1(y)$ is the cumulative proportion of total income up to the income y and $F(y)$ is the cumulative proportion of the population up to the individual with income y.

Deaton (2001) proposes a measure of relative deprivation for an individual *i* with income x at the provincial level and stratifies it by urban and rural regions:

$$(1/\mu)\int_{x}^{x^T}(y-x)dF(y) \quad \text{or} \quad (1/\mu)[1-F(x)][\mu^{+}(x)-x] \qquad (14)$$

where μ denotes mean income for those in the reference group, x^T is the highest income in the group. F(y) is the cumulative distribution of incomes among individuals in the group, and $\mu^{+}(x)$ is the average income of those with income higher than the individual with income x. The Deaton measure is the normalized difference between the average income of those with higher income and income x weighted by the proportion of those with income higher than the individual i. Its normalization process utilizes mean reference group income instead of individual income adopted in RDI. Besides, RDI is less sensitive to income distribution relative to Deaton index.

The potential overestimation of some relative status measures in high-income groups could be an important issue when incomes differ substantially across groups or when a panel dataset is used to measure relative status over time. The Deaton index takes into account this scale issue.

All relative status measures above presume that the distance between two agents matters, either in proportional or absolute terms. However, studies on animals suggest rank over distance in importance. To test whether it takes effect on human beings, individual's rank over incomes within the reference group are used (Eibner and Evans, 2005; Li and Zhu, 2006). Unlike most of the other measures, rank is unaffected by changes in the shape of the income distribution. Thus, unlike the other measures, rank does not reflect differences in income inequality across groups. In other words, Rank ignores the magnitude of income differences among individuals and incorporates less information on relative deprivation.

4.4.5 Empirical Strategy

I estimate the following household plasma donation model:

$$y_{i,P_i,t} = \alpha + \beta_1 \frac{\sum_{j \in P_i} y_{j,t-1}}{n_{i,t-1}} + \beta_2 RD_{i,t} + \gamma x_{i,P_i,t} + \delta \frac{\sum_{j \in P_i} x_{j,t}}{n_{i,t}} + \lambda_i + \phi_t + \varepsilon_{i,P_i,t} \qquad (15)$$

or in matrix notation,

$$Y = \alpha\iota + \beta_1 GY + \beta_2 RD + \gamma X + \delta GX + \lambda + \phi + \varepsilon \qquad (15')$$

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.[57]

Two strategies are applied in identifying reference group P_i - village boundaries and gift networks. First, identification based on natural villages is adopted, 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. Therefore, I utilize a sub-sample that has rich information on social networks. Large variations in the intensity of gifts and availability of cross-village links improve village-based peer group identification. More importantly, partially overlapping peer groups and overtime variations in peer group composition help disentangle the endogenous effect.

Corresponding to the three peer effect identification strategies discussed earlier, group average plasma donation is constructed in three ways to measure peer behavior.[58] The first way

[57] 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.

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

simply takes the average donation at the natural village level; the second way weighs alters' donation decisions by normalized pairwise gift values and then takes the average for each ego; while the third way reweighs alters' donation decisions by their network centrality and then takes the average for each ego. Since the first way is applied to the whole sample with no information on social networks, no adjustment in the intensity of relationships can be made. However, both the second and the third strategy are implemented on the sub-sample with rich information on gifts presented, so they capture the heterogeneous intensity of pairwise ties.

Three estimation strategies are implemented to deal with simultaneity in identifying peer effects β_1, 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 full-sample conventional IV estimation. Both the second and the third strategies define gift networks as the reference group in the sub-sample estimation with spatial instruments generated from network structure. Specifically, characteristics of peers' peers as well as further indirect peers serve as instruments. For the second strategy, average peer behavior is measured with or without being weighted by normalized gift intensity. The normalization takes the ratio of each gift spending to the maximum gift one spent in that year. For the third strategy, peers' donation decisions are weighted by their network centralities.

Denoted by $RD_{i,t}$, relative status indicators gauge the extent to which the negative impact β_2 affects members in a society differently and whether it is biased towards the lower tail of the distribution.[59] Both household-specific and community level inequality measures are adopted to

[59] The impact of inequality on plasma donation may be further complicated due to the fact that a more unequal income distribution might reduce stress, distrust and the resulting plasma donation among the middle class but aggravate it in the two tails of the distribution. Meanwhile, heterogeneity might present that some people are highly

make this comparison. Moreover, most empirical studies on relative status rely on sampling a few agents in a cross-sectional context, which impedes them from capturing a full and dynamic picture of within-group status distribution. My study alleviates these problems by utilizing a multi-wave census-type panel survey.

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 is controlled.[60] 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 for each year at the village level 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.[61] Shocks, such as family member death, serious diseases, natural disasters, and livestock death, are also included. Plasma donation compensation is excluded from income and relative status measures.

4.5 Empirical Results

4.5.1 Main Results and Robustness

My main estimation results are presented in the following order: I first show evidence using the main identification strategy – spatial IV estimations. Random effect estimations are followed

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competitive and others are conformists, and people differ in their pride and compassion towards the poor around them.

[60] 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.

[61] Blood donation behavior is usually concentrated where local transportation condition permits. Transportation condition varies among natural villages. In natural 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.

by network fixed effect and household fixed effect estimations without weighting. Then I test different weighting strategies. Further to the spatial IV estimations, I compare the results with conventional IV estimations. Other robustness checks are then conducted. Finally, results for status seeking in the above estimations are presented and discussed.

First, estimations with spatial instruments generated from the gift network data are presented in Table 4.5. Table 4.5a reports results without taking into account the intensity of peer influences. The first three columns without spatial instruments suggest that both peer influence and relative status significantly determine plasma donation decisions. The last three columns of Table 4.5a instrument peers' average plasma donation decisions by characteristics of excluded peers generated from gift network structure. These characteristics involve per capita income, education, share of the elderly, share of unmarried son, relative wage, cadre status, relative economic status, travel time to the local blood bank. F-tests of the excluded instruments in the first stage indicate that weak instruments are not a concern. Over-identification tests fail to reject the validity of the spatial instruments. Standard errors in all estimations are clustered at the administrative village level.

The spatial instrument estimations indicate that peer effects are highly significant in predicting individual donation behavior. The magnitude is smaller than without spatial instruments. A 0.1 unit higher peers plasma donation rate increases own probability by 0.018, and a 1% increase in peers plasma donation value leads to 0.116% increase in own donation value. Evaluated at the first family member donating plasma, one more family member in the reference group engages in plasma donation leads to a 0.024 higher chance that a second member in one's own family donates plasma, small in magnitude. The estimated peer effect suggests that disutility from stigma declines when more peers engage in plasma donation.

Further to Table 4.5a, Table 4.5b weights each peer's influence by their dyadic normalized gift value (namely, link intensity). The estimations in the first three columns confirm peer influence and status seeking. F-tests of the excluded instruments in the first stage rule out the possibility of weak instruments, and over-identification tests verify instruments' validity. The spatial instrument estimations find smaller peer influence than estimations without weighting. However, since the ratio of each gift spent to one's maximum gift spending in a year is used as the weight, it is important to note that the marginal effects are not fully comparable to Table 4.5a.

Throughout Table 4.5a-4.5b, all exogenous effects other than peers' mean relative wage are insignificant, suggesting that social interactions mainly operate through peers' behavior. Considering own characteristics, having an unmarried son is associated with higher incentive to donate plasma. The official stipulation prohibits the elderly from donating plasma, which corresponds to their significantly lower probability of donation. Minority status significantly reduces engagement in plasma donation. The evidence on the ratio of local wage to plasma donation compensation is mixed. Although the theory suggests that rising wage should attract people to work in the labor market, the mixed estimation results are plausible since the recent plasma donation compensation has been 2-3 times the daily market wage. Since 2008, the plasma donation compensation has nearly doubled, offsetting the rapid wage increase. 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.

In Table 4.6, I present results adopting the spatial instruments as well as centrality-based weighting approach in the social network sub-sample estimations. Bonacich centrality is utilized to weigh peer influence over plasma donation. The peer groups for both peer effects

identification and status seeking are defined based on gift networks. The effects of peer influence and relative status largely persist. Since centrality, unbounded in nature, is used as the weight, the marginal effects are not comparable to Table 4.5a.

Comparing spatial instrument estimations with different weighting strategies, it is concluded that the intensity of social interactions matters in peer effects identification. Specifically, the pairwise weighting based on gift values finds more significant peer effects on probability of donation and value of donation, and the centrality based weighting finds more salient peer effects on probability of donation. Since reference groups are all based on the same gift networks among estimations with different weighting, the differences in peer effects are most plausibly due to the intensity. The estimation without considering heterogeneous intensity tends to ignore peer effects.

Due to my interest in time-invariant variables and the concern that plasma donation decisions tend not to change much once people engage in, all results presented till now are based on random effect estimations. To test whether peer effects and status seeking can be explained by within network/household variations, results from both global network fixed effect estimations and household fixed effect estimations are presented in Table 4.7. R1 through R3 suggest that both peer effects and status concern significantly account for within network variation in plasma donation. Household fixed effects estimations in R4 through R6 further show that peer effects explain variation in two out of three plasma donation decisions: whether any household member engages in donation and the number of household members donating plasma. However, peer effects do not account for variation in donation value. Moreover, Within-household changes in relative status have insignificant effect on plasma donation.

Taking the estimated peer effects at face value, the network fixed effects estimation for the donation equation informs us that a 10% increase in the proportion of peers selling blood increases own probability of selling blood by approximately 4%. In other words, 1 additional average peer who sells blood increases own probability of selling blood by 2.5 percentage points. Over an average of about 18%, this is an increase of about 13%; The average peer group size is 17 and among these peers there is on average 3.1 who sale blood, so this is the effect of 32% increase in the share of peers who sale blood.

The community IV strategy with perfectly overlapping groups is widely adopted in previous literature on peer effect estimations. To compare results with the main estimation strategy in this paper, the conventional method is applied in Table 4.8. Estimation results without any instrument variable are presented in Panel A of Table 4.8. Both relative status measures and peer effects significantly affect plasma donation: whether to donate, how much to donate (RMB) and how many family members join this income generating activity. Peer effects and status seeking seem to matter in both R1 and R3 estimations, their marginal effects on having any household member donate plasma are much larger than having a second member donate. This result is consistent with the fact that the number of families with more than one plasma donor increases little compared to the number of families with only one plasma donor (Table 4.4), which reflects their reluctance in engaging in plasma donation activity for the whole family.

In the Panel B of Table 4.8, estimations adopting the conventional IV strategy are presented. 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 natural 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 and intensity of donation. The marginal effects demonstrate similar pattern as they are without IV. Compared to spatial instrument estimations, the marginal peer effects are much larger. Our results suggest that the conventional method based on perfectly overlapping peer groups might be overoptimistic about the magnitude of peer effects. Meanwhile, status seeking significantly determines plasma donation, which is not affected by whether peers' donation behavior is instrumented or not. However, the marginal status seeking effect is smaller.

While household-specific status concern is found, the community-specific inequality measure, i.e., the Gini coefficient, shows insignificant effect (Table 4.9). Though both ranges from 0 to 1, the variation that captures household status seeking is much larger than it is at the community level, suggesting that the household-specific measures might better capture risk-taking behavior due to status dispersion. Moreover, compared to whether donate plasma, household decisions on the number of members donating are less subject to the effect of relative status.

More household-specific status measures, including the rank & gini interaction, the Wildman status measure and percentile rank, are adopted in Table 4.10 to check robustness. Consistent with the Deaton measure, nearly all of these measures confirm that households in the lower social hierarchy are exposed to greater pressure to engage in plasma donation.

Additional robustness checks are presented in Table 4.11. First, 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. Secondly, I construct placebo peer groups via randomly assigned groups. Specifically, I randomly select five alternative households to construct a reference group for each household. Peer effects disappear, suggesting that gift networks capture the domain of social interactions. Finally, 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 significant. All the above checks indicate that the reference group definition and peer effects identification are robust.

4.5.2 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 4.12 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 4.13).

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.

4.5.3 Some Evidence on Negative Health Outcomes

Mixing several bloods in the same centrifuge among several donors in obtaining plasma, the excessive cost reduction motive for blood banks in rural China has been widely documented as a

root cause of blood contamination and the resulting high prevalence of Hepatitis C and HIV infection among commercial donors (Wu et al., 2001; Cohen, 2004). Meanwhile, blood banks in the surveyed region were shut down due to an outbreak of epidemic of infectious diseases. Therefore, positive causal relationship can be established between blood plasma donation and the potential risk of disease infection, which may further lead to negative (and even deadly) health impacts. In the field, I observed several tragic cases in which people died after frequent blood donation and were infected with deadly diseases.

Though information on Hepatitis and HIV infection is too sensitive to collect, in the second and the third waves of survey self-rated health status was collected at the individual level. Comparing current donors (in 2009) with non-donors among all who did not engage in blood donation (in 2006), it is found that the formal group has a lower absolute self-rating, a lower self-rating relative to peers in their age group, and a more serious deterioration in both health status over time. Regressing changes in individual level self-rated health status on changes in plasma donation decisions between 2006 and 2009, plasma donation is associated with significantly lower absolute self-rating and lower relative self-rating.

Blood donation may engender devastating impact on health and agricultural production. In the second wave, information on physical strength and farming was collected from 527 households before the local government intervened in and stopped us from collecting more information. Among them, 75 households engaged in blood plasma donation. 64.0% of donors become weak in strength and are easily infected with diseases. 67.6% of donors clearly feel lack of strength and experience physical discomfort in the busy season.

Information on risk awareness associated with blood donation was also collected from the same sample. Working in factories in the coastal region is vulnerable to work accidents.

However, among migrant workers 61.9% believe that blood donation is more risky than industrial injury. Even for households with disabled migrant workers due to work accidents, 19 out of 32 cases still believe that blood donation is more risky. Due to the sensitivity of the issue, only a limited number of blood donors were asked whether they had any health check before donation, 6 out of 15 donors answered no. Sharing insanitary centrifuge machine in collecting plasma, the cross infection will be very serious if any donor carries infectious diseases.

4.6 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. The census nature of the household survey further aids me in measuring relative socioeconomic status along the income spectrum and therefore distinguishes status seeking from status-neutral peer influences.

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 matters 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.

Status seeking plays an important role in shaping risk-taking behavior. The poor are generally faced with greater pressure to raise social status, thus creating incentives to frequently donate plasma. The finding calls for redistributive policies to reduce stigmatized behavior. 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.

The finding that status seeking not captured by the community-specific inequality measures warns us that well-accepted inequality measures, such as the Gini coefficient, may obscure heterogeneous individual incentives along the distribution and fail to deliver accurate policy implications. Consistent with my empirical findings, the theoretical derivation of the Hypothesis 2 shows sufficient but demanding conditions, which may not be satisfied in the actual social hierarchy. This finding also alerts us that stigmatized behavior tends to cluster in unequal communities, especially towards the group of the lowest social rankings. An appropriate intervention should be explicitly targeting the lower tail of unequal communities.

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

Appendix I: Proof of Propositions

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 ($h\to 1$), 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

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

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

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.

Proof of Proposition 1

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

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

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

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

(A9)

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

Proof of Proposition 2

To investigate how dispersion of income and social status affect plasma donation decision, let $F(\theta_i, \xi')$ be a mean-preserving spread of $F(\theta_i, \xi)$. The average intensity to donate plasma is

$$\begin{aligned} \overline{h} &= \int_{\theta_{\min}}^{\theta_{\max}} h(\theta, \overline{h}, w) dF(\theta, \xi) \\ &= F(\underline{\theta}(\overline{h}, w), \xi) + \int_{\underline{\theta}(\overline{h}, w)}^{\overline{\theta}(\overline{h}, w)} h(\theta, \overline{h}, w) dF(\theta, \xi) \end{aligned} \quad \text{(A10)}$$

where $h(\theta, \overline{h}, w) = 1$ if $\theta \in [\theta_{\min}, \underline{\theta}]$ and $h(\theta, \overline{h}, w) = 0$ if $\theta \in [\overline{\theta}, \theta_{\max}]$. Differentiating (A10) with respect to ξ and rearranging, we have

$$\frac{\partial \bar{h}}{\partial \xi} = -\frac{\int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \theta} \frac{\partial F(\theta, \xi)}{\partial \xi} d\theta}{1 - \int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} dF(\theta, \xi)} \qquad \text{(A11)}$$

Since $1 > \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} > 0 \ \ \forall \theta$, and $\int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} dF(\theta, \xi) < \int_{\theta_{\min}}^{\theta_{\max}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} dF(\theta, \xi) < 1$ holds in a stable equilibrium. Therefore, the denominator of (A11) is positive, and we have

$$sign(\frac{\partial \bar{h}}{\partial \xi}) = sign[-\int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \theta} \frac{\partial F(\theta, \xi)}{\partial \xi} d\theta] \qquad \text{(A12)}$$

where $\partial h(\theta, \bar{h}, w) / \partial \theta < 0$. Therefore, whether average plasma donation intensifies is determined by the direction of changes in plasma donation from households in the range of $\theta \in [\underline{\theta}, \bar{\theta}]$. The latter is indeterminate, due to the fact that the sign of $\partial F(\theta, \xi) / \partial \xi$ depends on θ and may vary over $[\underline{\theta}, \bar{\theta}]$. However, a sufficient condition ensures an increase in the overall plasma donation intensity when income distribution becomes more unequal (as the result of mean-preserving spread). Specifically, if $\partial F(\theta, \xi) / \partial \xi > 0 \ \ \forall \theta \in [\underline{\theta}, \bar{\theta}]$, plasma donation intensifies.

