CORNELL UNIVERSITY

MASTER THESIS

Social Interactions in the Presence of Community Shock

A thesis submitted in fulfillment of the requirements for the degree of Master of Science

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"Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism."

Cornell University

Abstract

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Master of Science

Social Interactions in the Presence of Community Shock

by

Social networks play a vital role in rural China. Households are not isolated; they are connected via a network through various cooperative, sharing, and gift exchange behaviors. In the absence of well-functioning formal institutions, such social networks often serve as the informal contracts. This paper develops a model of risk sharing in the wake of an earthquake, and examined the determinants of the self-enforcing conditions. Based on the theoretical result, we further provide empirical evidence of the labor sharing behavior of 1420 rural household before and after the 2008 Sichuan earthquake. We found that the households exposed to higher intensity of earthquakes significantly reduced their effort in investing in and maintaining the labor sharing network. We further examined gift-exchange, another important social interactions that links various households in rural China as a robustness check. We found that people significantly reduce their gift giving behavior in the aftermath of the disaster: one degree increase in earthquake intensity is associated a reduction in gift frequency for one 0.85 to 1 times per year in 2009, and 0.26-0.41 times per year in 2011, respectively. The potential channel is that the unexpected natural disaster introduced a shift in time discount factor, and people were "living like there's no tomorrow" (Filipski et al., 2015), reduced the reliance on informal social networks, and cut down social investment for the future. While other channels proposed in the model, such as income, income correlation coefficient, risk aversion rate, and network size are not significant.

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This thesis is dedicated to my beloved family.

Chapter 1

Background

1.1 Introduction

Social networks have been gaining growing popularity in the economic literature during the past decade. This question is of essential importance in the developing world, since social networks often serve as the informal contracts in the absence of well-functioning formal institutions (Chandrasekhar, Kinnan, and Larreguy, 2014). Social interactions among agents play an important role in various domains of the peasants' daily lives, from production to credit. For example, shared labor in farmwork helps to reduce the contractual cost in hiring an extrafamily labor; gift-exchange mechanism and non-interest loans are substitutes for the formal credit market; word-of-month information and friends' reference enables non-farm job searching (Munshi and Rosenzweig, 2015; Montgomery, 1991). Understanding how social interactions work in the developing world has great policy implications for improving the welfare of the poor.

One of the most fundamental functions for social networks in rural areas is risk sharing, which has been explored intensively for decades in the field of development economics (Fehr, Gächter, and Kirchsteiger, 1997, Fafchamps and Lund, 2003, Bloch, Genicot, and Ray, 2008,Takasaki et al., 2011). The informal network of mutual insurance that is enforced by social pressure ties individuals together when a disaster occurs (Douty, 1972). Examples of the village level, mutual support includes gift giving, work-sharing arrangements, reciprocal interest-free credit, shared meals, communal access to land, and sharing bullocks (Fehr, Gächter, and Kirchsteiger, 1997; Scott, 1976). Gifts and free interest loans from a close network of friends and relatives help to smooth consumption in the face of idiosyncratic risk (Bloch, Genicot, and Ray, 2008; Fafchamps and Lund, 2003). Labor-sharing arrangements, which are determined mainly by network endowment, could help the poor farmers find extrafamily labor that is rare due to constraints on labor liquidity (Gilligan, 2004; Takasaki et al., 2011), and it helps to reduce the adverse effects of idiosyncratic production shocks (Dercon, Hoddinott, and Woldehanna, 2005).

One central question is: is the risk sharing network self-enforcing? To our knowledge, whether the social network as an informal risk-sharing contract is self-enforcing and the determinants of self-enforcing condition before and after a shock still remains to be explored. This paper will answer this question and fill this research gap both theoretically and empirically. We will firstly present a theoretical framework to analyze how networks operate in the aftermath of a disaster. We also provide empirical evidence using a three-year panel data collected in rural Sichuan, China from both before and after the 2008 Sichuan earthquake. The econometric results indicated that people were less willing to invest in and maintain the social network if they suffered heavily from the earthquake.