A Specific Example: To further illustrate the sufficient condition, it is specified that households' income $\theta_i w$ in the community is subject to a uniform distribution $\theta_i \in [m - \xi, m + \xi]$, where m is the average level of labor quality and ξ is a mean-preserving spread parameter. The probability distribution function and cumulative distribution function take the following form:

$$f(\theta, \xi) = 1 / 2\xi \qquad F(\theta, \xi) = [\theta - (m - \xi)] / 2\xi$$

The average intensity of plasma donation is

$$\bar{h} = \frac{1}{2\xi} \{[\underline{\theta}(\bar{h}(\xi), w) - (m - \xi)] + \int_{\underline{\theta}(\bar{h}(\xi), w)}^{\bar{\theta}(\bar{h}(\xi), w)} h(\theta, \bar{h}, w) d\theta\} \qquad \text{(A13)}$$

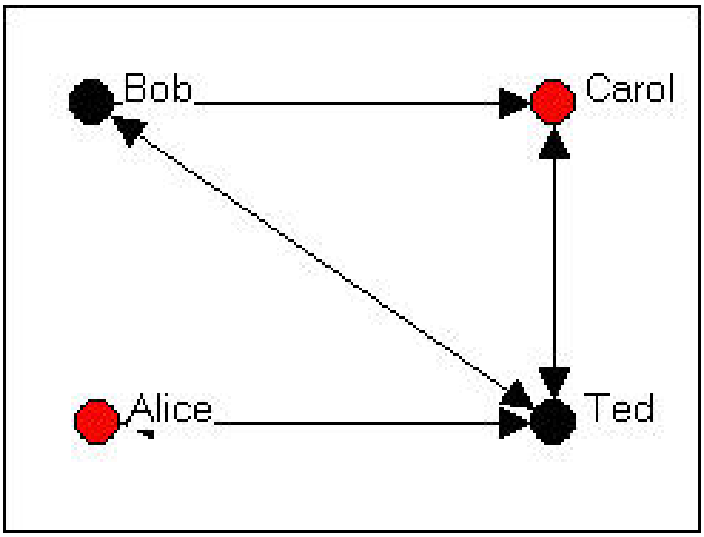
Differentiating $\bar{h}$ with respect to ξ, we have

$$\frac{\partial \bar{h}}{\partial \xi} = -\frac{\frac{1}{2\xi^2}[\int_{\underline{\theta}}^{\bar{\theta}} h(\theta, \bar{h}, w) d\theta + \underline{\theta} - m]}{1 - \frac{1}{2\xi} \int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} d\theta} = -\frac{\frac{1}{\xi}(\bar{h} - \frac{1}{2})}{1 - \frac{1}{2\xi} \int_{\underline{\theta}}^{\bar{\theta}} \frac{\partial h(\theta, \bar{h}, w)}{\partial \bar{h}} d\theta} \qquad \text{(A14)}$$

where the denominator is positive, $\partial \bar{h} / \partial \xi > 0$ if $\bar{h} < 1/2$. Therefore, in the case of uniform income distribution with second-order stochastically dominating shifts, the average plasma

donation intensifies if $\overline{h} < 1/2$. In Table 4.4, it is easily seen that the participation rate of plasma donation in each village satisfies this condition.

Appendix II: 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 III: Bonacich centrality

Bonacich centrality is mainly based on the adjacency matrix G of network g, in which an entry in a square corresponding to a pair {i, j} denotes whether there exists a link from i to j. Specifically, 1 (0) denotes there is (no) direct connection between a pair of agents. It should be noted that adjacency matrix is asymmetric, i.e., a link from i to j does not necessarily mean a link from j to i. In adjacency matrix G, entries in the main diagonal are set to be 0. G^k denotes the k-th power of the matrix, where $G^0 = I$. In G^k, an entry g_{ij}^k measures the amount of walks of length k that exist between players i and j in network g.

Define a matrix $M(g,\alpha\sigma)$, which is well-defined when $\alpha\sigma$ is sufficiently small. Its entry $m_{ij}(g,\alpha\sigma) = \sum_{k=0}^{\infty}(\alpha\sigma)^k g_{ij}^k$ measures the total amount of walks in g from i to j where walks of length k are weighted by $(\alpha\sigma)^k$.

$$M(g,\alpha\sigma) = [I - \alpha\sigma G]^{-1} = \sum_{k=0}^{\infty}(\alpha\sigma)^k G^k \quad (A15)$$

Given the parameter $\alpha\sigma$, Bonacich centrality vector is defined as $C_b(g,\alpha\sigma) = [I - \alpha\sigma G]^{-1} J$, where Bonacich centrality of node i $C_b(i;g,\alpha\sigma) = \sum_{j=1}^{n} m_{ij}(g,\alpha\sigma)$. I is a n*n identity matrix, and J is a n*1 column vector of ones.

It is straightforward to observe that Bonacich centrality is no smaller than 1.

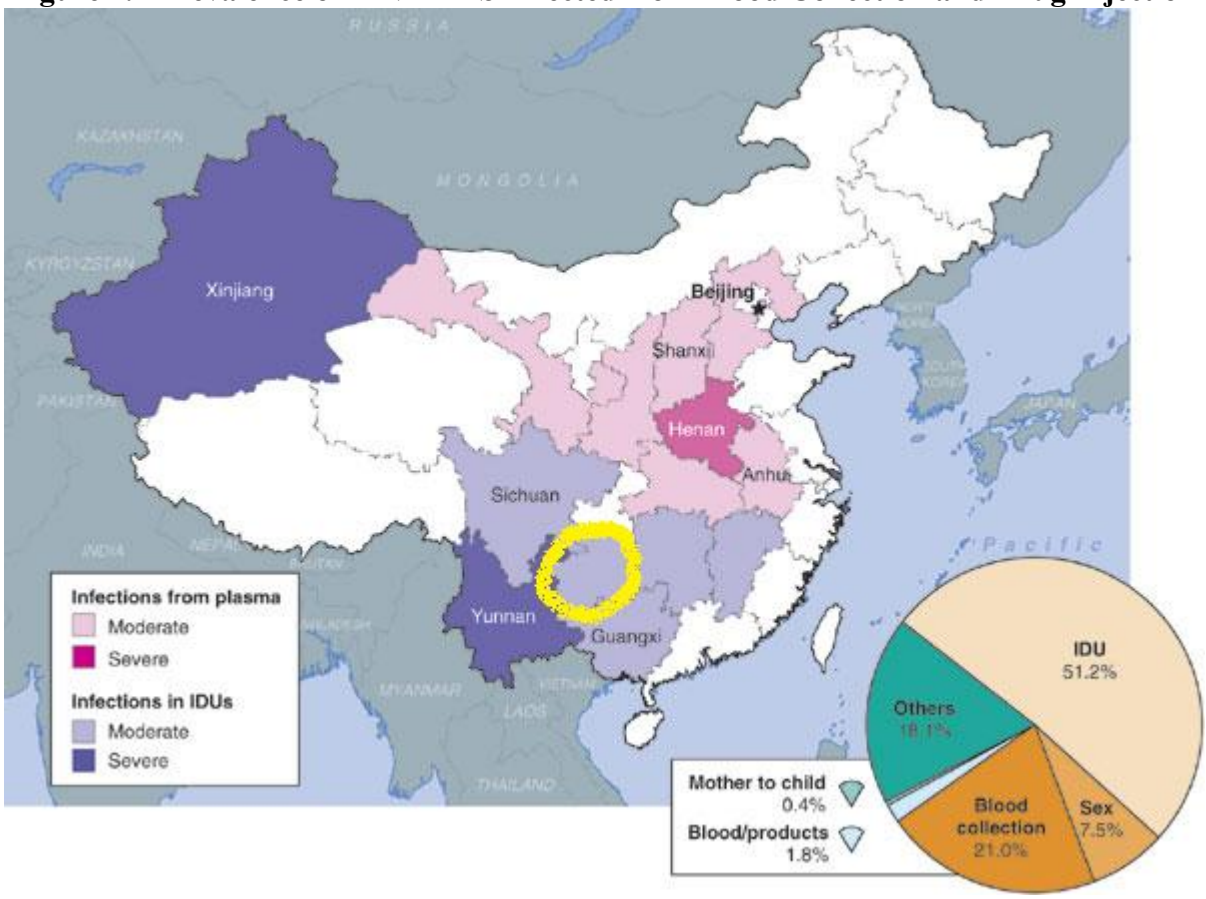
$$C_b(i;g,\alpha\sigma) = m_{ii}(g,\alpha\sigma) + \sum_{j\neq i}^{n} m_{ij}(g,\alpha\sigma) = \begin{cases} >1 \ if \ \alpha\sigma > 0 \\ =1 \ if \ \alpha\sigma = 0 \end{cases} \quad (A16)$$

In my analysis, Bonacich centrality with positive attenuation factors generated by the UCINET software are adopted in one of the weighting scenarios, and I accept the idea that being connected to neighbors with more connections makes one more powerful.

Bonacich centrality demonstrates major advantages over other centrality measures. While other measures exclude the case that actions of an agent influence neighbors which in turn feedback on the initiator, Bonacich centrality takes it into consideration; second, some other measures solely depend on the length of the shortest paths between nodes in a network. However, it is possible that ties are not perfectly reliable and other paths of different lengths may take effects. Fortunately, both direct and indirect influences in a network are captured by

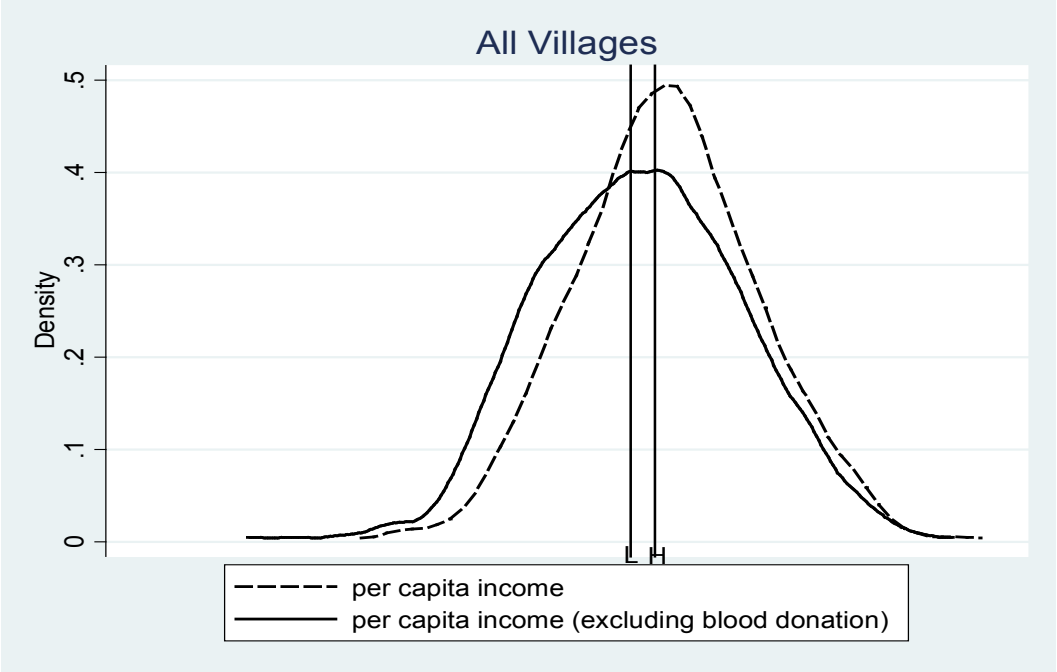
Bonacich centrality; meanwhile, one node might be centrally tied to a large number of others, but those others might be disconnected from the network as a whole. Bonacich centrality takes peers' centrality into account; moreover, all other centrality measures except Bonacich centrality are parameter-free (Calvó-Armengol et al., 2009); finally, Bonacich centrality has behavioral foundation derived from Nash equilibrium of a non-cooperative game, while other centrality measures are mainly geometric in nature (Ballester et al., 2006). Jackson (2008) derives Bonacich centrality using the framework of a linear interaction of behaviors among peers where individual behavior is a weighted average of peers' behavior.

Figure 4.1 Prevalence of HIV-AIDS Infected from Blood Collection and Drug Injection



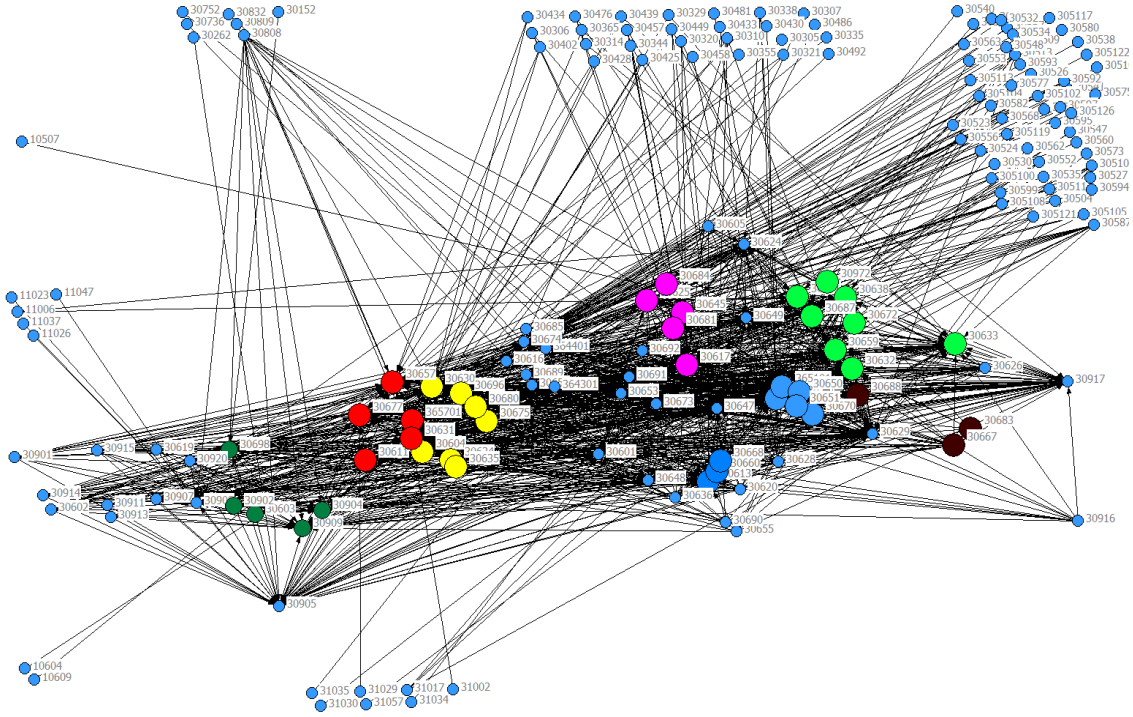
Source: Cohen (2004).
Notes:
[1] This figure describes the situation of HIV infection up to 2004. Outbreaks of HIV infection in China have been mainly caused by drug injection (IDUs) and plasma collection, which altogether have accounted for more than two thirds of China's HIV infection, and 250,000 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 4.2 Distribution of Per Capita Income Including / Excluding Plasma Donation



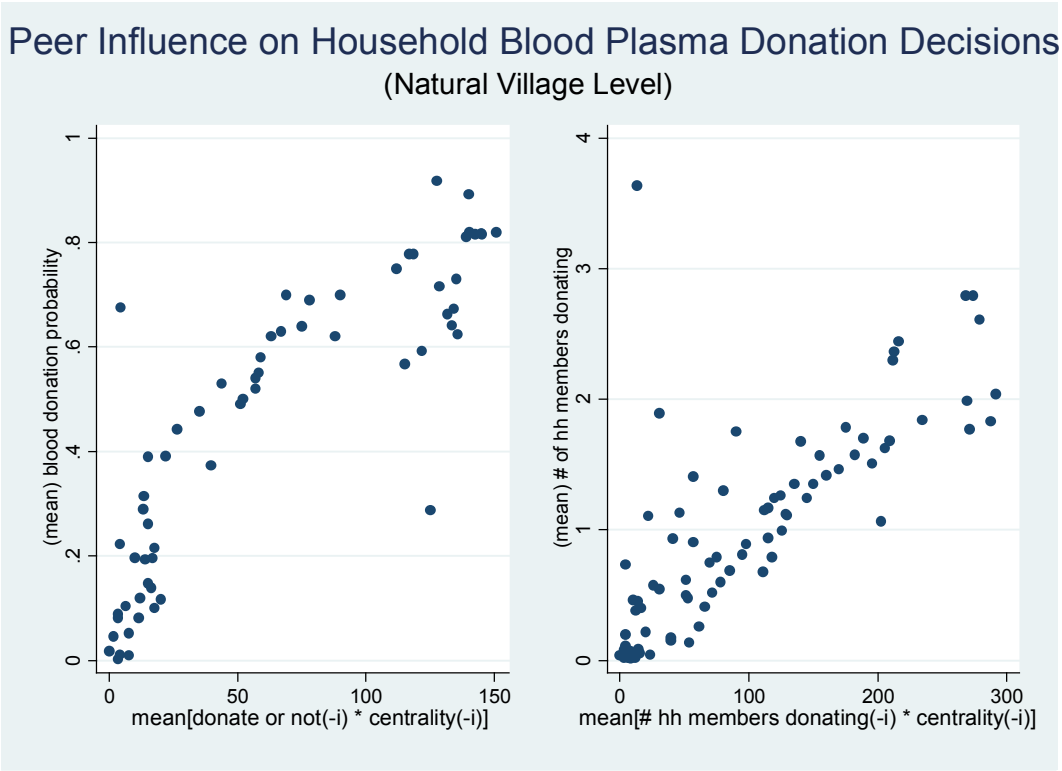
Source: Authors' 2004 survey data
Note: Two vertical lines, "L" and "H", refer to the low (668RMB) and high (892RMB) official poverty lines stipulated by the Chinese government.

Figure 4.3 Long-term Gift Exchange Network in One Village



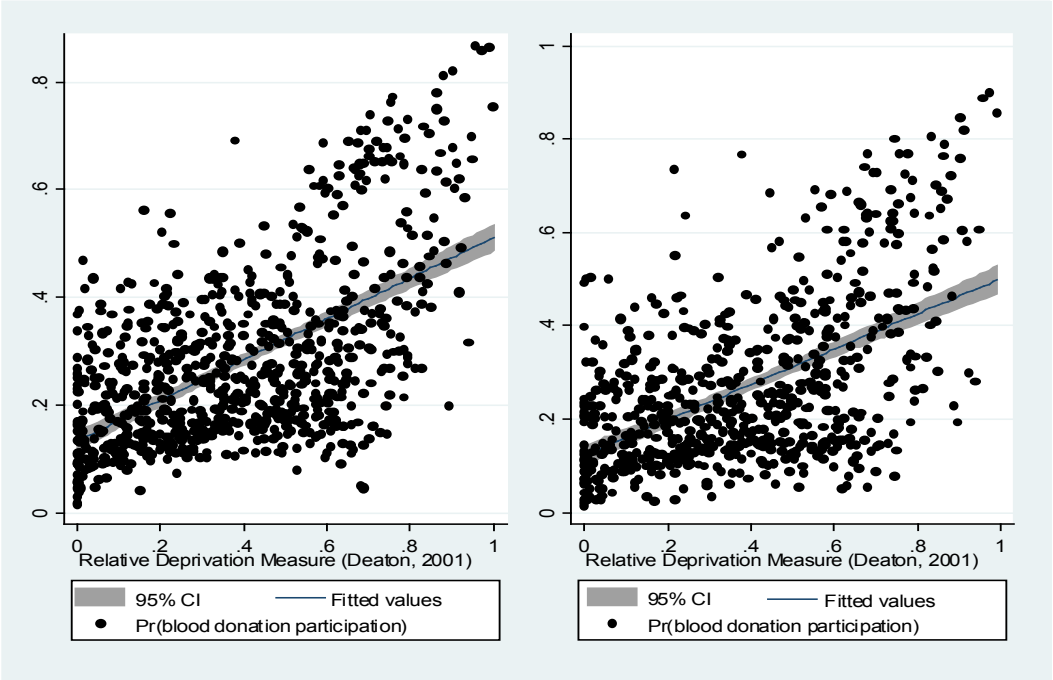
Source: Authors' gift network data from one of the eighteen villages.
Note: Dots of the same color show households in the same clan. Dots to the boundaries show households from other villages. The dots (households) are based on actual geographic locations.