Another gap in the network literature in the developing societies is the availability of high quality network data. Different from data retrieved from on-line sources (Facebook data, etc), the information of social links is costly to obtain through household surveys and is often inaccurate. Ideally, researchers survey each individual to identify all the network nodes, and capture the lists of each respondent's connection (Bramoullé, Galeotti, and Rogers, 2016). But this brings two potential problems: (1) if the questions are cumbersome to answer (recall the relationship with each of the other households in the survey) , it is easy to lose respondents (Fafchamps and Gubert, 2007) or get partial answers, (2) sometimes the questions are relatively easier (i.e. "to recall the person you turn to when in trouble" (Fafchamps and Lund, 2003), "to name some friends in the network" (Elliott and Golub, 2013)), but the subjective answers of social links are discordant (individual i cites j but j doesn't cite i). These issues will bring further identification problem (Comola and Fafchamps, 2014).

A pioneering work is Chen (2007), in which the author collected information on pairwise connections of gifts exchange from the gift-record books of 335 rural households in Guizhou, China, along with information on kinship and relatedness to match each of the 9820 potential gift-link. Another network dataset is jointly collected by Bharatha Swamukti Samsthe (BBS) and the research team of Jackson, which covers 13 types of relationships between any two individuals from 75 Indian villages [1]. Studies on information diffusion process and was conducted based on this dataset (Jacobs et al., 2013, Banerjee et al., 2013).

Due to the feasibility and cost of field work, the adoption of economic experiment to study social networks in the developing world has also been gaining popularity (Fehr, Gächter, and Kirchsteiger, 1997). However, the answers from hypothetical questions (such as dictator games) may not be a good estimator for real-world behaviors (Gray, 2013). For example, the dictator game and other experiment show that people tend to share and cooperate, even though they might not necessarily do so in the real world (Helbing and Balietti, 2010, Hoffman, McCabe, and Smith, 1996). Therefore, to estimate cooperative behavior using real world data would provide a more accurate evidence, and contribute to the the existing empirical literature.

In this paper, we build a more approachable measurement for networking behavior, which helps us to lessen the reliance on a perfect data. The standard network theory suggests that there are two types of "connectedness" in a system, the first one is at the level of structure- the linkages among individuals; and the second one is at the level of behavior- the implicit consequences of agent's actions on everyone else in the network (Easley and Kleinberg, 2010). We rely on the second type of connection, and use the frequency of networking behavior to describe the strength of social networks. The frequency is a self-reported level for a certain behavior. [2] This approach is also consistent with the recent network theory using the repeated games to model informal insurance. Some similar approaches in previous literature include Bloch, Genicot, and Ray, 2008, where they count the number of

[1] See Banerjee, Chandrasekhar, Duflo, and Jackson (2013), and publicly available at http://economics.mit.edu/faculty/eduflo/social

[2] We investigated seven network-based behaviors, including labor sharing in agricultural production, information sharing on non-farm jobs, informal borrowing and lending, helping in proctoring the workers in house construction, helping in taking care of the children and elders, helping in holding a wedding ceremony, helping in holding a funeral. Those different measures for network behavior help us to better understand the social interactions in the aftermath in Sichuan. We choose the first one as the main behavior of intereat in this paper.

rounds of communication as the "level".

This paper therefore contributes the literature in three ways. First, it develops a simple model to examine the determinants of self-enforcing risk sharing contracts among members of a network. Second, it provides empirical evidence to advance our understanding about the long term impact of natural disaster as a determinant of such self-enforcing constraints. Third, it attempts to measure the network density based on the frequency of interactions among agents using the regular household survey data.

The paper is organized as follows. Chapter 1.2 provides literature review on the impact of natural disasters and various determinants for social interactions. Chapter 1.3 provides background information about the 2008 Sichuan earthquake, the earthquake intensity measurement, and describes the dataset. Chapter 2 develops a theoretical model to analyze the risk sharing arrangement and the role of natural disaster. Chapter 3 provides empirical evidence of labor sharing behavior in the aftermath of a disaster that are based on the theoretical findings. Gift-exchange as another form of social interaction has also been examined as a robustness check.