Figure 4.4 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 natural village level. The vertical axis takes the mean of own plasma donation decisions at the natural village level. Each dot represents one natural village.

Figure 4.5 Relative Deprivation and Predicted Rate of Plasma Donation Participation



Source: Authors' survey data

Notes: The left figure and right figure respectively show the relationship between one's own predicted probability of plasma donation and relative status (1=lowest status; 0=highest status) using main estimation equation (15) with (right figure) and without (left figure) adding control variables.

Table 4.1 Summary Statistics by Three Administrative Villages (2004)

	Village 1	Village 2	Village 3	Total
Number of natural villages	9	5	4	18
Distance to county seat (km)	10	8	2.5	6.8
Number of households	257	151	393	801
Total population	1089	535	1449	3073
Share of minority households (%)	76.6	12.6	6.7	30.8
Share of household members aged 60 and above (%)	14.2	17.9	12.5	14.1
Share of households with migrants (%)	30.7	55	43.3	41.4
Share of household members who migrate (%)	12.3	13.5	12	12.4
Male head of household (%)	93.5	94.8	91.6	92.8
Education of household head (years)	2.87	3.06	3.98	4.44
Household average year of schooling	2.19	2.67	3.67	2.97
Per capita cultivated land (mu)	0.87	0.86	1.1	0.98
Percentage of flat land (%)	40	20.7	80	53.4
Land rental rate (Yuan per mu)	30	50	100	60
Share of households with TV (%)	39.3	39.7	61.6	50.3
Share of households with bicycles or motorcycles (%)	2.3	3.3	19.3	10.9
Share of households with phones (%)	8.9	15.2	23.4	17.2
Having difficulty with access to drinking water	79.4	80.1	39.2	59.9
Share of households with local non-farm jobs (%)	49.5	43.7	66.5	56.6
Share of households with self-employment (%)	7.4	3.3	7.4	6.6

Source: Authors' survey data

Table 4.2 Income and Consumption by Three Administrative Villages (2004-2009)

	Admin Village 1			Admin Village 2			Admin Village 3			Total		
	2004	2006	2009	2004	2006	2009	2004	2006	2009	2004	2006	2009
Main Sources of Income (Percent)												
Farming	26.3	26.7	23.7	31.0	37.4	29.5	37.0	31.5	26.1	33.3	31.4	33.1
Livestock	12.3	13.3	13.1	9.1	10.9	10.8	6.0	3.4	2.1	8.1	6.8	6.9
Local non-farm and self-employment	18.2	13.8	13.1	6.4	16.7	13.9	32.3	39.9	35.0	24.0	30.0	23.8
Remittance from migrants outside the county	7.8	22.4	11.6	10.9	10.2	9.4	7.3	10.7	6.6	8.0	13.1	8.8
Disaster relief, anti-poverty programs, deforestation subsidies	5.1	2.9	6.1	2.5	6.9	5.8	1.9	0.5	4.8	2.8	2.0	5.4
Gift income	3.2	4.5	4.7	11.7	11.6	8.4	4.9	11.1	10.7	5.6	9.1	8.2
Plasma donation income	13	4.6	7.2	15.7	1.7	4.7	7.6	0.7	1.6	10.9	2.2	4.1
Main Expenditures (Percent)												
Food	53.8	51.1	48.1	47.1	42.9	36.5	45.4	38.5	34.3	47.8	42.2	35.5
Clothing	4.4	4.4	4.6	3.1	3.7	4.1	4.0	4.9	4.1	4.0	4.6	4.2
Fuel	5.9	6.4	6.7	5.4	6.9	7.3	10.2	9.5	8.0	8.4	8.3	7.5
Telephone	1.1	2.1	5.3	1.3	2.4	3.8	1.5	3.5	6.4	1.4	3.0	5.5
Medical care	14.1	16.7	15.1	24.7	16.8	16.9	15.2	15.2	11.2	16.4	15.8	13.5
Education	9.0	10.0	9.6	7.9	12.2	14.0	8.8	12.3	14.1	8.7	11.7	12.9
Gift and festival spending	6.4	9.2	10.1	6.8	13.9	16.1	8.9	15.9	17.5	7.9	13.9	15.2

Source: Authors' survey data; Times to send gifts was not in the 2004 wave, therefore denoted by "-".

Table 4.3 Poverty and Income Inequality by Three Administrative Villages (2004-2009)

	Admin Village 1			Admin Village 2			Admin Village 3			Total		
	2004	2006	2009	2004	2006	2009	2004	2006	2009	2004	2006	2009
Per capita annual income (RMB)	1009	1111	1262	1274	1638	1655	1749	2420	2442	1404	1817	2855
Income inequality (Gini)	42.4	45.3	46.5	42.3	52.0	61.8	40.2	42.8	50.9	43.1	48.2	55.2
Income inequality excluding plasma donation (Gini)	46.6	46.9	47.4	44.7	52.5	63.5	42.4	43.0	51.4	46.3	49.0	56.6
(Mean) Deaton relative deprivation index	0.441	0.432	0.444	0.409	0.484	0.584	0.418	0.406	0.500	0.423	0.432	0.495
Income below poverty line of 892 RMB (%) (P0)	54.1	52.5	30.7	41.1	44.1	33.3	23.4	21.1	13.1	37.3	36.3	22.4
poverty-gap below poverty line of 892 RMB (P1)	22.4	23.3	13.0	15.8	17.9	16.1	8.1	7.5	6.1	14.5	15.0	10.1
squared poverty-gap below poverty line of 892 RMB (P2)	12.2	13.6	7.8	7.7	9.6	10.5	3.9	3.7	4.2	7.5	8.3	6.4

Source: Authors' survey data.

Table 4.4 Blood Plasma Donation by Three Villages (2004-2009)

	Admin Village 1			Admin Village 2			Admin Village 3			Total		
	2004	2006	2009	2004	2006	2009	2004	2006	2009	2004	2006	2009
Participation rate in donating plasma (%)	46.4	16.9	23.9	31.1	7.6	10.2	21.0	6.1	8.5	31.2	10.1	14.1
Mean per capita plasma donation (RMB)	197	56.6	178.0	235.5	22.4	93.7	113.4	11	33.0	163.2	28.6	93.8
Cash compensation (nutrition subsidy) for plasma donation (580cc)	80	80	150	80	80	150	80	80	150	80	80	150
# households without plasma donor	140	236	229	104	146	132	308	367	387	552	749	749
# households with one plasma donor	110	34	50	44	9	12	81	23	35	235	66	97
# households with two or more plasma donors	11	14	22	3	3	3	1	1	1	15	18	26
Proportion of women among plasma donors (%)	-	-	90.0	-	-	38.5	-	-	88.9	-	-	80.3

Source: Authors' survey data

Table 4.5a Spatial Instruments Identification on Peer Effect and Status Seeking
(Network Sub-sample, Ego Random Effect Estimation, No Weighting, 2004-2009)

	Without spatial instruments			With spatial instruments		
	Donate or not (Linear Prob)	Donation Value (log) (OLS)	# hh members Donate (Oprobit)	Donate or not (Linear Prob)	Donation Value (log) (2SLS)	# hh members Donate (iv+Oprobit)
Endogenous Effect						
Mean plasma donation rate (peers)	0.394***			0.176**		
	(0.035)			(0.070)		
Mean Plasma donation Value (peers) (log)		0.097***			0.116*	
		(0.040)			(0.064)	
Mean # of hh members donate (peers)			0.038***			0.024***
			(0.005)			(0.009)
Own Characteristics						
Per capita income	0.005	-0.014	-0.005	0.004	-0.027	-0.005
	(0.007)	(0.026)	(0.005)	(0.006)	(0.047)	(0.005)
Edu	-0.003	-0.019	-0.003	0.000	-0.019	-0.003
	(0.005)	(0.031)	(0.004)	(0.005)	(0.068)	(0.004)
Share of elderly	-0.286***	-0.867**	-0.226***	-0.378***	-0.123	-0.224***
	(0.089)	(0.408)	(0.089)	(0.110)	(0.669)	(0.076)
Share of unmarried son	0.215***	1.210***	0.154**	0.205***	1.276***	0.155***
	(0.073)	(0.450)	(0.067)	(0.068)	(0.447)	(0.052)
Deaton RD	0.167**	0.294	0.160**	0.150**	0.459	0.027***
	(0.079)	(0.450)	(0.081)	(0.060)	(0.373)	(0.007)
Ratio of farm wage to plasma compensation	-0.377**	-0.565	-0.257*	-0.313*	-0.849	-0.255*
	(0.184)	(1.111)	(0.149)	(0.174)	(1.507)	(0.150)
Travel time to blood bank	-0.001*	-0.002*	-0.000	-0.001*	-0.002	-0.000
	(0.001)	(0.003)	(0.000)	(0.001)	(0.004)	(0.000)
Shocks	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous Effect (or Contextual Effect)						
Mean Per capita income (peers)	0.001	-0.127*	-0.000	-0.001	-0.030	-0.000
	(0.009)	(0.067)	(0.007)	(0.009)	(0.073)	(0.006)
Mean Edu (peers)	-0.014	-0.095	-0.011	0.007	0.193*	-0.010
	(0.012)	(0.077)	(0.009)	(0.013)	(0.115)	(0.011)
Mean Share of elderly (peers)	0.181	0.348	0.122	0.395*	1.099	0.121
	(0.218)	(1.455)	(0.150)	(0.224)	(1.557)	(0.165)
Mean share of unmarried son (peers)	0.083	0.667	0.030	0.100	-0.586	0.026
	(0.136)	(0.804)	(0.096)	(0.129)	(1.294)	(0.058)
Mean deaton_rd (peers)	-0.132	-0.910	-0.144	-0.221	0.720	-0.150
	(0.137)	(0.898)	(0.101)	(0.135)	(1.142)	(0.091)
Mean Ratio of farm wage to plasma (peers)	-0.524**	-1.429	-0.344*	-0.757***	-0.409	-0.369**
	(0.249)	(1.536)	(0.201)	(0.268)	(1.679)	(0.185)
Mean Travel time to blood bank (peers)	-0.001	-0.004	-0.001	-0.001	-0.027	-0.001
	(0.003)	(0.018)	(0.002)	(0.003)	(0.034)	(0.002)

Shocks	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Instruments (Exogenous Characteristics of Excluded Peers)						
Mean Per capita income				0.226	-2.286*	-0.072
				(0.319)	(1.396)	(0.341)
Mean Edu				-0.950***	-5.504***	-0.811***
				(0.224)	(0.984)	(0.240)
Mean Share of elderly				-8.061*	-75.190***	-14.068***
				(4.712)	(20.971)	(5.111)
Mean share of unmarried son				-11.394***	-35.630*	-9.252*
				(4.416)	(20.670)	(4.965)
Mean deaton_rd				4.519***	30.808***	5.332***
				(1.277)	(5.456)	(1.372)
Mean cadre status				8.441***	12.624	9.439***
				(2.345)	(10.362)	(2.534)
Mean Ratio of farm wage to plasma income				8.807***	91.060***	9.671***
				(2.367)	(10.695)	(2.567)
Mean Travel time to blood bank				-0.007	0.039	-0.005
				(0.009)	(0.038)	(0.009)
F test excluded instruments	-	-	-	13.49	31.21	14.41
p-val over-identication test	-	-	-	0.153	0.617	0.219
(Pseudo) R2	0.361	0.242	0.270	0.332	0.314	0.327
N	486	486	486	464	464	464

Notes:

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

[2] Marginal effects are presented. Most households have no more than 2 members donating plasma. Therefore, the marginal effect for ordered probit estimation compares 2 household members donating plasma with less than 2 members donating.

[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, education, share of the elderly, share of unmarried son, relative wage, cadre status, relative economic status, travel time to the local blood bank.

[4] Shocks include funerals, big diseases, livestock deaths and natural disasters.

Table 4.5b Spatial Instruments Identification on Peer Effect and Status Seeking
(Network Sub-sample, Ego Random Effect Estimation, Weighted by Gift Link intensity, 2004-2009)

	Without spatial instruments			With spatial instruments		
	Donate or not (Linear Prob)	Donation Value (log) (OLS)	# hh members Donate (Oprobit)	Donate or not (Linear Prob)	Donation Value (log) (2SLS)	# hh members Donate (iv+Oprobit)
Endogenous Effect						
Mean plasma donation rate (peers)	0.413***			0.267***		
	(0.044)			(0.099)		
Mean plasma donation Value (peers) (log)		0.118***			0.143**	
		(0.044)			(0.072)	
Mean # of hh members donate (peers)			0.047***			0.034**
			(0.008)			(0.014)
Own Characteristics						
Per capita income	0.010	-0.014	-0.005	0.004	-0.028	-0.003
	(0.009)	(0.026)	(0.005)	(0.006)	(0.047)	(0.003)
Edu	-0.004	-0.019	-0.003	-0.000	0.022	-0.004
	(0.005)	(0.032)	(0.004)	(0.006)	(0.069)	(0.003)
Share of elderly	-0.291***	-0.884***	-0.230***	-0.385***	-0.120	-0.261***
	(0.089)	(0.408)	(0.089)	(0.109)	(0.668)	(0.072)
Share of unmarried son	0.213***	1.208***	0.153***	0.203***	0.386	0.138***
	(0.072)	(0.450)	(0.066)	(0.068)	(0.593)	(0.054)
Deaton RD	0.147**	0.298	0.037**	0.148**	0.467	0.036***
	(0.063)	(0.449)	(0.015)	(0.061)	(0.373)	(0.009)
Ratio of farm wage to plasma compensation	-0.405**	-0.612	-0.280*	-0.349**	-0.783	-0.220*
	(0.185)	(1.111)	(0.153)	(0.172)	(1.507)	(0.120)
Travel time to blood bank	-0.001	-0.002	-0.000	-0.001	-0.001	-0.000
	(0.001)	(0.003)	(0.000)	(0.001)	(0.004)	(0.000)
Shocks	Yes	Yes	Yes	Yes	Yes	Yes
Exogenous Effect (or Contextual Effect)						
Mean Per capita income (peers)	0.001	-0.128	-0.001	-0.001	-0.026	-0.002
	(0.010)	(0.067)	(0.007)	(0.009)	(0.072)	(0.008)
Mean Edu (peers)	-0.015	-0.094*	-0.012	0.006	-0.182	-0.013
	(0.012)	(0.077)	(0.009)	(0.013)	(0.116)	(0.010)
Mean Share of elderly (peers)	0.177	-0.370	0.121	0.385*	0.931	-0.029
	(0.216)	(1.456)	(0.151)	(0.222)	(1.573)	(0.159)
Mean Share of unmarried son (peers)	0.077	0.643	0.033	0.087	0.578	0.089
	(0.136)	(0.805)	(0.096)	(0.129)	(1.292)	(0.092)
Mean deaton_rd (peers)	-0.149	-0.921	-0.153	-0.231*	0.685	-0.098
	(0.141)	(0.898)	(0.102)	(0.133)	(1.142)	(0.093)
Mean Ratio of farm wage to plasma (peers)	-0.532**	-1.466	-0.344*	-0.783***	0.306	-0.461***
	(0.249)	(1.538)	(0.202)	(0.265)	(1.682)	(0.140)
Mean Travel time to	-0.001	-0.013	0.000	-0.001	-0.029	0.000

Blood bank (peers)	(0.003)	(0.018)	(0.002)	(0.003)	(0.034)	(0.002)
Shocks	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
F test excluded instruments	-	-	-	17.13	25.50	28.10
p-val over-identication test	-	-	-	0.652	0.625	0.475
(Pseudo) R2	0.311	0.246	0.229	0.318	0.317	0.280
N	486	486	486	464	464	464

Notes: follow Table 4.5a.

Table 4.6 Spatial Instruments Identification based on Centrality Weighting
(Network Sub-sample, Ego Random Effect Estimation, 2004-2009)

	R1 Donate or Not	R2 Donation Value	R3 # hh Members Donate
Mean prior plasma donation decision	0.037***	0.097*	0.005***
	(0.009)	(0.058)	(0.001)
Deaton RD	0.135**	0.409	0.032***
	(0.060)	(0.376)	(0.011)
N	464	464	464
(Pseudo) R2	0.247	0.309	0.304

Notes: [1] For each household, its Peers' plasma donation decisions are weighted by corresponding centrality. Mean prior plasma donation decision is calculated via taking mean over peers' weighted plasma donation decisions.
[2] Centrality is a sociology concept that measures the activeness of a node in a network. Appendix III presents a detailed discussion of the Bonacich centrality measure used in this paper.
[3] The centrality measure is unbounded. Therefore, the coefficients are incomparable to previous results in Table 4.5 and Table 4.6.
[4] Other notes follow Table 4.5a.

Table 4.7 Network and Ego Fixed Effect Estimations on Peer Effect and Status Seeking
(Network Sub-sample, 2004-2009)

	R1	R2	R3	R4	R5	R6
	Network Fixed Effect			*Household Fixed Effect*		
	Donate or Not	Donation Value	# hh Members Donate	Donate or Not	Donation Value	# hh Members Donate
Mean prior plasma donation decision	0.431***	0.525*	0.008**	0.204**	0.015	0.164*
	(0.163)	(0.296)	(0.004)	(0.081)	(0.086)	(0.089)
Deaton RD	0.202***	0.506	0.009***	0.039	-0.568	0.071
	(0.058)	(0.561)	(0.002)	(0.076)	(0.547)	(0.090)
N	464	464	464	464	464	464
(Pseudo) R2	0.146	0.065	0.402	0.294	0.113	0.244

Notes: The fixed effect panel model is estimated at the network (peers and excluded peers) level and household level. Other notes follow Table 4.5a.

Table 4.8 Conventional IV Identification on Peer Effect and Status Seeking
(Full Sample, Household Random Effect Estimation, 2004-2009)

	R1	R2	R3
	Donate or Not (Linear Prob)	Donation value (log) (2SLS)	# hh members donate (Ordered Probit)
	Panel A: Without IV Strategy		
Mean prior plasma donation decision	0.425***	0.177***	0.046***
	(0.064)	(0.028)	(0.011)
Deaton RD	0.079***	0.375**	0.011***
	(0.030)	(0.157)	(0.004)
N	1507	1507	1507
(Pseudo) R2	0.203	0.191	0.229
	Panel B: With IV Strategy		
Mean prior plasma donation decision	0.947***	0.267***	0.106***
	(0.325)	(0.061)	(0.014)
Deaton RD	0.066*	0.381**	0.013***
	(0.037)	(0.158)	(0.004)
Excluded Instruments			
Lagged travel time to local blood bank	-0.002***	-0.025***	-0.001***
	(0.000)	(0.001)	(0.000)
Lagged average income in the community	-0.002	-0.182***	-0.003
	(0.003)	(0.047)	(0.004)
Lagged access to tap water	-0.097***	-2.751***	-0.144***
	(0.011)	(0.123)	(0.014)
Lagged travel time to nearest clinics	-0.016***	-0.987***	-0.024***
	(0.006)	(0.051)	(0.007)
N	1507	1507	1507
(Pseudo) R2	0.464	0.414	0.229
F test - excluded instruments	17.80	53.01	16.96
Over-identification test (p-value)	0.167	0.908	0.109

Notes: [1] Marginal effects are presented. Most households have no more than 2 members donating plasma. Therefore, the marginal effect for ordered probit estimation compares 2 household members donating plasma with less than 2 members donating.
[2] The instrumental variables are lagged by 2-3 years. Specifically, the 2009 values are lagged to 2006 values, while the 2006 values are lagged to 2004 values.