1.2 Literature Review

Our paper contributes to the network formation in the presence of a community shock. Network formation is of key interest to economists. Presumed that network formation and agents' behaviors are connected, vast theoretical literature examines the self-organizing network relations using game-theoretic approaches, which include the existence of stable and efficient networks (Jackson and Wolinsky, 1996, Jackson and Nouweland, 2005, Galeotti, Goyal, and Kamphorst, 2006), the evolution of network in a dynamic setting (whether it is fixed, shrinking or growing over time)(Gomes and Jehiel, 2005, Manea and Leishman, 2011, Lee and Fong, 2013). In a more complex dynamic setting with risk, Blume et al., 2011 and Blume et al., 2013 developed the strategic network formation in the presence of contagious risk to capture the trade-off between the benefit of link formation and the potential contagious risk. Under this situation, the socially stable networks lies in the points where most of the available welfare has been lost. The contagious risk including epidemic disease, financial contagion is of interest in the real world; but the non-contagious risks, such as a community level natural disaster, also exert tremendous impact on the society. Would a natural disaster disturb or enhance the stability of the cooperative agreement? How do the agents anticipate the future potential gain and the period payoffs in the aftermath of a disaster? These issues are all of particular interest in evaluating the performance of social networks and provide targeted policy suggestions to improve the social welfare. To our knowledge none have analyzed the network formation under common and unexpected shock, which is the focus of this paper.

However, the primary contribution of this paper is not theoretical; rather, it aims to provide the empirical evidence of how natural disasters impact social networking behavior, and build a simple model to examine the self-sustainable condition of informal networks. To achieve these goals, we will firstly review the impact of disasters on human behavior, followed by various determinants of network-based cooperation and sharing. Finally, we put particular attention to risk sharing and provide a review on relevant topics.

1.2.1 A review on impact of natural disasters

Natural disasters not only cause devastating psychical damage, life losses, and reduce the economic growth (Pelling, Özerdem, and Barakat, 2002; Rose et al., 1997), they also impact people's mental health and behavior in the long run. The medical literature documented intensively on the Post-Traumatic Stress Disorder (PTSD). Economic studies focus more on the behavioral and preference changes related to PTSD. For example, natural disasters update people's beliefs and perceptions towards to a riskier place (Skidmore and Toya, 2002). The increased potential risk of natural disaster may make people more apt to cooperate (Yamamura, 2010), reduce the expected risk of physical capital, and lead to increased human capital investment as a substitution for physical capital (Toya and Skidmore, 2007).

A number of studies have demonstrated the positive effect of social networks and social capital in disaster recovery process(Aldrich, 2012a; Nakagawa and Shaw, 2004; Aldrich, 2012b; Tse, Wei, and Wang, 2013; Yamamura, 2010). But the reverse direction, i.e. the impact of disaster on social networks have been ambiguous. On the positive side, Veszteg, Funaki, and

Tanaka, 2015 found that mutual trust increased in the aftermath of the 2011 Thohoku earthquake using a trust game; Yamamura, 2016 showed that the 1995 Great Hanshin-Awaji (Kobe) earthquake significantly enhanced agents' social investment through group activity participation; Siegel, Bourque, and Shoaf, 1999 suggested that an altruistic (social cohesion) may have arisen in the aftermath of the 1994 Northridge earthquake in California. On the negative side, Fleming, Chong, and Bejarano, 2014 discovered that reciprocity within community is lower one year after the 2010 Chilean earthquake, while the trust level were not affected. The impact could also be mixed: Castillo and Carter, 2011 found that intermediate shocks enhance social interactions, while extreme shocks undercut cooperation. Therefore, it is crucial to understand the underlying mechanism through which the earthquake impact social networks.