Table 4.9 Comparing Household-specific Relative Status and Community Inequality

	R1-Gini	R2-Deaton	R3-Gini	R4-Deaton	R5-Gini	R6-Deaton
	Panel A: Spatial Instruments Identification					
	Donate or not (Linear Prob)		Donation value (log) (2SLS)		# hh members donate (ordered probit)	
Mean prior plasma donation decision	0.143*	0.176**	0.113**	0.116*	0.036***	0.024***
	(0.082)	(0.070)	(0.065)	(0.064)	(0.013)	(0.009)
Relative status (Gini *or* Deaton)	0.292	0.150**	3.683	0.459	0.077	0.027***
	(0.384)	(0.060)	(2.236)	(0.373)	(0.047)	(0.007)
N	464	464	464	464	464	464
Pseudo R2	0.295	0.332	0.308	0.314	0.303	0.327
	Panel B: Conventional Instrument Variables Identification					
Mean prior plasma donation decision	1.085***	0.947***	0.247***	0.267***	0.109***	0.106***
	(0.269)	(0.325)	(0.060)	(0.061)	(0.014)	(0.014)
Relative status (Gini *or* Deaton)	-0.423***	0.066*	-1.650***	0.381**	-0.030*	0.013***
	(0.131)	(0.037)	(0.623)	(0.158)	(0.018)	(0.004)
N	1507	1507	1507	1507	1507	1507
(Pseudo) R2	0.194	0.464	0.191	0.414	0.223	0.229

Notes:

[1] This Table aims to compare the impact of status seeking using the household-specific measure versus the community-specific measure. Due to the space limit here, results from more household-specific measures are presented in Table 4.10.

[2] Other notes follow Table 4.5a.

Table 4.10 Testing Alternative Relative Status Measures

	Donate or Not			Donation Value			# hh Members Donate		
	Rank*Gini / 1000	Wildman /1000	Rank /1000	Rank*Gini / 1000	Wildman /1000	Rank /1000	Rank*Gini / 1000	Wildman /1000	Rank /1000
Relative status (three measures)	0.133**	0.017**	0.085***	0.665**	0.036	0.423***	0.022***	0.003**	0.013***
	(0.059)	(0.008)	(0.028)	(0.299)	(0.042)	(0.144)	(0.008)	(0.002)	(0.004)
N	1507	1507	1507	1507	1507	1507	1507	1507	1507
(Pseudo) R2	0.197	0.191	0.199	0.188	0.186	0.191	0.227	0.224	0.229

Notes:

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

[2] Other notes follow Table 4.5a.

Table 4.11 More Robustness Checks on Peer Effects
(Network Sub-sample, RE Estimations, 2004-2009)

	R1	R2	R3
	Donate or Not	Donation Value	# hh Members Donate
1. Baseline	0.176**	0.116*	0.024***
	(0.070)	(0.064)	(0.009)
2. Drop geographic location from characteristics of excluded peers	0.204**	0.115*	0.013**
	(0.081)	(0.063)	(0.006)
3. Drop age profile from characteristics of excluded peers	0.159*	0.109*	0.008**
	(0.086)	(0.065)	(0.004)
4. Placebo peer groups	-0.023	0.071	0.017
	(0.072)	(0.067)	(0.013)
5. Drop gift links due to funerals	0.216**	0.131*	0.027*
	(0.087)	(0.074)	(0.014)

Notes:
[1] robust standard error in parentheses;*significant at 10%;**significant at 5%;***significant at 1%
[2] Other notes follow Table 4.5a.

Table 4.12 The Potential Mechanism: Testing Directional Peer Effects Hypothesis
(Network Sub-sample, Alter Fixed Effect Estimation, 2004-2009)

	R1 Donate or Not	R2 Donation Value	R3 # hh Members Donate
Mean prior plasma donation decision	0.157	-0.232	0.132
	(0.235)	(0.181)	(0.269)
N	336	336	336
Pseudo R2	0.285	0.248	0.247

Notes:
[1] 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.
[2] 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.
[3] Other notes follow Table 4.5a.

Table 4.13 The Potential Mechanism: Expectation Interactions or Preference Interactions?
(Network Sub-sample, After the Shutdown of Local Blood Bank (2006, 2009))

	R1 Donate or Not	R2 Donation Value	R3 # hh Members Donate
	Household Fixed Effect Estimations		
Mean prior plasma donation decision	0.517***	0.160	0.155*
	(0.166)	(0.135)	(0.090)
N	382	382	382
Pseudo R2	0.635	0.246	0.228

Notes:
[1] Only observations after the outbreak of Hepatitis C epidemic are included in the estimations.
[2] Other notes follow Table 4.5a.

Table 4.14a Summary Statistics on Self-rated Health Status (2006 and 2009)

	Mean	SD
Non-donor in both 2006 and 2009		
Change in absolute self-rating	0.139	1.077
Change in relative self-rating	0.268	1.097
Non-donor in 2006 but donor in 2009		
Change in absolute self-rating	1.848	1.093
Change in relative self-rating	1.914	0.951
Donor in 2006 but non-donor in 2009		
Change in absolute self-rating	0.250	0.957
Change in relative self-rating	0.200	0.632
Donor in both 2006 and 2009		
Change in absolute self-rating	1.612	0.997
Change in relative self-rating	1.605	0.933

Notes: Both absolute self-rating and relative self-rating of health status range from 1-5. 1 corresponds to the healthiest status, while 5 points to the least healthy status. Relative self-rating evaluates health status compared to peers of similar age.

Table 4.14b Association between Blood Donation and Individual Self-rated Health Status (2006 and 2009)

	R1	R2
	Change in absolute self-rating	*Change* in relative self-rating
Changes in Donation Decisions	1.401***	1.231***
	(0.193)	(0.171)
Control Variables	Yes	Yes
N	753	1058
(Pseudo) R2	0.063	0.045

Notes:

[1] *significant at 10%;**significant at 5%;***significant at 1%.

[2] Both absolute self-rating and relative self-rating of health status range from 1-5. 1 corresponds to the healthiest status, while 5 points to the least healthy status.

[3] Control variables involve changes in per capita income, major shocks, income inequality and demographic characteristics.

[4] The difference in sample sizes between two regressions is due to missing values in self-rating.

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CHAPTER 5

COSTLY POSTURING: RELATIVE STATUS, CEREMONIES AND EARLY CHILD DEVELOPMENT

5.1 Introduction

It is common wisdom that the best way to cut hunger and malnutrition is through income growth. However, Deaton (2010) uncovers a famous food puzzle: despite rapid economic growth in the past several decades in India and China, calorie consumption per capita has declined and the rate of improvement in nutritional status has been relatively slow. Surprisingly, when given more resources, the poor tend to eat less basic staple food but consume greater amounts of tastier, albeit less nutritious, food (Jensen and Miller, 2008). Moreover, the poor are more likely to spend their extra income on entertainment and social festivals (Banerjee and Duflo, 2007). A question arises: why, amid income growth, do the poor prefer to consume less food at the potential high cost of nutritional status?

Of course, there are many potential explanations to the puzzle. Reductions in physical activities and thus the need for calories associated with economic growth is one representative explanation (Deaton, 2010). However, this channel alone cannot explain why the child malnutrition rate in India has barely improved in the past several decades, considering that children's physical activities might not have declined as much as adults. In this paper, we offer

an alternative explanation: due to social pressures and concerns for status, the poor are forced to cut basic necessities in order to afford gifts for social events in their communities.

In many low income countries, rural people live in closely knit communities. It is a social norm that people are compelled to attend weddings, funerals, and other social festivals in their communities and present a gift. In a recent book (2011), Banerjee and Duflo provide the following insightful observation on the phenomenon of *keeping up with the Joneses*:

"Poor people in the developing world spend large amounts on weddings, dowries, and christenings. Part of the reason is probably that they don't want to lose face, when the social custom is to spend a lot on those occasions. In South Africa, poor families often spend so lavishly on funerals that they skimp on food for months afterward."

Because the poor have limited resources, the fiscal burden of hosting or taking part in these social events is much higher for the poor than the rich. In order to save money for hosting the events or preparing a gift, the poor may have to cut back basic necessities such as food. Such a reduction in food intake may have a lasting detrimental impact on the nutritional and health status of the poor. In other words, the reductions in food intake and stagnant improvement in nutritional status are likely to be caused by increased social spending.

It is challenging to test the *squeeze effects* of *keeping up with the Joneses* using commonly available household surveys, since they normally sample only a few households in a community, making it impossible to measure relative concerns. In this paper, we use a primarily collected census-type panel household survey in 18 villages in rural China to test the *squeeze effects* of social spending on children's health outcomes. The dataset is unique in several ways. First, all of

the households in the villages are measured in three waves. Since the villages are in remote and poor mountainous areas, each village forms a good reference group. Therefore, we are able to measure the relative deprivation status for each household over years. Relative income status, rather than absolute income level, is utilized due to the strong evidence that people's motives to consume visible goods are context-specific and that attending costly social events are clearly positional consumption in the Chinese custom. Second, all of the children's anthropometric information was collected in the third wave survey in 2009. Third, we collected detailed information on funerals, weddings, and all other ceremonies in the past ten years. Moreover, consumption of detailed subcategories of food items was collected from each household member.

Because the number of social events held by other households in a village is largely beyond the control of a family, we use it as an identification strategy to examine the impact of fetal exposures to costly social events on children's health outcomes. However, if the health outcome and number of social events are both influenced by some unobserved factors, the above identification strategy will be biased. For example, a village with a higher mortality rate may be inherently less healthy, therefore displaying higher rate of underweight and stunting among children. To alleviate this concern, we classify social events into negative and positive shocks. Among all social events, funerals are more likely to be associated with bad economic conditions, while other ceremonies (e.g. weddings, coming-of-age, house building) tend to represent good economic status. We separately examine the impact of fetal exposures to negative and positive shocks on child health outcomes and find the results are robust no matter whether the positive or negative shock variable is used.

We focus on the impact of frequent social events that occur at the very beginning of life—the fetal period. Our results show that it is the children of the poor who are more vulnerable to the shocks of social events. Those born to mothers who were exposed to frequent social events during their pregnancies are more likely to display higher rates of stunting and underweight (too short and skinny for their age). For the poor, attending social events may yield an unintended negative consequence on their children's health outcomes. However, avoiding social networking with neighbors may result in social exclusion.

The rest of the paper is organized as follows: Section 2 provides evidence that social spending squeezes the poor's food consumption; section 3 examines the impact of prenatal exposures to social shocks on child health outcomes; and Section 4 concludes.

5.2 Social Spending and Food Consumption

5.2.1 Literature on Social Spending

It has been increasingly recognized in the economics literature that people care about their relative standing in a society and that the concern for status shapes both consumption and savings behavior (Veblen, 1989; Duesenberry, 1949; Esterlin, 1974; Sen, 1983; Frank, 1985; Van de Stardt et al., 1985). The literature on relative concern and status consumption is largely focused on rich people and high-income countries. It is widely documented that the rich care about status and tend to indulge conspicuous consumptions. Recently, there is an emerging body of literature showing that the poor are also subject to relative concerns—the phenomenon of *keeping up with the Joneses* applies to the poor as well. For example, the poor prefer to consume designer-label goods in Bolivia (Kempen, 2003); lavish weddings are ubiquitous in India (Banerjee and Duflo, 2007); funerals in Ghana (The Economist, 2007) and South Africa (Case et

al., 2008) cost more than one year's household income; and in Nepal, rural residents' expected adequate level of consumption is largely influenced by the average consumption of the other people living in the same village (Fafchamps and Shilpi, 2008). Powered by relative concerns in a manner similar to the rich, the poor also tend to spend more of their extra income on status goods and in visible social occasions.

Apart from relative concerns, social norms may also dictate the behavior of social spending. In developing countries, social networks, particularly within villages, can provide informal insurance (Udry, 1990). Gift exchanges play an important role in lubricating social networks. For instance, in the event of a family member's death, the pooled gifts from social networks can help the survivors to defray part of what are quite often costly funeral expenses. Attending and presenting a gift at friends' and neighbors' weddings, funerals, and other social occasions is a social norm in many parts of the world.

Though gift-giving is largely reciprocal, it takes time and effort to build and maintain social networks. In China, a family is supposed to pay back previously received gifts later on according to the prevalent market price of gift size per occasion (Yan, 1996). Unfortunately, gift price has been escalating in recent years due to worsening inequality and particular demographic patterns. Specifically, some people get rich and spend heavily on social events, while others have to follow (Chen et al., 2011). Unbalanced sex ratio under the one child policy also strengthens the fast increasing gift trend that families with unmarried son send more gift as a marriage market signal (Brown et al., 2011). However, households get gift back only when they have major ceremonies to hold or suffer from major idiosyncratic shocks, none of which occur regularly. Ceremonies on average cost more than twice the income from gifts received and are becoming even more costly (Chen et al., 2011). Therefore, reciprocal gift exchange is not very effective in

smoothing consumption. Even if some gifts are returned at a critical time point, those not in the form of food or fungible may not improve child nutrition.

It is an open question as to which of the above two channels, i.e., concern for relative standing or social norms, better explains the observed social spending behavior among the poor. Putting that aside, however, both mechanisms predict that the poor tend to spend more of their extra money on more socially visible goods and activities.

5.2.2 Patterns of Social Spending in Rural China

The objective of this paper is not to test the mechanisms behind social spending but rather to present empirical evidence that social spending poses a heavy burden on the poor using a unique dataset from China.[62] China is largely a *guanxi* (network) society. Participating in and presenting gifts at funerals, weddings, and other ceremonies held by fellow villagers have been regarded as social norms in Chinese villages for thousands of years. Despite its ubiquitousness in daily life, there is surprisingly little empirical evidence in the economics literature on the patterns of social spending across income groups and over time in Chinese societies.

The dataset for this study comes from three waves of census-type household survey conducted in 18 villages in Puding County, a nationally designated poor county in Guizhou Province in China (Appendix Figure 5.1).[63] The survey collected detailed information on household demographics, income, consumption and transfers. The first wave of the survey included 801 households at the beginning of 2005. The second wave of the survey was

[62] In another paper, Chen et al. (2011) look at the relative importance of peer effects, status concern, and risk pooling on the escalation of social spending in rural China and conclude that peer effects and status concern well explain the observed gift spending pattern in rural China. Meanwhile, risk-sharing is not the underlying determinant.

[63] This survey was jointly conducted by the International Food Policy Research Institute (IFPRI), the International Center for Agricultural and Rural Development (ICARD) at the Chinese Academy of Agricultural Sciences (CAAS), and Guizhou University.

administered in early 2007 and 833 households was interviewed. In January 2010, the third wave follow-up survey was conducted and 872 households were interviewed.

The survey area offers an ideal setting to study the relationship between social spending and food intake among the poor for several reasons. First, poverty rate is quite high in the county. As shown in Table 5.1, in 2004, more than one-third of people lived below the national poverty line. Using the higher international poverty line of one dollar per day, the poverty incidence is higher. Second, despite the initial high incidence of poverty, the real per capita income has grown rapidly at an annual rate of more than 10% from 2004 to 2009. Even for the poor households below the $1.25 international poverty line, we still observe annualized income growth rate at 3.7%. However, we do not observe any improvement in most categories of basic food intake. This provides us with a good opportunity to study Deaton's food puzzle as to why the improvement in nutritional status has been stagnant among the poor amid rapid income growth. Third, our survey villages are in rather isolated and mountainous areas. In such an isolated environment, villagers naturally interact much more frequently with each other within the same village than with those residing outside their home village. As a result, the villages form clearly defined reference groups.[64] By surveying all the households in the villages, we are able to accurately measure relative income status for each household within a village.

In the second and third waves of the survey, we asked the households to report major events, including weddings, funerals, coming-of-age ceremonies, during the past ten years, as well as the related expenses and gifts received. In this area, all the households keep a gift book, which lists the amount of all gifts received and the names of gift givers in major ceremonies held by them. In the third wave of the survey, we used digital cameras to record gift books from all

[64] Because of the high degree of isolation from the outside, people within a village know each other well. Three small neighboring villages of ethnic Miao group form a strong bond among themselves. Therefore, we combine them when defining a reference group.

the households in three out of eighteen villages. The data enable us to examine the patterns of social spending in different social occasions over time and across income groups.

Table 5.2 presents the average gift size per occasion, number of weddings and funerals, and participation rate of funerals within a village from 2004 and 2008, based on the gift record data collected in 3 out of 18 villages. Four salient features are apparent from the table. First, average gift size per occasion has increased from 2004 to 2008. Second, the difference in gift size between rich and poor is minimal. The poor at the bottom 25% of income distribution on average spend even more on a gift per occasion than their top 25% counterpart in the same village across all the years. The finding is consistent with our field observation that in the surveyed areas, there is an implicit "market price" for gift size per occasion that people follow when extending a gift. Third, participation at funerals is almost universal within a village. As shown clearly from the last column, more than 95% of households attend fellow villagers' funerals. Fourth, participation rates between the rich and the poor in social events are very similar, especially for funerals. Figure 5.1 shows that households in the poorest income group participate more widely in funerals than the third and fourth highest income groups. This is consistent with the findings by Brown et al. (2011) that participating in funerals is largely driven by social norms. The rather standard gift size and nearly universal participation rate of major ceremonies indicate that the average gift expenditure per capita in a village should be positively related to the number of ceremonies held in a year. This is apparently the case, as shown by the strong positive correlation between the two variables in Figure 5.2.

5.2.3 The Squeeze Effects of Social Spending on Food Consumption

Because the poor have limited financial resources, social spending poses a much heavier fiscal burden on the poor than the rich. In order to afford a gift to attend a social festival, they have to make a sacrifice elsewhere. Living on the margin, they have little to cut back. Tightening their financial belt and skimping purchases of meat, sugar and other food items for a few weeks after the ceremony is often the default option for the poor. Figure 5.3 plots the share of cash expenditure spent on gifts and food by relative status, measured by Deaton relative deprivation Index (2001, shortened as RD index hereafter).[65] For those with lower relative status (larger value along the horizontal axis), we can clearly see that the drop in the share of food expenditure is accompanied by the increase in the share of gift expenditure. In principle, they could eat more food and suffer less from malnutrition by simply spending less on gifts. But apparently they did not make such a choice. By comparison, for those households with higher status (smaller values along the horizontal axis), both lines barely move.