1.2.2 A review on determinants of social exchange, cooperation, and sharing

Development economists have long examined the interpersonal interactions among the poor. Such interpersonal behaviors include cooperation, sharing, and exchanges, which help to form an informal contract when formal institutions are weak or absent (Fafchamps and Gubert, 2007, Townsend, 1994,Udry, 1994). In this section, we review the determinants of those networking behaviors from literature spanning development economics, game theory, social network theory, and the behavioral economics.

Firstly, *economic incentives* are one major determinant in individual's decision making process. The basic assumption is that individuals are self-interested and they can form and server links. They benefit from connections while pay a cost of maintaining it (Watts, 2003, Jackson and Wolinsky, 1996). Unequal income distribution in a network may lead to instability in social capital through rising mistrust and stress. Thus the households in lower social ranking may have stronger incentives to participate in the social behaviors with "positional externalities", such as blood donation, gift giving, etc.(Chen and Zhang, 2010) In non-repeated situations, economic incentives are key factors (Tabellini, 2008).

Secondly, people are forward-looking, and thus *expectation towards future* influences social exchange. In every period, people take into consideration the cost of forming and maintaining links against potential future rewards and future reciprocity in a long run or in a short run (Bala and Goyal, 2000,Coate and Ravallion, 1993). The former on, potential rewards, is calculated based on time discount factor. While the latter one, reciprocity, has been regarded as the intrinsic motivation for the enforcement of many informal contracts, where people are kind to the ones who helped them, and punish those who hurt them (Fehr, Gächter, and Kirchsteiger, 1997). A default in current period transaction may be prevented by threatening the potential defaulter to be excluded from future transactions (Udry, 1994, Barr, Dekker, and Fafchamps, 2012). In repeated situations, this reputation consideration plays a more important role (Fehr, Gächter, and Kirchsteiger, 1997, Tabellini, 2008). Due to the feature of expecting future returns, Bourdieu, 1986 points out that social connections are the product of investment strategies rather than givens. It is also noticeable that individuals are not just forward-looking, but also learn from the past. Therefore, previous interactions help to form one's social capital (Nahapiet and Ghoshal, 1998), and determine the cost of creating, maintaining, or terminating the relationship with another agent(Lee and Fong, 2013).

Thirdly, besides self interest, people's social behaviors are also influenced by the environment where they share *common values*, and where *peer effect* exists. Social norms plays an important role in forming the link. For example, people cannot refuse a gift, or not to contribute a gift in others' ceremony under the pressure of social norms, even if this is against their self-interest. (Comola and Fafchamps, 2014) And social norms in the common environment significantly impact one's sharing action in a network(Bandiera, Barankay, and Rasul, 2010; Galeotti, Ghiglino, and Squintani, 2013; Nahapiet and Ghoshal, 1998) Peer pressure shape the incentive to cooperative(Kandel and Lazear, 1992). Individuals' behaviors are largely influenced by the choices of their friends and acquaintances via a social network. A worker's productivity is significantly higher when she works with more able friends (Bandiera, Barankay, and Rasul, 2010,Dolfsma, Eijk, and Jolink, 2009).

Fourth, *social distance* plays a key role. Blood ties and friendship benefit cooperative arrangement (Kimball, 1988), and risk is more likely to be shared in tightly knit group(De Weerdt, 2002). Empirical evidences have shown that socially close pairs maintain high levels of cooperation even when the enforcement is moved using an field experiment in 34 Indian villages (Chandrasekhar, Kinnan, and Larreguy, 2014); 97% of the informal loans were between neighbours and relatives in rural Nigerian villages (Udry, 1994); close friends and relatives are more than three times as likely to join the same risk pooling group (Genicot et al., 2011). The Darwinist perspective also illustrates that helping family members help to expand the gene pool (Cartwright, 2016, Dovidio et al., 2017).