To further test the *squeeze effects* of social spending on the food consumption of people with low status, in Table 5.3 we run an seemingly unrelated regressions (SUR) on the share of food and gift cash expenditure. Ceremonies held by other families within the same village are largely exogenous shocks to a family. Since the 18 villages are in the same township, they are likely to be subject to the same covariate natural shocks, if any, mitigating some concerns about unobserved idiosyncratic natural shocks. However, one may still argue that the number of ceremonies might capture some unobserved factors which also determine consumption patterns. For example, it is possible that residents in a richer village can afford more wedding, house building and coming-of-age ceremonies (positive shocks) than those in a poorer village and they

[65] We will discuss the measure in detail in the next section.

are likely to consume more food. In contrast, the population in villages with greater number of funerals (negative shocks) may be generally poorer. Consequently, they may have less money to buy food. Therefore, the positive and negative shocks may bias the estimation of food consumption in different directions. Although it is difficult to find good instruments to ameliorate the concern on the potential endogneity problem of the ceremony variable, we run separate regressions by using positive and negative shocks to see if the estimates fall in a narrow band. If both positive and negative shocks yield similar results, we can confidently rule out the potential bias as a result of endogneity.

In the first set of regressions (R1), we include the number of ceremonies other than funerals held by fellow villagers,[66] Deaton Relative Deprivation Index (RD), the interaction term between the above two variables, as well as a set of control variables at the household level, and year and village fixed effects. The coefficient for the interaction term in the food share equation is statistically significant and negative. This suggests that those with lower status spend less on food consumption than their richer counterparts, provided that they attend the same number of ceremonies in a given year. Similarly, the coefficient for the interaction term in the second set of regressions (R2) remains negative and significant, suggesting *squeeze effects* of social spending on food consumption among those in the lower social spectrum.

5.3 Quantifying the Effect of Social Spending on Child Health Outcomes

5.3.1 Fetal Origins Hypothesis

To resolve Deaton's food puzzle, next we need to test if a cut in food intake as a result of social spending comprises nutritional status, in particular that of children. A burgeoning body of

[66] Throughout the estimations in this paper, we take the log form for the number of funerals and other ceremonies.

literature on fetal origins hypothesis suggests that *in utero* is a critical period for human development. *In utero* exposures to malnutrition are likely to adversely affect health outcomes in later life (Barker and Osmond, 1986; Barker et al., 1989).

However, it is impossible to directly test this hypothesis using human subjects in a controlled experiment. The empirical literature largely relies on natural shocks, such as famine and drought, to identify the casual effect of prenatal exposures to malnutrition on long-term health outcomes. For example, studies based on the Dutch Famine (1944-1945) reveal that the famine had negative impacts on various health related outcomes, such as mental disorder in early adulthood, schizophrenia, and lower glucose tolerance in adults (Neugebauer et al., 1999; Brown et al., 2000; Hulshoff Pol et al., 2000; Ravelli et al., 1998). Similar fetal origins effects are found in studies on the 1918 flu (Almond, 2006) and the Chernobyl radioactive fallout (Almond et al., 2009). Children born during a drought in rural Zimbabwe show a higher rate of stunting in the subsequent two years (Hoddinott and Kinsey, 2001). Maccini and Yang (2009) show that high rainfall at the very beginning of life is associated with better health and education outcomes in later life for Indonesian women.

Yet, not all empirical studies based on natural shocks confirm the fetal origins hypothesis. For instance, studies on the survivors of the Leningrad Siege (1941-1944) in general conclude that those exposed to starvation in the fetal stage do not show much difference in health outcomes from cohorts born outside Leningrad and in other years in the later stages of life. One key reason is that in the event of severe shocks like the Leningrad Siege, only the healthier survive and can be observed in later life. Therefore, the presence of mortality selection renders it less likely for researchers to observe the negative health impact on the survivors later on. Mu and Zhang (2011) show that prenatal exposures to the Chinese Great Famine (1959-1961) result in

higher disability rates for female survivors but not for males, largely because of much larger excess male mortality rates during the famine. Exposure to milder shocks, however, might facilitate the testing of fetal origin hypothesis, since scarring effects for survivors are much less likely to be offset by selective mortality in extreme fetal exposures.

The studies based on natural shocks have provided tremendous insight on the fetal origins hypothesis in extreme events. However, estimates of the effects of mild exposures may be more relevant to policy than estimates of the effects of disasters. Almond and Currie (2011) argue that the immediate mortality and economic disruption from the 1918 flu or the China famine are sufficient to imply that any reasonable measure to prevent such catastrophes is likely to pass a cost-benefit calculation, thereby showing that there was additional damage to fetal health from these disasters merely "makes the rubble bounce."

Moreover, most people, even the poor, do not suffer from natural shocks as severe as famine. Instead, they face more frequent, yet minor, social shocks —funerals and wedding that they are obligated to attend. Do children born to mothers exposed to more frequent social shocks have worse health outcomes as predicted by the fetal origins hypothesis? To our knowledge, no studies have examined the impact of prenatal exposures to social shocks on child health outcomes.

In the third wave of our survey, we collected anthropometric information for all the children in our sample. The data enables us to address the above question. We use three variables—height-for-age, stunting and underweight—as major child health outcome measures. Stunting and underweight are defined based on two standards: the WHO standard and the standard of China Center for Disease Control and Prevention (CDC).

Height-for-age measures the cumulative long-term nutritional status an individual has obtained over the life course, while weight-for-height or BMI-for-age measures more acute changes. Weight-for-age and underweight may confound the height-for-age measure. A stunted child would have a low weight-for-age z-score due to his low height even if his weight-for-height z-score is normal. If *squeeze effects* due to prenatal exposure to social shocks are found, it should be mainly related to height-for-age and stunting status but to a much lesser extent related to weight-for-age[67] or underweight and not related to weight-for-height. A comparison of the most important anthropometric indicator in this paper – height-for-age z-score – between our IFPRI-CAAS Guizhou sample and the matched CHNS 2004 & 2006 Guizhou sample is drawn in the Appendix Figure 5.2 and help confirm the data representativeness.

As shown in Table 5.4, nearly half of children born in 2008 are stunted. Despite impressive annual rates of income growth at more than 10% from 2004 and 2008, the stunting rate had not declined, but rather rose slightly in the sample villages. The problem is more acute among girls, whose stunting rate increased from 41.4% in 2004 to 55.6% in 2008. The rate of underweight shows a similar pattern. Overall, the prevalent high stunting and underweight trend is consistent with He and Chen (2004) that in impoverished counties in Guizhou and Guangxi the most recent stunting and underweight rates are around 60% and 30%, respectively. As illustrated, the Deaton food puzzle can be observed in rural China as well.

[67] Weight-for-age is not adopted in this paper due to the concern for measurement errors. The third wave survey took place in January, the coldest time of the year when people often wear heavy winter clothes. However, it is hard to weigh children's clothes, in particular those of newborns. Therefore, the measurement for the weight of young babies is likely less accurate. In the wake of potential large measurement errors on anthropometric information among newborns, we exclude those born in 2009 (i.e., 1-12 months after birth) from our empirical analysis. The doted vertical reference line in the Appendix Figure 2 shows this cut-off point. More importantly, we have to exclude those samples because our 2009 survey was conducted in January 2010 during which social events were frequently held. Without the complete number of events including January, the definition for number of social events in lunar year 2009 is inaccurate.

The observed Deaton puzzle may have something to do with *in utero* exposures to social shocks. Table 5.5 reports the average height-for-age z-score for children born between 2004 and 2008 according to low and high income groups in villages with more frequent and less frequent social shocks (number of all ceremonies). The last column measures the difference-in-differences (DID) of the z-score. Almost all the values are negative, suggesting that it is children of the poor income groups who exhibit lower z-scores when exposed to more frequent social shocks at the fetal stage. Because of the small sample size for each cohort, we cannot compute the *t*-value of the DIDs. In the last row, we pool together all the children born between 2004 and 2008. The DID value is significant and negative. While this simple analysis based on two-by-two discrete groups shows some suggestive evidence on the *squeeze effects* of social spending on child health outcomes, it is interesting to further investigate if there is a linear negative relationship between the continuous variables of z-scores and number of ceremonies. Figure 5.4 depicts the height-for-age z-score against the number of ceremonies exposed in the fetal period for the high and low income status groups. For the low-income status group, the greater number of exposures to ceremonies, the lower value of z-score. In contrast, the figure does not reveal an obvious pattern between z-scores and social shocks for the high-income group.

The simple DID analysis and bivariate plot provide tentative evidence in support of the *squeeze effects* of fetal exposures to social events. In order to more rigorously verify the *squeeze effects*, we need to control for more variables in more quantitative analyses.

5.3.2 Measuring Reference Groups and Relative Status

Before going to the quantitative analyses, we need to first define reference groups and measure relative status. The theoretical models on relative concerns often take reference groups

as given. However, in empirical analyses, defining reference groups is more of an art than science. People interact with others in different cycles in their work and family life. Identifying and measuring reference groups are always a great challenge for empirical research on social interactions.

The challenge might be greater in cities than in rural areas. In rural areas in developing countries, people often live in a rather close community. Two recent studies on China show that rural people often use their home village as a reference group (Knight, Song and Gunatilaka, 2007; Mangyo and Park, 2011). In our surveyed area, the villages are located in an area renowned for its Karst landform, which presents a barrier for frequent interactions across villages. Therefore, in this paper, we primarily use villages as reference groups in our empirical analyses.[68]

Having defined reference groups, next we need to measure relative concerns, as they are often mentioned as a key motive behind social spending in the literature (e.g. Brown et al., 2011; Chen et al., 2011). In this paper, we adopt the widely used Deaton RD index (2001). The index captures the idea that a person is deprived if others in the group possess something that one does not have. It closely follows the spirit of Frank, Levine, and Dijk (2010) and Hopkins and Kornienko (2004).[69]

The Deaton RD index originated from Yitzhaki (1979) and Wildman (2003). The level of deprivation experienced by an individual i with income y[70] relative to another individual with

[68] We also check the robustness of our results using alternative reference groups - surname networks within a village.
[69] Frank, Levine and Dijk (2010) define "Expenditure Cascade" in an economy where every agent judges own behavior based on others closest above them. Hopkins and Kornienko (2004) develop a rank-based theoretical model that captures the status concern motive for lower ranked agents. In the model, rising average income of their fellow residents triggers a competition for status that extends all the way down to the bottom of the distribution. Moreover, Hopkins and Kornienko (2004) relate positional spending to a measure of income inequality, which pave the way for us to empirically identify status seeking and social influences.
[70] Y can be defined in the dimension of income, consumption, assets and so on. Here income is utilized, which includes both in-kind and cash income.

income z is formulated as,

$$D(i;y) = z - y \quad \text{if } y < z \quad \text{or} \tag{1}$$

$$D(i;y) = 0 \qquad \text{if } y \geq z \tag{2}$$

Based on this formula, an individual would feel more deprived as the number of individuals in society with more income than this individual increases. Thus, an overall measure of deprivation for the individual i is computed by summing the differences in income and weighting it with the proportion of people with higher income than the individual i. The above measures tend to overstate relative deprivation of individuals in high-income reference groups. This could be a very important issue when incomes differ substantially across groups. To make scale invariant, Deaton (2001) proposes a measure of relative deprivation for an individual i with income x:

$$(1/\mu)\int_{x}^{x^T}(y-x)dF(y) \quad \text{or} \quad (1/\mu)[1-F(x)][\mu^{+}(x)-x] \tag{3}$$

where μ denotes mean income for those in the reference group, x^T is the highest income in the group. *F(y)* is the cumulative distribution of incomes among individuals in the group, and $\mu^{+}(x)$ is the average income of those with income higher than the individual with income x. The Deaton RD index normalizes difference between average income of those with higher income and income x weighted by the proportion of those with income higher than the individual i. The Deaton RD index takes into account differences in the scale of income distribution across groups. Unlike other deprivation measures, such as deprivation of absolute income (Li and Zhu, 2006), the Deaton RD index is scale invariant. In others words, it will not automatically double as everyone's income doubles.

5.3.3 Quantifying the Effect of Social Shocks on Child Health Outcomes

The standard child nutritional and health demand function, derived from a welfare maximization framework, often includes income, food prices, access to healthcare, genetic make-up, and other individual characteristics (Behrman and Deolalikar, 1988; Strauss and Thomas, 1995, 2008). In this paper, we include the Deaton relative deprivation measure as well as its interactions with variables of interest as additional variables. The specification can be written as:

$$Outcome_{ijt} = \alpha RD_{j,t=1} * CAB_{j,t=1} + \beta RD_{j,t=0} * CBB_{j,t=0} + \gamma_0 RD_{j,t=1} + \gamma_1 RD_{j,t=0} + \gamma_2 CAB_{j,t=1} + \gamma_3 CBB_{j,t=0} + \alpha_c \cdot C_{ijt} + \alpha_p \cdot PCG_{jt} + \alpha_p \cdot p_t + \alpha_h \cdot H_{jt} + \alpha_s \cdot S_{jt} + \upsilon_v + \delta_t + \varphi_{vt} + \varepsilon_{ijt} \quad (4)$$

where $Outcome_{ijt}$ denotes child *i*'s nutrients intake and health status in household *j* at time *t*; RD_{jt} denotes relative status for household *j*; C_{ijt} is a vector of child i's characteristics, including age, sex and birth order; PCG_{jt} is a vector of characteristics of the principal care giver, including household head sex, education, ethnicity, cadre status, mothers' height[71], and major shocks (illnesses and natural disasters); p_t denotes a vector of local food prices; and H_{jt} is a vector of local health facility characteristics, such as distance to the closest clinic center. Other household characteristics, including share of the elderly, household size, per capita income are controlled for. υ is a set of administrative village[72] fixed effects that account for any time-invariant differences between villages (such as geography) that may also be correlated with social events and child health outcomes. δ is a set of year of birth fixed effects, which account for any year-to-year changes in birth conditions that occur for the surveyed region that

71 Fathers' health status is not included, since some of them were migrating out to work during our survey. In most cases, mothers and children were left behind in the villages.

72 An "administrative village" is the lowest level bureaucratic entity comprised of several villages. The surveyed 18 villages belong to 3 administrative villages, one with 10 villages, each of the other two with 4 villages respectively.

potentially correlate with social events (such as business cycles). The baseline model in Panel A Table 5.7 includes both year and administrative village fixed effects. In Panel B Table 5.7, we further include a set of administrative village-specific linear time trends that address the concern that the trend in social events within some villages is spuriously correlated with the trend in child health outcomes across villages over time. In Panel C Table 5.7 and all the other regression tables, we further control for administrative village x year fixed effects φ_{vt}. To account for the possibility that the stochastic error terms (ε_{ijt}) are correlated within villages over time, the estimations are clustered at the year x village level. The results are robust when the estimations are clustered at the village level.

Two time periods are critical in the identification of *squeeze effects*: the fetal period (t=0) and the period after birth (t=1). $CBB_{j,t=0}$ is the number of ceremonies held by other families within the same home village in the year prior to child i's birth. Similarly, $CAB_{j,t=1}$ is the number of ceremonies held by others during child i's birth year. The main coefficients of interest are γ_2, γ_3, α and β. The magnitude and significance level of these coefficients as well as $\gamma_2 + \alpha RD_{jt}$ and $\gamma_3 + \beta RD_{jt}$, shows us degrees of exposures to social events shocks in the fetal period or after birth matter to child health outcomes.

As discussed earlier, although the number of all ceremonies held by other families within a village is largely beyond an individual household's control, the number of ceremonies may reflect a village's wealth level as well as other underlying unobserved factors, which may potentially influence child health outcomes. To address this concern, we distinguish negative shocks (number of funerals) from positive shocks (e.g. weddings, coming-of-age and other ceremonies). If positive and negative shocks also represent the underlying unobserved health

conditions in a village which are correlated with child health outcomes, then the estimations based on positive and negative shocks will yield biases in opposite directions. Therefore, separate regressions using positive and negative shocks provide us with a lower and upper bound of the effect. If both sets of regressions produce significant results with similar magnitude and the same sign, it suggests that there are indeed squeeze effects.

The simultaneous identification of prenatal social events shocks $CBB_{j,t=0}$ and social events shocks after birth $CAB_{j,t=1}$ do not confound each other. In our survey, dates of birth were recorded based on household registration book, which follows the western calendar. However, dates of social events were recorded according to respondents' recall, and local rural residents adopt lunar calendar in their everyday life, which spans from February to January. Though we do not have information about the exact timing of all social events for all 18 villages, complete gift record books we collected from 3 out of 18 villages provide us with rich information about the timing. Since the three villages are very similar in terms of socioeconomic conditions to the other 15 villages, we infer that the pattern of timing in Figure 5.5 generally applies to all these villages.

As shown in Figure 5.5, most ceremonies (except funerals and childbirths[73]) are planned and held at the end of the lunar year, i.e., January, when nearly all families come back to celebrate the Chinese lunar new year. The timing of major social events in the lunar calendar combined with dates of birth in the western calendar makes sure that children in the prenatal period are exposed to most social events in the year prior to birth (t=0), while most social events in the birth year (t=1) occur after child birth.

[73] Though child birth generally occurs in a good year, the timing of pregnancy also determines the timing of delivery and may demonstrate other seasonal / climate / weather patterns. Therefore, in both left Figure 5 and all empirical estimations we exclude the number of child birth from the good year shock category. The results are not much affected compared to estimations with childbirth events, since childbirth is much less costly than other events. Observed from the guest size and gift size recorded in the gift books, only closest relatives come to celebrate childbirth, and most gifts are cheap in-kind goods (mostly in the form of *red eggs*). Moreover, many local residents preserve the tradition to organize wedding and child birth as a single event due to the high organizing cost.

Even if funerals are most often unplanned and held throughout a year, they demonstrate a seasonal pattern in our sample - a disproportionate share of them are between November and the following January (Figure 5.5) - due to the demographic characteristics that more people die in winter than in other seasons. This fact ensures a clean identification using the number of funerals.

Considering that the normal gestation period is 38-42 weeks, the clustered number of social events towards the end of the lunar year guarantees children born before the end of the following September had prenatal exposure to most of these social events. The earlier the birth date, the later a child is exposed to clustered social events during the fetal period. However, for children born between October and December, none of them directly experienced social events shocks in the prior year. In the robustness checks, we restrict our sample to children born between February and September.

5.3.4 Main Empirical Results on the Squeeze Effects

Building upon the findings in Figure 5.4 and Table 5.5, we run separate regressions on three child health outcome variables,—height-for-age z-score, stunting, and underweight,—in low and high income groups. The specification is the same as in equation (4) except that it excludes the interaction terms of RD. Table 5.6 reports the regression results for the key variable of interest, the number of funerals (or other ceremonies) exposed in prenatal period and after birth, respectively. Children born to mothers in low income groups, who are exposed to more funerals or other ceremonies during their pregnancies, show lower height-for-age z-scores and display higher rates of stunting and underweight. Doubling the exposure to funerals or other ceremonies in the network on average corresponds to 1-1.5 standard deviation lower height-for-age z-score.

In contrast, the health outcomes of children born to richer families do not appear to be vulnerable to social event shocks experienced in the year prior to their birth. More social events experienced by children in rich families are even associated with insignificantly better height-for-age z-score. For them, more social events in the neighborhood mean more social capital than social burden and mobilize resources towards children. Unlike *in utero* exposures, the number of social events exposed after birth have little to do with child health outcomes. The findings in this table indicate that the health outcomes of children born to poor families are associated with the number of social events held in their village in the year before their birth.

One might question this arbitrary division of the sample into low and high income groups. In Table 5.7, we regress the three health outcome variables on the whole sample by interacting the Deaton RD measure with the incidence of funerals or other ceremonies at the village level in the year prior to or in the year after child birth. Regardless of whether we use the number of funerals or other ceremonies, the interaction terms of *in utero* exposures to the number of social shocks incurred prior to birth with the Deaton RD measure are statistically significant, negative in the regression on height-for-age z-scores, and positive in regressions on stunting and underweight rates. In comparison, none of the coefficients for the interaction term between the Deaton RD measure and the number of funerals or other ceremonies after birth is significant. Considering that a larger value of the RD measure means a lower status, the significant interaction terms mean that children from households with lower economic status and are prenatally exposed to social event shocks are more likely to be shorter and develop higher rates of stunting and underweight than those from higher status households.

In Panel A of Table 5.7, the baseline estimations with year fixed effects and administrative village fixed effects are presented. In Panel B of Table 5.7, administrative village-specific year

trends are further controlled for. The first derivative of equation (4) with respect to the number of social events tells us that households whose Deaton RD index above or equal 0.21-0.41 significantly suffer from net *squeeze effects*, while the mean RD index over the three-wave survey is around 0.45. In other words, the cutoff point for net *squeeze effects* applies to two thirds of the households with higher relative deprivation level. Panel C in Table 5.7 adopts administrative village x year fixed effects, which capture more general village-specific unobservable factors over time. The *squeeze effects* are significant and marginal effects are similar. Specifically, households with Deaton RD values above or equal 0.14-0.34 suffers significantly from net *squeeze effects*.

5.3.5 Robustness Checks and Other Findings

One common finding worth noting in Table 5.7 is that *squeeze effects* are almost always much more significantly demonstrated in the longer term nutritional status measures, i.e., height-for-age and stunting, than in the shorter term measure, i.e., underweight status, suggesting the long-term negative impact of prenatal exposure to costly social events. However, underweight may not be a good measure for comparison, since a child suffering from stunting is very likely to also suffer from underweight only because the small stature. Therefore, it is worthwhile to further get rid of the potential confounded longer and shorter term effects. If the main driving force of stunting is *in utero* exposure to malnutrition, we should expect that the effects are not captured by more acute health measures. In Table 5.8, estimations using weight-for-height z-score find that the squeeze effects are not embodied in the contemporaneous nutritional status, which strengthens our argument that the fetal origins effect is the main driving force behind bad child health outcomes.In addition to running separate regressions using positive and negative

shocks to check the potential bias of unobserved factors, we also run a falsification test on the *squeeze effects* by lagging the variable on the number of funerals and other ceremonies by one year. In other words, in this test the variable labeled "# of social events before birth" actually corresponds to the number of social events held in a village two years ahead of child birth, which ought to be unrelated to prenatal health status, rather than in the year prior to birth. If some unobserved factors instead of the squeeze effect drive the result, we would expect that the coefficient remains significant in the falsification test. Results show that all the coefficients for the interaction terms in Table 5.9 are statistically insignificant. Thus, the number of funerals in years other than the year prior to child birth does not seem to affect child health outcomes.

Though the timing of social events in three typical villages informs us the general pattern of events' distribution towards December and January, we do not know the exact dates of ceremonies in the other fifteen villages. Therefore, we cannot match them with the months of mothers' pregnancies. Instead, we simply count the number of all ceremonies held by other families in the home village in the year prior to a child's birth and use it as a measure of fetal exposures to social shocks. This simple procedure may result in measurement errors. For example, if a child is born between October and December this year, then ceremonies held in the last year won't directly affect the child's *in utero* development. As a robustness check, we restrict our sample to those children born between February and September. Children in this sample are definitely conceived in the lunar year (between February and the following January) prior to their birth, and the feature of social events' clustering towards the end of the lunar year further ensures direct exposures. Table 5.10 repeats the main regressions in Table 5.7 on the restricted sample. The coefficients for the interaction terms between the Deaton RD measure and

the number of funerals or other ceremonies prior to birth are statistically significant and in the expected sign. The findings are consistent with those reported in Table 5.7.

Although people are familiar with each other within villages, villagers from the same family clan are still likely to interact more frequently among themselves than with other clans. If it is true, then using villages as reference groups would likely bias the regression results. We classify households whose heads share the same surnames as the same network. Households belonging to a larger surname network tend to participate in more social events.

Table 5.11 presents the regression results. The regressions follow the same specifications as in Table 5.7 except that we replace villages with surname networks as a reference group. Specifications in the upper panel use the number of funerals within villages. The coefficients for the first interaction term are largely statistically significant, showing that funerals held in surname networks tend to lower the height-for-age z-score and increase the probability of underweight for children from lower-status households. As shown by the significant coefficients in the height-for-age z-score regression in the lower panel, when using the number of other ceremonies as an indicator of social spending, the *squeeze effects* still show up. It is noted that none of the interaction terms between RD measures and the number of funerals or other ceremonies after birth is significant. Overall, regressions based on two different reference groups yield largely consistent results—prenatal exposures to social event shocks have an unintended negative consequence on the health outcomes of children born to lower-status families.

The literature on fetal origins hypothesis has shown that mortality selection associated with extreme natural shocks may mask the identification of long-term negative impact on health (Mu and Zhang, 2011). In the event of severe shocks, the most fragile fraction of the population is more likely to die first. As a result, the survivor population tends to be healthier than the general

population in the absence of shocks. In other words, the presence of mortality selection will make it harder to discern the adverse effect of fetal origins. The population in the 18 villages in our sample was not subject to any major natural shocks. The social events, albeit a heavy fiscal burden for the poor, are unlikely to lead to excess mortality. The presence of excess mortality, if any, will only strengthen our results as the selection effect tends to trump the scarring effect (Pearson, 1912; Bozzoli et al., 2010).

Another potential selection problem is that children may have moved to cities with their migrant parents, thereby leaving behind an unhealthy group of children in the villages. Our surveys were conducted right before the Chinese New year when almost all migrants return home and children are at home for their winter break. Comparing the list of respondents' names from the 2006 survey with that of the 2009 survey, we do not find any attrition. Although many young people have taken migratory jobs throughout most time of the year, they generally leave their children behind with grandparents in their home villages because of the high cost of living and discrimination against migrants' children in urban schools.

The stunting and underweight cutoff values are based on the WHO standard. The Chinese population is on average shorter and lighter in weight than the world average, thereby likely implying a cutoff value. The China Center for Disease Control (CDC) publishes its own cutoff values for the Chinese population. In Table 5.12, we report the main results with the same specifications to Table 5.7 by replacing the WHO standard with the CDC standard. Both the sign and magnitude of prenatal *squeeze effects* are quite similar to those based on the WHO standard. Once again, we do not find a noticeable effect on exposures to social shocks after birth.

In the above tables, we do not distinguish between the different impacts on boys and girls. In the human biology literature, it has been widely documented that boys are more susceptible to

adverse nutritional environment than girls in the early life. To examine the potential gender difference, in Table 5.13, we run separate regressions on the health outcomes of boys and girls. The upper panel reports the results using the number of funerals as proxy for social spending, while the lower panel uses other ceremonies to represent social events. We find that boys from lower status households who are prenatally exposed to the same number of funerals display worse height-for-age z-score than those from higher status families. However, prenatal exposures to social events do not seem to affect girls' health outcomes. The findings are largely consistent with the literature that girls are more robust than boys in early life and the fact that unavailable ultrasound technology prevents local parents from gender biased resource allocation.

Finally, since height-for-age z-scores can be both positive and negative, we cannot directly take a logarithm on them. Instead, in our main regression, we simply use the original z-scores as a dependent variable, although most of the right-hand variables are in logarithmic form. To explore whether this linear-log specification yields drastically different results, following Hoddinott and Kinsey (2001) we transform the z-scores into percentiles according to international standards and then take the logarithm of the percentile. In general, the results on the *squeeze effects* of *in utero* exposures to social shocks remain largely the same as using z-scores. To save space, the results under this specification are not reported but available upon request.

5.4 Conclusions

It has been widely noted that the improvement in nutritional status among the poor in developing countries lag far behind income growth. Deaton (2010) and Banerjee and Duflo (2007) have asked: why don't the poor eat more with their extra income?

In this paper, we argue that social spending can squeeze out food consumption, which in turn compromises nutritional status. In developing countries, most of the poor live in a close

community where they know each other well. Their consumption decisions are shaped not only by their own preferences and budget constraints, but also by peers in their communities. When peer pressure and relative status are of importance, people tend to spend more on visible goods and activities (like social festivals) at the expense of less visible goods, including food.

Gift exchange is almost a universal phenomenon in developing countries. One important feature of gift exchange is reciprocity. In many rural areas, it is a social norm to attend neighbors' weddings, funerals, and other major ceremonies. Because of the reciprocal nature of gift exchange and "mandatory" participation, gift-giving places a much heavier burden on the poor than on the rich. In order to afford a gift, the poor often have to forgo the consumption of meat, eggs, and other food items for weeks after attending a social event. Such a squeeze on food intake can extract an unintended long-term toll on the children of pregnant women. In contrast, because they have financial slack and food consumption accounts for a small share of their budget, the rich do not need to worry about food consumption when engaged in conspicuous behavior.

Using a unique census-type household survey collected in remote mountainous villages in China, we are able to clearly define reference groups and empirically examine the impact of social spending on food consumption and nutritional status. We find that children born to households with lower income status develop shorter and lighter physical stature if their home villages held a greater number of social events in the year prior to their birth.

A question thus arises: given the negative impact of social spending on child health outcomes, why don't the pregnant women avoid attending fellow villagers' social festivals in the first place? There are several possible explanations. First, people may not be aware of the negative health consequence of prenatal exposures to social events. To our knowledge, this paper

is one of the first papers to provide empirical evidence showing the existence of such an effect. It is likely that a more informed mother will be more careful in making a choice between eating adequate and healthy foods and attending a neighbor's social event.

Second, when rewards for higher status are high and punishment for lower status is grave, people, in particular the poor, will intensify their competition in status goods consumption (Hopkins, 2010). In China, sex ratios have become increasingly unbalanced (Bulte *et. al*, 2011). As a result, the marriage market competition has intensified greatly over the past several decades. Under such a marriage market squeeze, the poor have to vigorously signal their wealth through bigger houses, more generous bride price payments, lavish wedding banquets, and active participation in social events within their village. In fact, the competition in social spending is more intensive among the poor segment of the population in rural China (Brown et al., 2011; Chen et al., 2011).

In this paper, we have focused mainly on child health outcomes. *In utero* exposures to adverse events may also affect education achievement and earning potentials in later life (Almond and Currie, 2011). As predicted by the fetal origins hypothesis, people who are exposed to a malnourished environment before birth are likely to develop a series of chronic diseases in adult life. As a future research project, it is interesting to continue to follow the population in the villages over a longer period of time and quantify the impact of *in utero* exposures to social events on education achievement, earnings, and health outcomes in later stages of life.

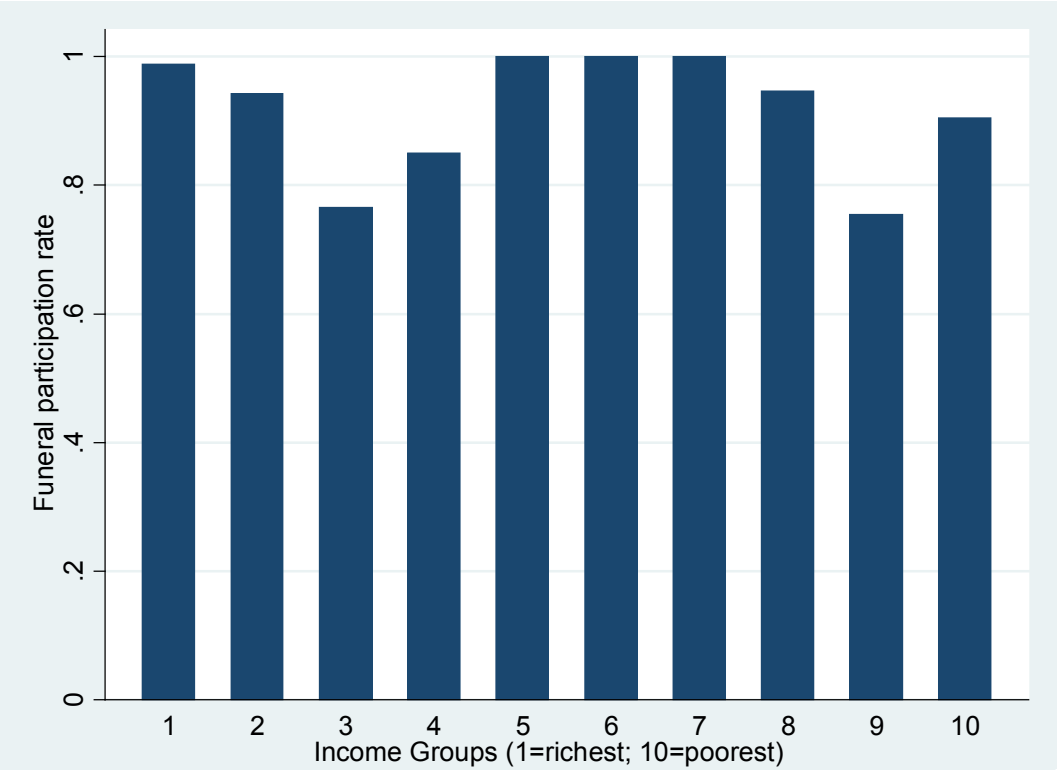


Figure 5.1: Income Level and Funeral Attendance Rate in Local Villages

Sources: Authors' Gift record data

Notes: By each year and each village, all the households are divided into 10 groups by per capita income. The vertical axis represents the participation rate of funerals by income groups.

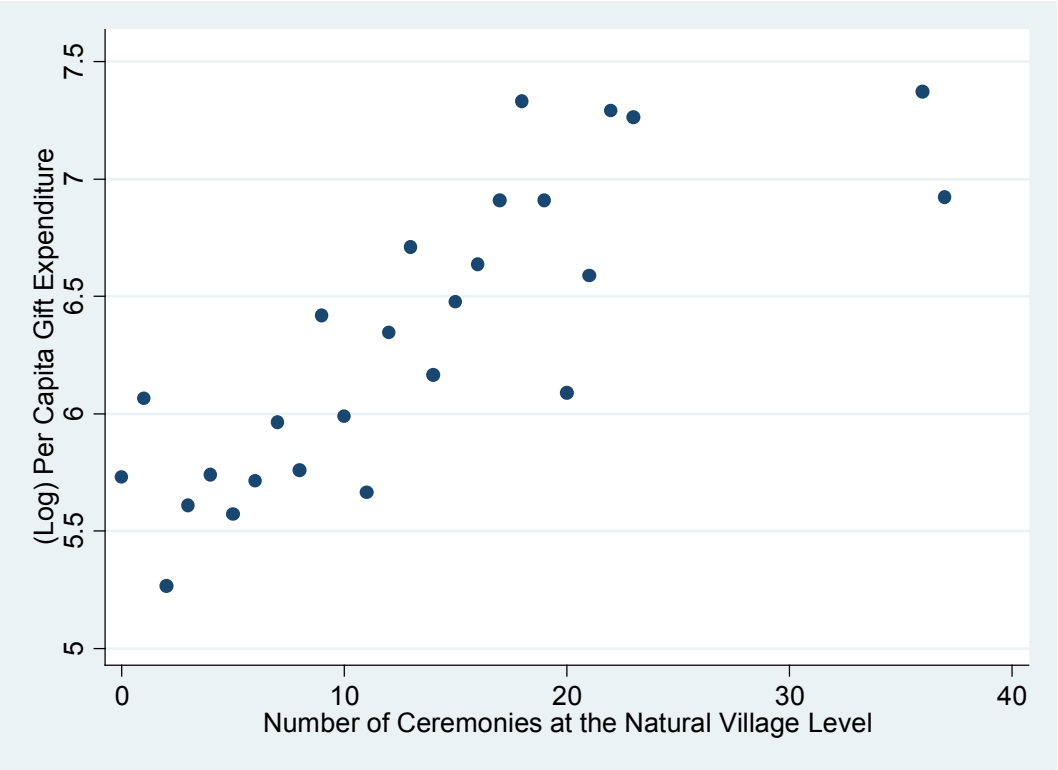


Figure 5.2 Average Per capita Gift Expenditure and Number of Ceremonies in a Village

Sources: Authors' survey data

Notes: The figure is computed based on our three-wave household survey data in 2004, 2006 and 2009 in Guizhou Province. The horizontal axis stands for the number of ceremonies at the village level in the three years, while the vertical axis represent the average per capita gift expenditure (log) at the village level in the corresponding year.

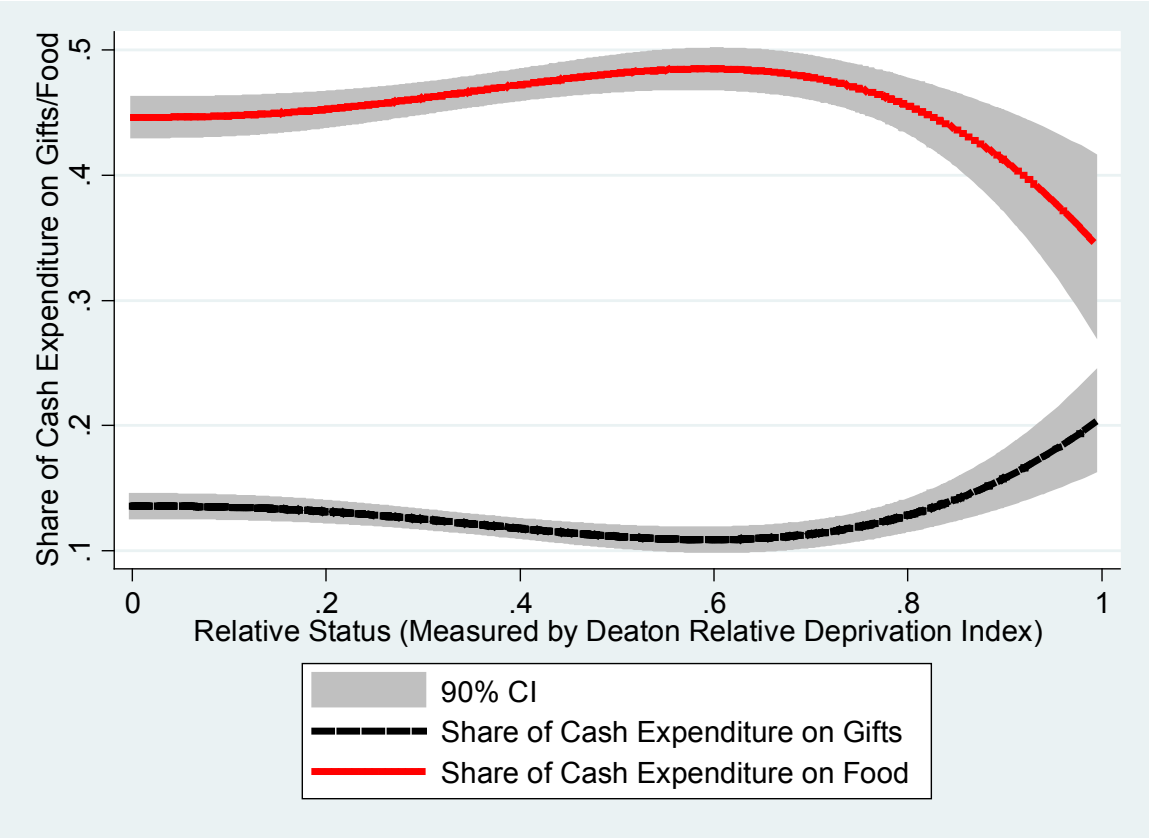


Figure 5.3 Share of Cash Expenditure Spent on Gifts and Food

Sources: Authors' survey data
Notes: Deaton index ranges from 0 to 1 with 1 corresponding to the lowest status and 0 standing for the highest status. All households surveyed in 2004, 2006 and 2009 are used to generate this figure.