Other factors include personal *risk aversion rate, trust, emotion*, as well as *exogenous intervention*. Farmers with high risk aversion form cooperatives which involves substantial sharing of output, and can provide insurance at lower cost (Kimball, 1988). Trust is associated with the closeness among friends and relatives because of intrinsic motivations, such as guilt (Genicot et al., 2011). Holländer, 1990 conceptualized cooperative and sharing behavior as emotional activity motivated by the expectation of social approval. Such approvals include sympathy (v.s. antipathy), love (v.s. hate), gratitude (vs. resentment), joy (vs. grief), pride (vs. shame), admiration (vs. contempt). Through social exchange the members of group form standard behavior which is shared and confirmed by everyone. Under this situation, even though the social exchange allocation is not Pareto-efficient, it may provide more of the collective good and thus "higher group welfare" compared with other allocations (optimal planning allocation or hypothetically ideal market allocation excluding approval incentives). The exogenous impact, such as the opening of a market or government intervention for collective goods, may also affect agents' outside option (Lee and Fong, 2013), and exert an negative effect on voluntary cooperation (Holländer, 1990). This determinant is consistent with our hypothesis that lack of formal institution fosters the formation of informal contract to serve functional purposes, such as the allocation of goods and labor in the absence of a perfect market (Jackson and Wolinsky, 1996, Fafchamps and Lund, 2003, Townsend, 1994, Udry, 1994).

In sum, the determinants for social exchange, sharing, and cooperation could be concluded as four major aspects: self-interest motivation, social norms and peer effects, expectation towards future, outside institutional intervention. Those factors from previous theories and empirical evidences help us to analyze the mechanism of the changes in social networks in the aftermath of a natural disaster.

1.3 Background and Data

1.3.1 The 2008 Sichuan Earthquake

The 2008 Sichuan earthquake, also known as the Wenchuan earthquake, took place on May 12 with the epicenter in Sichuan province. The earthquake reached a magnitude of 8.0 on the Richter scale, and caused a large amount of physical and economic damage across Sichuan province in southwestern China. Over 68,000 people were reported dead in Sichuan province, and over 374,000 were reported injured by falling debris and building collapses. It was the deadliest earthquake for more than 30 years in China. The earthquake was also felt in nearby provinces, and as far as northern China, such as Beijing. It was also followed by numerous aftershocks spreading the entire region in the following years[3].

A three-year reconstruction project was carried out by the central government, 1 trillion RMB (about US $ 146.5 billion) financial support from the government and millions of donations from society was spent for the recovery in the affected communities.

Following the immediate rescue plan, the central government announced a three-year reconstruction plan worth 1 trillion RMB, which is approximates the annual GDP in Sichuan Province in 2007. The funding was allocated to rebuilding housing (29%), infrastructure (21%), enterprises (14%), and public services (11%) (Huang, 2010). Besides the central government-oriented aid (NGA), the non-governmental organizations aid (NNA), and the International humanitarian aid (IHA), the Chinese government also developed an innovative reconstruction framework, the national counterpart aid (Xu and Lu, 2012). Under this framework, 18 most affected counties in the earthquake in Sichuan province were supported by 18 provinces in China, and each of these provinces was required to commit one percent of its annual GDP to help to re-build the houses, roads, and other types of assistance.

[3]https://en.wikipedia.org/wiki/2008_Sichuan_earthquake

1.3.2 Earthquake Intensity Measurement

Previous economic studies use distance to epicenter as a popular proxy for earthquake severity. But it might be an accurate measurement as the intensity is also related to soil type and geographical conditions. A better proxy for earthquake severity is instrumental intensity, which is based on a combined regression of recorded peak acceleration (rate of change of speed g), and peak velocity (the greatest speed, rate of movement, cm/s). But as the shake maps are generated automatically within seconds after an earthquake, the acceleration and velocity values are often raw and not checked by humans. This may intrigue measurement errors. Moreover, ground motions can vary significantly over short distances, and thus the shake maps are rough approximates. The criticism is that "at small scales, they should be considered unreliable" [4].