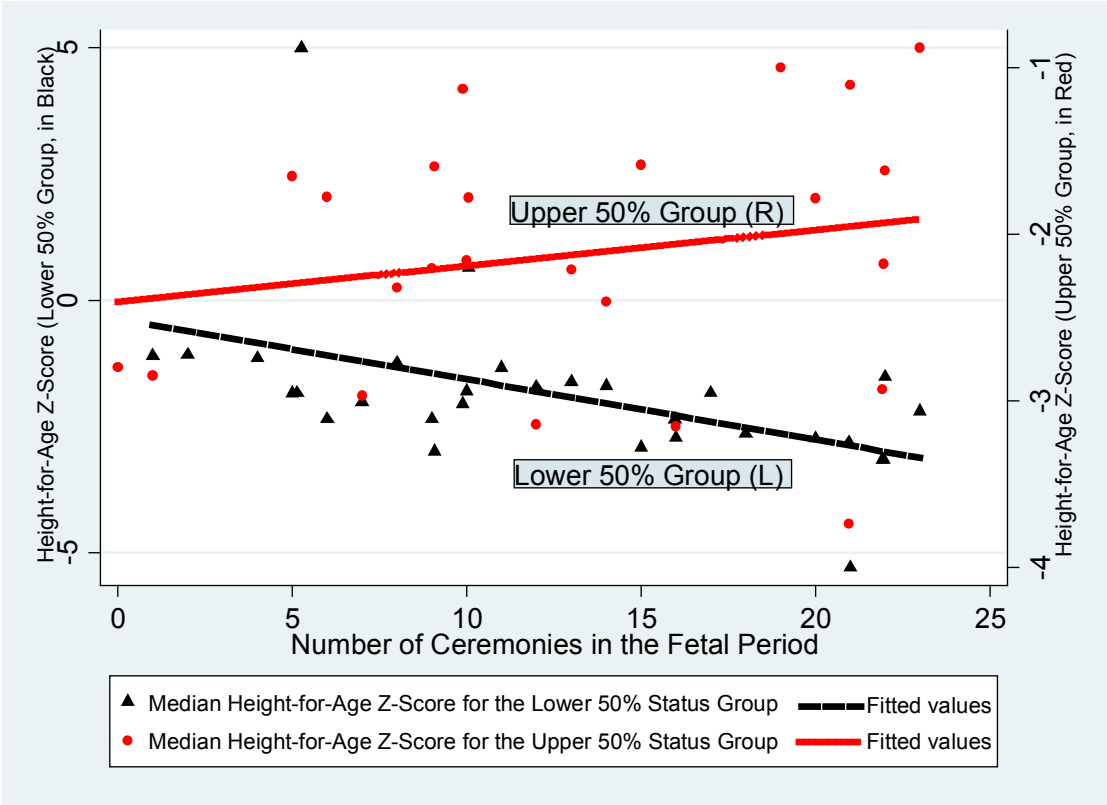


Figure 5.4 Number of Ceremonies and Height-for-Age Z-Score by Income Status Group

Notes: The high and low-income groups are divided based on the difference between household income and village median household income in the year prior to a child's birth. Because the income data are only available for three years when surveys were conducted, we use income data in 2004 to define income status in 2003 and 2004, data in 2006 to match income status in 2005 and 2006, and data in 2009 to infer income status in 2007. The anthropometric information for children born 2004-2008 are taken from the 2009 survey. The vertical axis represents the median height-for-age z-score corresponding to the number of ceremonies at the village level between 2003 and 2007.

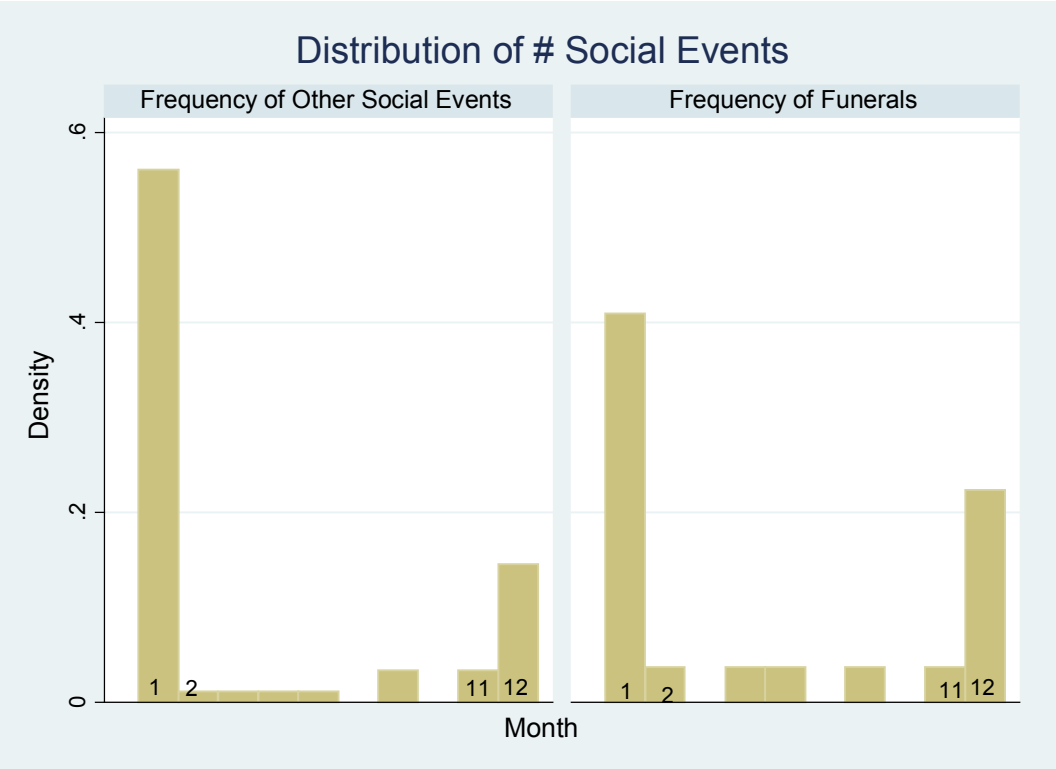


Figure 5.5 Distributions of Social Events by Month

Sources: Authors' Gift record data

Notes: Information on all ceremonies between 2005 and 2009 was collected from all households in three out of eighteen villages in rural Guizhou. Weddings and funerals are excluded from the left figure.

Table 5.1 Summary Statistics on Major Economic Indicators of Guizhou Household Surveys in 2004, 2006 and 2009

	Three Wave		
	2004	2006	2009
Per capita real annual income (RMB)	1404	1817	2855
Income below poverty line $1.25 per day using 2005 PPP (%) (P0)	71.3	64.1	52.7
Income below official national poverty line 892 RMB per year (%) (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
Income inequality (Gini)	43.1	48.2	55.2
(Mean) Deaton relative deprivation index	0.423	0.432	0.495
Share of consumption (%)			
Food	47.8	42.2	35.5
Gift and festival spending	7.9	13.9	15.2
Cash and In-kind Food Consumption (RMB)			
Grain	312.9	300.9	273.7
Condiment (salt, vegetable oil and animal oil)	134.9	138.8	115.8
Vegetable, fruit, tea, drink, cigarette and tobacco	134.1	236.1	229.0
Vegetable and fruit	-	126.9	170.8
Tea, drink, cigarette and tobacco	-	109.2	58.2
Meat, egg and dairy product	76.3	94.9	60.0

Source: Authors' survey data

Notes:

[1] The 2005 purchasing power parity (PPP) exchange rate is at the "China-rural" level http://iresearch.worldbank.org/PovcalNet/jsp/index.jsp . The Poverty lines for 2004-2009 are adjusted according to published annual inflation rate in various issues of *China Statistic Year Book.*

[2] The poverty line 892 RMB per year in terms of PPP equals $ 0.61 per day.

[3] Deaton Relative Deprivation Index (Deaton, 2001) measures household-specific relative status in a village. It is valued between 0 and 1. The larger the number, the lower the relative status, and the more relatively deprived a household is.

[4] All items of food consumption have been adjusted for inflation based on *China Statistic Year Book* published by NBS. All values are in RMB.

[5] Compared to the 2004 survey, in the 2006 and 2009 household survey more detailed information on subcategories of cash food expenditure was collected.

Table 5.2 Summary Statistics on Major Ceremonies in Three Villages

Year	Female Wedding		Male Wedding		Funeral		All the ceremonies		Gift giving per occasion by income group (CNY)			% of villagers attending funerals
	Gift size (CNY)	# of ceremonies	Gift size (CNY)	# of ceremonies	Gift size (CNY)	# of ceremonies	Gift size (CNY)	# of ceremonies	bottom 25%	middle 50%	top 75%	
2004	41.6	0.77	54.1	1.65	41.5	3.19	45.8	9.29	49.8	44.1	45.5	100%
2005	59.9	0.77	47.8	1.47	40.4	2.03	50.2	9.82	47.9	53.1	47.1	100%
2006	71.8	0.94	55.7	0.94	30.7	2.13	43.7	12.18	53.4	38.7	43.2	95.1%
2007	59.9	1.13	41.2	2.06	54.7	4.30	57.9	9.00	63.0	50.2	62.6	99.1%
2008	60.5	1.31	63.5	1.75	92.5	3.32	71.9	9.38	67.3	75.4	66.1	98.6%

Source: Authors' Gift record data

Notes:

[1] The gift spending data were based on gift records kept in all the households in three villages collected in the 2009 survey. They have been adjusted into constant 2004 price (RMB) using rural consumer price index published in *China Statistic Yearbook* (China National Statistical Bureau, various issues). A household's income status is based on its income standing in a village at a given year. Because the income data are available only for three years when surveys were conducted, we use household income surveyed in 2006 to proxy income status in 2005, and income data in 2009 to proxy income status in 2007 and 2008.

[2] The gift books record all the gifts received and the corresponding names of gift givers in different occasions. Based on these names, we can compute the participation rate for major events, such as funerals, within each village.

Table 5.3 The Effect of Funerals and Other Ceremonies on the Share of Food and Gift Cash Expenditure

	R1-Food Share	R1-Gift Share	R2-Food Share	R2-Gift Share
	SUR estimation		*SUR estimation*	
Rd * # of *ceremonies*	-0.068***	-0.010		
	(0.022)	(0.014)		
# of *ceremonies*	0.031**	0.009		
	(0.013)	(0.008)		
Rd * # of *funerals*			-0.041*	0.027*
			(0.025)	(0.016)
# of *funerals*			0.022	-0.001
			(0.015)	(0.010)
Year fixed effect	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes
(Pseudo) R2	0.242	0.277	0.230	0.269
N	1834	1834	2048	2048

Notes:

[1] The SUR estimation represents simultaneous regressions on the shares of cash expenditure spent on food and gift.

[2] The number of ceremonies refers to all major ceremonies excluding funerals held by others villagers in a village in the year prior to a child's birth. The number of funerals refers to funerals held by others villagers in a village in the year prior to a child's birth.

[3] Robust standard errors are in parentheses. The estimations are clustered at the year X village level. The symbols *, **, and *** indicate confidence levels at 90%, 95%, and 99%, respectively.

Table 5.4 Height-for-age Z-scores, Stunting Rate (%) and Underweight Rate (%)

Birth year	Total			Boys			Girls		
	Z-score	Stunting (%)	Underweight (%)	Z-score	Stunting (%)	Underweight (%)	Z-score	Stunting (%)	Underweight (%)
					WHO Standard				
2004	-1.93	45.59	16.18	-2.01	48.72	15.39	-1.82	41.38	17.24
2005	-2.10	40.39	13.46	-2.16	40.00	13.33	-2.01	40.91	13.64
2006	-2.23	53.19	17.02	-2.48	56.00	12.00	-1.99	50.00	22.73
2007	-1.88	33.96	16.98	-2.09	41.38	17.24	-1.58	25.00	16.67
2008	-2.55	45.00	16.67	-2.38	40.48	14.29	-2.91	55.56	22.22
					China CDC Standard				
2004	-2.48	55.88	23.53	-2.55	53.85	28.21	-2.39	58.62	17.10
2005	-2.53	50.00	13.46	-2.60	53.33	13.33	-2.40	45.46	13.64
2006	-2.53	59.57	19.15	-2.77	64.00	16.00	-2.29	54.55	22.32
2007	-2.22	47.17	16.98	-2.37	51.72	17.24	-2.00	41.67	16.19
2008	-2.61	46.67	13.33	-2.37	42.86	9.52	-2.94	55.56	22.22

Notes: Children's anthropometric indicators were taken from the 2009 survey. Stunting is defined as height-for-age z-score less than two standard deviations (SD) of the WHO standard and the China CDC standard. Underweight is defined as weight-for-age z-score less than two standard deviations (SD) of the WHO standard and the China CDC standard.

Table 5.5 Ceremony Frequency and Height-for-Age Z-scores by Income Group

Ceremony / Income Status	Frequent (1)	Less frequent (2)	(1)-(2)	Difference-in-Difference
		Birth year: 2004		
Lower 50%	-2.89	-1.66	-1.23 (3)	
Upper 50%	-1.04	-1.25	0.21 (4)	(3)-(4)= -1.44
		Birth year: 2005		
Lower 50%	-2.41	-1.98	-0.43 (3)	
Upper 50%	-2.01	-1.64	-0.37 (4)	(3)-(4)= -0.06
		Birth year: 2006		
Lower 50%	-3.06	-2.71	-0.35 (3)	
Upper 50%	-1.44	-1.41	-0.03 (4)	(3)-(4)= -0.32
		Birth year: 2007		
Lower 50%	-2.92	-0.42	-2.50 (3)	
Upper 50%	-2.12	-1.57	-0.55 (4)	(3)-(4)= -1.95
		Birth year: 2008		
Lower 50%	-3.27	-2.86	-0.41 (3)	
Upper 50%	-2.66	-2.18	-0.48 (4)	(3)-(4)= 0.07
		Birth year: 2004-2008		
Lower 50%	-2.87	-1.87	-1.00 (3)	
Upper 50%	-1.84	-1.70	-0.14 (4)	(3)-(4)= ***-0.86* (0.48)***

Notes:
The groups of "frequent" and "less frequent" are defined based on whether the number of ceremonies in a village is below or above the median number of ceremonies in our sample for a given year. The "Lower 50%" and "upper 50%" income groups are defined according to a household's income status compared to the median household income within its village in the year prior to a child's birth. In the last row, all the cohorts born between 2004 and2008 are combined. The standard errors are presented in parentheses.

Table 5.6 Exposures to Funerals and Other Ceremonies on Child Health Outcomes by Income Group

	R1-high	R2-low	R3-high	R4-low	R5-high	R6-low
	Height for Age (*OLS*)		Stunting (*Linear Probability*)		Underweight (*Linear Probability*)	
	Panel A: Funerals					
# of funerals *before* birth	0.421	-0.999*	-0.115	-0.056	-0.115	0.126**
	(0.313)	(0.586)	(0.095)	(0.102)	(0.084)	(0.051)
# of funerals *after* birth	0.39	0.084	-0.041	0.092	-0.178**	-0.072
	(0.417)	(0.407)	(0.119)	(0.081)	(0.067)	(0.062)
(Pseudo) R2	0.371	0.239	0.365	0.314	0.23	0.329
N	117	117	117	117	117	117
	Panel B: Other Major Ceremonies					
# of ceremonies *before* birth	-0.11	-1.458***	-0.028	0.255**	0.064	0.073
	(0.472)	(0.445)	(0.146)	(0.115)	(0.102)	(0.069)
# of ceremonies *after* birth	-0.155	-0.182	0.109	0.042	-0.108	0.08
	(0.386)	(0.576)	(0.122)	(0.140)	(0.098)	(0.090)
(Pseudo) R2	0.367	0.336	0.259	0.382	0.179	0.31
N	117	117	117	117	117	117

Notes: [1] Due to the small sample size, we divide the sample into high income group (R1, R3 and R5) and low income group (R2, R4 and R6) according to the difference between a household's income and the median income of households having child aged 1-5.
[2] The number of ceremonies and funerals refer to the total number of ceremonies (excluding funerals) and funerals held by others villagers in a village in the year prior to a child's birth. The health outcome measures are based on the WHO standard.
[3] Household level characteristics (ceremony frequency before and after child birth, predicted per capita income, head sex, education, cadre status, share of youth, share of the elderly, household size, share of migrants, minority identity, mother's height, other shocks), child characteristics (age dummy, sex, birth order), year fixed effects, village fixed effects and year X village fixed effects are also included but not reported here. The estimations are clustered at the year X village level.
[4] Robust standard errors are in parentheses. The symbols *, **, and *** indicate confidence levels at 90%, 95%, and 99%, respectively.

Table 5.7 Main Results: Exposures to Funerals and Other Ceremonies, Relative Status, and Child Health Outcomes

	R1-ceremony	R2-funeral	R3-ceremony	R4-funeral	R5-ceremony	R6-funeral
	Height for Age (*OLS*)		Stunting (*Linear Prob*)		Underweight (*Linear Prob*)	
	Panel A: Village and Year Fixed Effects Included					
Deaton Rd * # of events *before* birth	-1.599***	-2.123***	0.452*	0.541**	0.065	0.445*
	(0.671)	(0.712)	(0.269)	(0.248)	(0.219)	(0.230)
Deaton Rd * # of events *after* birth	0.838	0.677	-0.296	-0.183	0.050	-0.117
	(0.567)	(0.581)	(0.286)	(0.241)	(0.144)	(0.137)
(Pseudo) R2	0.382	0.389	0.293	0.302	0.200	0.219
AIC	592	576	188	239	224	211
	Panel B: Panel A + Village-specific Linear Time trends					
Deaton Rd * # of events *before* birth	-2.523***	-2.097***	0.615**	0.443*	0.040	0.348*
	(0.618)	(0.777)	(0.279)	(0.250)	(0.189)	(0.204)
Deaton Rd * # of events *after* birth	0.712	0.024	-0.404	-0.096	0.093	-0.055
	(0.690)	(0.530)	(0.288)	(0.205)	(0.121)	(0.130)
# of events *before* birth	0.525	0.860**	-0.205	-0.260*	0.062	-0.161
	(0.375)	(0.383)	(0.143)	(0.146)	(0.099)	(0.117)
# of events *after* birth	-0.538	-0.020	0.246*	0.055	-0.089	-0.061
	(0.389)	(0.422)	(0.143)	(0.144)	(0.081)	(0.090)
(Pseudo) R2	0.273	0.243	0.201	0.180	0.112	0.135
AIC	976	986	332	338	221	217
	Panel C: Panel A + Village X Year Fixed Effects					
Deaton Rd * # of events *before* birth	-2.627***	-2.241**	0.580**	0.401	0.134	0.377*
	(0.659)	(0.872)	(0.288)	(0.268)	(0.208)	(0.214)
Deaton Rd * # of events *after* birth	0.863	0.109	-0.439	-0.093	-0.013	-0.066
	(0.759)	(0.693)	(0.320)	(0.222)	(0.119)	(0.163)
# of events *before* birth	0.378	0.768	-0.121	-0.230	0.016	-0.170
	(0.458)	(0.460)	(0.178)	(0.150)	(0.127)	(0.112)
# of events *after* birth	-0.480	0.045	0.214	0.019	-0.008	-0.064
	(0.419)	(0.469)	(0.166)	(0.138)	(0.083)	(0.095)
(Pseudo) R2	0.287	0.256	0.227	0.231	0.120	0.161
AIC	986	996	338	345	232	221
N	234	234	234	234	234	234

Notes: see notes [2]-[4] for Table 5.6. To save space, Panel A does not show estimation results for # of events before and after birth.

Table 5.8 Falsification Test: Main Results using Contemporaneous Health Measure – Weight-for-Height Z-Score

	R5-ceremony	R6-funeral
	Weight-for-Height Z-Score (*OLS)*	
Deaton Rd * # of events *before* birth	0.692	0.571
	(1.335)	(1.239)
Deaton Rd * # of events *after* birth	0.311	-0.010
	(0.803)	(1.200)
# of events *before* birth	0.477	0.762
	(0.654)	(0.590)
# of events *after* birth	-0.038	-0.079
	(0.455)	(0.522)
(Pseudo) R2	0.206	0.210
N	231	231
AIC	1163	1162

Notes: see notes [2]-[4] for Table 5.6. Village fixed effects, year fixed effects and village X year fixed effects are controlled.

Table 5.9 Falsification Test: The Squeeze Effects of Exposure to Social Events on Early Child Health Outcomes

	R1	R2	R3
	Height-for-Age Z Score	Stunting	Underweight
	Panel A: Funerals		
Rd * # of funerals *before* birth	-0.408	0.027	0.059
	(0.295)	(0.059)	(0.051)
Rd * # of funerals *after* birth	0.069	-0.040	-0.015
	(0.183)	(0.039)	(0.035)
# of funerals *before* birth	0.236	-0.033	-0.029
	(0.205)	(0.028)	(0.032)
# of funerals *after* birth	-0.014	0.013	0.024
	(0.118)	(0.022)	(0.026)
(Pseudo) R2	0.192	0.213	0.160
N	234	234	234
	Panel B: Other Major Ceremonies		
Rd * # of ceremonies *before* birth	-0.437	-0.232	-0.021
	(0.605)	(0.164)	(0.135)
Rd * # of ceremonies *after* birth	0.213	-0.155	0.017
	(0.606)	(0.181)	(0.107)
# of ceremonies *before* birth	-0.051	0.337**	-0.027
	(0.441)	(0.140)	(0.088)
# of ceremonies *after* birth	0.326	0.016	0.028
	(0.360)	(0.092)	(0.067)
(Pseudo) R2	0.385	0.327	0.167
N	234	234	234

Notes: The specification is similar to Table 5.7 except that we lag the number of funerals / other major ceremonies for each age cohort by one year. Robust standard errors are in parentheses. Village fixed effects, year fixed effects and village X year fixed effects are controlled. The estimations are clustered at year X village level. The symbols *, **, and *** indicate confidence levels at 90%, 95%, and 99%, respectively.

Table 5.10 Robust Check: Exposures to Social Events on the Health Outcomes of Children Born Between February and September

	R1	R2	R3
	Height-for-Age	Stunting	Underweight
	Panel A: Funerals		
Rd * # of funerals *before* birth	-3.364***	0.824**	0.740**
	(1.064)	(0.341)	(0.294)
Rd * # of funerals *after* birth	-0.197	-0.044	-0.140
	(0.802)	(0.363)	(0.202)
# of funerals *before* birth	0.723	-0.338*	-0.449**
	(0.571)	(0.173)	(0.175)
# of funerals *after* birth	0.498	-0.035	-0.010
	(0.479)	(0.206)	(0.137)
(Pseudo) R2	0.246	0.251	0.248
N	146	146	146
	Panel B: Other Major Ceremonies		
Rd * # of ceremonies *before* birth	-4.141***	0.459*	0.863***
	(0.933)	(0.258)	(0.269)
Rd * # of ceremonies *after* birth	0.351	-0.335	-0.268
	(0.879)	(0.239)	(0.191)
# of ceremonies *before* birth	1.350**	-0.189	-0.538***
	(0.665)	(0.181)	(0.195)
# of ceremonies *after* birth	-0.557	0.240*	0.158
	(0.452)	(0.127)	(0.134)
(Pseudo) R2	0.277	0.189	0.177
N	146	146	146

Notes: The specification is the same as Table 5.7 except that we restrict our sample to children who were born between February and September. Robust standard errors are in parentheses. Village fixed effects, year fixed effects and village X year fixed effects are controlled. The estimations are clustered at year X village level. The symbols *, **, and *** indicate confidence levels of 90%, 95%, and 99%, respectively.

Table 5.11 Robust Check: The Squeeze Effects of Exposure to Social Events on Child Health Outcomes using Alternative Reference Groups

	R1	R2	R3
	Surname Networks		
	Height-for-Age Z-Score	Stunting	Underweight
	Panel A: Funerals		
Rd * # of *funerals* before birth	-2.242**	0.302	0.444*
	(1.009)	(0.304)	(0.238)
Rd * # of *funerals* after birth	0.379	-0.088	-0.103
	(0.780)	(0.239)	(0.180)
# of *funerals* before birth	0.639	-0.171	-0.170
	(0.493)	(0.161)	(0.116)
# of *funerals* after birth	-0.047	0.030	-0.057
	(0.477)	(0.142)	(0.099)
(Pseudo) R2	0.256	0.196	0.166
N	232	232	232
	Panel B: Other Major Ceremonies		
Rd * # of *ceremonies* before birth	-2.199***	0.310*	0.16
	(0.623)	(0.178)	(0.197)
Rd * # of *ceremonies* after birth	0.873	-0.409**	0.028
	(0.730)	(0.200)	(0.134)
# of *ceremonies* before birth	0.359	-0.09	-0.022
	(0.419)	(0.124)	(0.121)
# of *ceremonies* after birth	-0.279	0.209*	-0.043
	(0.383)	(0.104)	(0.086)
(Pseudo) R2	0.274	0.257	0.121
N	232	232	232

Notes: The specification is the same as Table 5.7 except that we replace villages with surname networks as reference groups. Surname networks are confined to the boundaries of a village. Village fixed effects, year fixed effects and village X year fixed effects are controlled. Robust standard errors are in parentheses. The estimations are clustered at the year X village level.

Table 5.12 The Impact of Fetal Exposures to Social Events on Early Child Health Outcomes (the China CDC Standard)

	R1-Ceremony	R2-Funeral	R1-Ceremony	R2-Funeral	R3-Ceremony	R4-Funeral
	Height-for-Age Z-Score		Stunting		Underweight	
Deaton Rd * # of events *before* birth	-2.615***	-2.089***	0.965***	0.509**	0.075	0.242
	(0.644)	(0.773)	(0.292)	(0.244)	(0.167)	(0.192)
Deaton Rd * # of events *after* birth	0.971	0.181	-0.322	0.173	-0.303*	-0.191
	(0.737)	(0.635)	(0.282)	(0.185)	(0.153)	(0.165)
# of events *before* birth	0.332	0.668*	-0.323*	-0.291**	0.118	-0.042
	(0.422)	(0.395)	(0.172)	(0.128)	(0.109)	(0.111)
# of events *after* birth	-0.496	0.066	0.061	-0.151	0.061	-0.026
	(0.402)	(0.439)	(0.144)	(0.123)	(0.095)	(0.100)
(Pseudo) R2	0.299	0.264	0.258	0.222	0.154	0.169
N	233	233	233	233	233	233

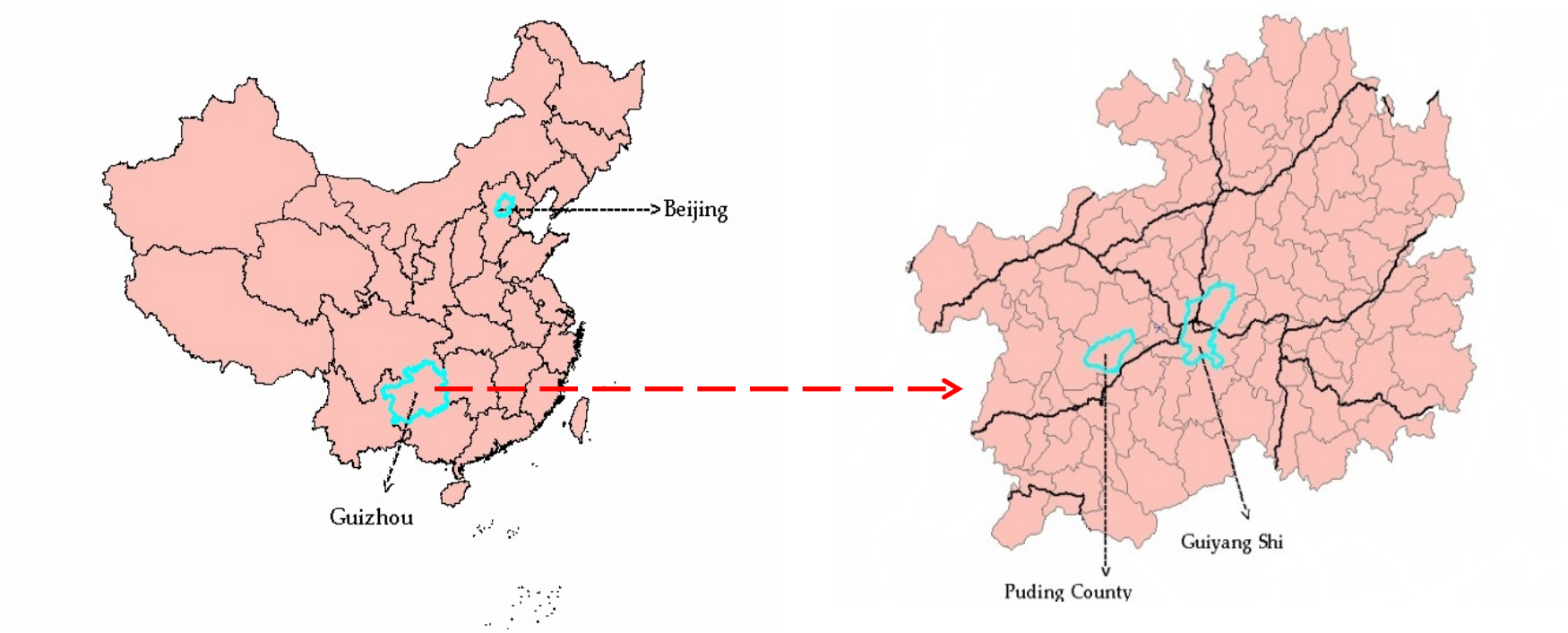
Notes: Village fixed effects, year fixed effects and village X year fixed effects are controlled. Robust standard errors are in parentheses. The estimations are clustered at the year X village level.

Table 5.13 Exposures to Funerals and Other Ceremonies and Child Health Outcomes by Gender

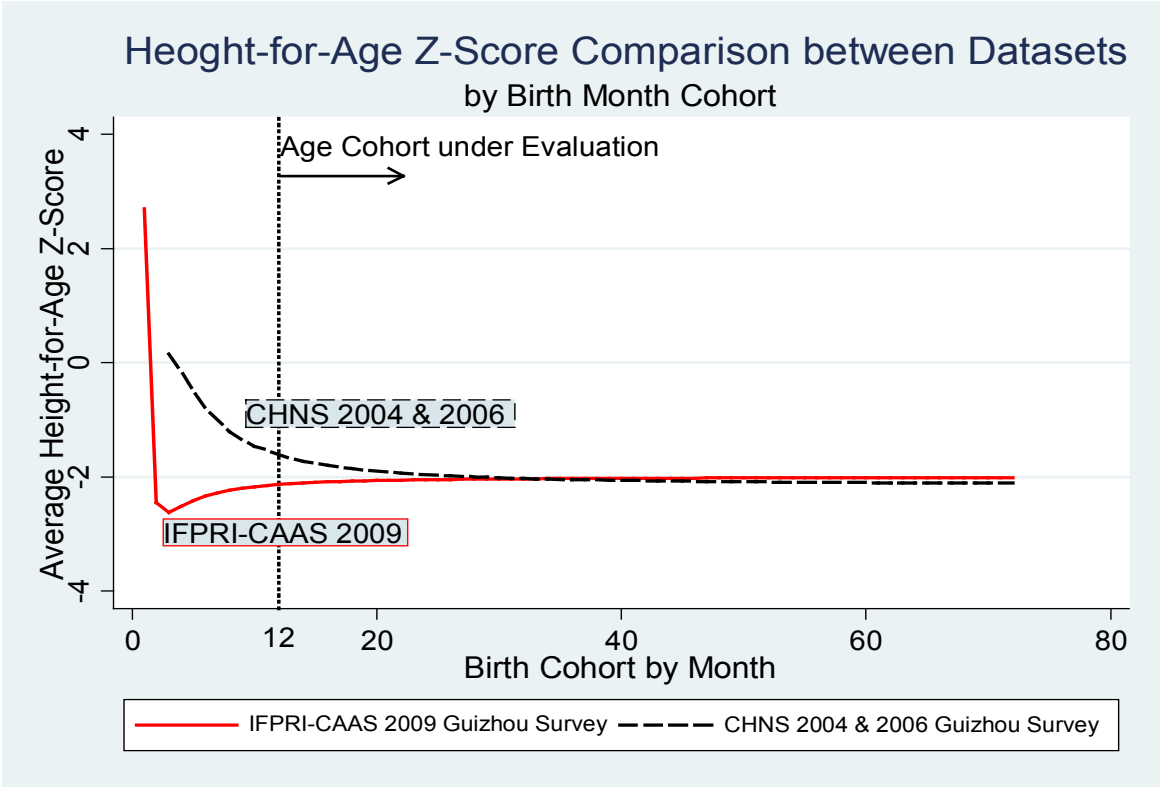
	R1-Boy	R2-Girl	R3-Boy	R4-Girl	R5-Boy	R6-Girl
	Height-for-Age z score *OLS*		Stunting (*Linear Probability)*		Underweight (*Linear Probability)*	
			Panel A: Funerals			
Rd* # of *funerals* before birth	-3.848**	0.14	0.246	0.475	0.329	0.300
	(1.703)	(1.023)	(0.366)	(0.397)	(0.295)	(0.381)
Rd* # of *funerals* after birth	1.462	-1.227	-0.232	0.24	-0.147	0.05
	(1.202)	(1.236)	(0.255)	(0.515)	(0.244)	(0.258)
# of *funerals* before birth	1.539*	-0.568	-0.195	-0.166	-0.148	-0.029
	(0.791)	(0.511)	(0.194)	(0.209)	(0.157)	(0.237)
# of *funerals* after birth	-1.207*	1.296	0.243	-0.267	0.07	-0.226
	(0.676)	(0.822)	(0.175)	(0.271)	(0.136)	(0.148)
(Pseudo) R2	0.336	0.392	0.324	0.335	0.233	0.251
N	138	95	138	95	138	95
			Panel B: Other Major Ceremonies			
Rd* # of *ceremonies* before birth	-2.903***	1.307	0.377	-0.047	0.003	-0.045
	(1.065)	(1.552)	(0.354)	(0.685)	(0.259)	(0.432)
Rd* # of *ceremonies* after birth	0.628	-0.227	-0.354	0.358	0.089	0.087
	(1.194)	(1.848)	(0.330)	(0.738)	(0.176)	(0.343)
# of *ceremonies* before birth	0.796	-2.297**	-0.058	0.255	0.056	0.315
	(0.660)	(0.931)	(0.214)	(0.425)	(0.151)	(0.247)
# of *ceremonies* after birth	-0.799	0.838	0.263	-0.277	0.121	-0.376**
	(0.704)	(1.062)	(0.173)	(0.387)	(0.114)	(0.183)
(Pseudo) R2	0.343	0.42	0.336	0.325	0.228	0.252
N	138	95	138	95	138	95

Notes: The number of funerals and other major ceremonies refer to the total number of relevant events held by others villagers in a village in the year prior to a child's birth. Village fixed effects, year fixed effects and village X year fixed effects are controlled. Robust standard errors are in parentheses. The estimations are clustered at year X village level. The symbols *, **, and *** indicate confidence levels at 90%, 95%, and 99%, respectively.

Appendix Figure 1: A Map of the Location of Surveyed Region



Appendix Figure 2: Height-for-Age Z-Score for CHNS Guizhou Data and Our IFPRI-CAAS Sample



Sources: Our IFPRI-CAAS 2009 wave Guizhou survey has a sample size of N=276 in the age range of 1-72 months. To closely match our sample, CHNS 2004 & 2006 subsample from Guizhou province is the best option available. The CHNS data comes from an ongoing international collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention, available via http://www.cpc.unc.edu/projects/china. Both waves of survey were conducted in 9 provinces. In total, there are 137 children in the age range of 1-72 months in rural Guizhou.

Notes: This paper evaluates the impact of prenatal exposure to social events for children between 12-72 months. The patterns of z-score between the two datasets after the 12th month are very similar. However, our IFPRI-CAAS survey is of census type, which better represents the demographic pattern in China – unbalanced sex ratio. The *China 1% Population Survey 2005* indicates that sex ratio at birth in Guizhou province is 128:100 (Zhu et al., 2009), in rural Guizhou this number should be even higher. Sex ratio between 1-72 months in the IFPRI-CAAS sample is around 139:100, while the ratio is 70:100 in CHNS 2004 & 2006 Guizhou sample.

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