Some psychological and economic studies use self-reported earthquake stress as indicator for the severity of earthquake. Each individual was given a life-events inventory, and she or he answered how upsetting or aversive the earthquake was on a 4-point Likert-type scale with the end points not at all and extremely. But the subjective measures may induce endogeneity in the regression.

In this paper, we use the Modified Mercalli Intensity (MMI) maps as the measurement for earthquake intensity. The advantage of MMI is that quantifies the observed effects of an earthquake on the Earth's surface, humans, objects of nature, and man-made structures on a scale (USGS). Therefore, it is more accurate to approximate the real effect of an earthquake. An abbreviated description of the levels of Modified Mercalli intensity is shown in Figure 1.1. [5]

[4] https://escweb.wr.usgs.gov/share/shake2/haywired/about.html

[5] These "Instrumental Intensities" are based on a combined regression of peak acceleration and velocity amplitudes vs. observed intensity for eight significant California earthquakes (1971 San Fernando, 1979 Imperial Valley, 1986 North Palm Springs, 1987 Whittier, 1989 Loma Preita, 1991 Sierra Madre, 1992 Landers, and 1994 Northridge). http://earthquake.usgs.gov/earthquakes/shakemap/background.php

Estimated Population Exposed to Earthquake Shaking

Estimated Modified Mercalli Intensity		I	II-III	IV	V	VI	VII	VIII	IX	X
Est. Population Exposure		--*	--*	1,547k*	63,801k*	18,835k	4,006k	1,245k	528k	2k
Perceived Shaking		Not Felt	Weak	Light	Moderate	Strong	Very Strong	Severe	Violent	Extreme
Potential Structure Damage	Resistant	none	none	none	V. Light	Light	Moderate	Moderate/Heavy	Heavy	V. Heavy
	Vulnerable	none	none	none	Light	Moderate	Moderate/Heavy	Heavy	V. Heavy	V. Heavy

*Estimated exposure only includes population within calculated shake map area

FIGURE 1.1: Modified Mercalli Intensity (MMI) Measurement
Sources: U.S. Geological Survey. http://earthquake.usgs.gov/earthquakes/shakemap/background.php

1.3.3 Data

We merged three databases of the household survey in Sichuan province in 2007, 2009, and 2011 with about 1500 households. The pre-disaster and post-disaster information from both earthquake and non-earthquake places forms a unique natural experiment, which allow us to estimate the social and economic impact of the natural disaster on local communities. The first database is the Sichuan component of the annual rural panel administered by the Research Center for the Rural Economy (RCRE), which is an annual national rural panel since 1984. Our data includes 800 households in Sichuan province from 16 villages, and four of these villages are affected by the earthquake. The second database is a supplementary survey administrated jointly by the RCRE and the International Center for Agricultural and Rural Development (ICARD), which includes several follow up questions regarding the earthquake and farmer's coping strategies towards the disaster. The third database is the Sichuan Rural Household and Migration Survey (SRHMS) administrated jointly by Shanghai University of Finance and Economics and ICARD. It includes about 700 households from 6 villages in Mianzhu County starting from 2007, one year before the earthquake, and repeated in 2009 and 2011. Mianzhu County became one the most severe affected counties in the 2008 earthquake. The SRHMS and the RCRE database have enough common questions that allow us to combine them together. By merging the three databases we construct a unique database of around 1500 sample spanning Sichuan province, including a prior disaster baseline (See Table 1 for summary statistics used in this study).

Figure 1.2 presents the epicenter and magnitude of the earthquake, as well as the locations of our sample villages. We use GIS software to match each village with MMI map from the USGS website. [6] The layered color corresponds to the MMI table in Figure 1.1, where red color is the most severe earthquake, followed by yellow and green. The dots represent the sample villages, they are spanning over Sichuan province. The big pentagram is the epicenter, and the smaller pentagrams are the aftershocks.

[6] Available at http://earthquake.usgs.gov/earthquakes/shakemap/ as of June 2015.

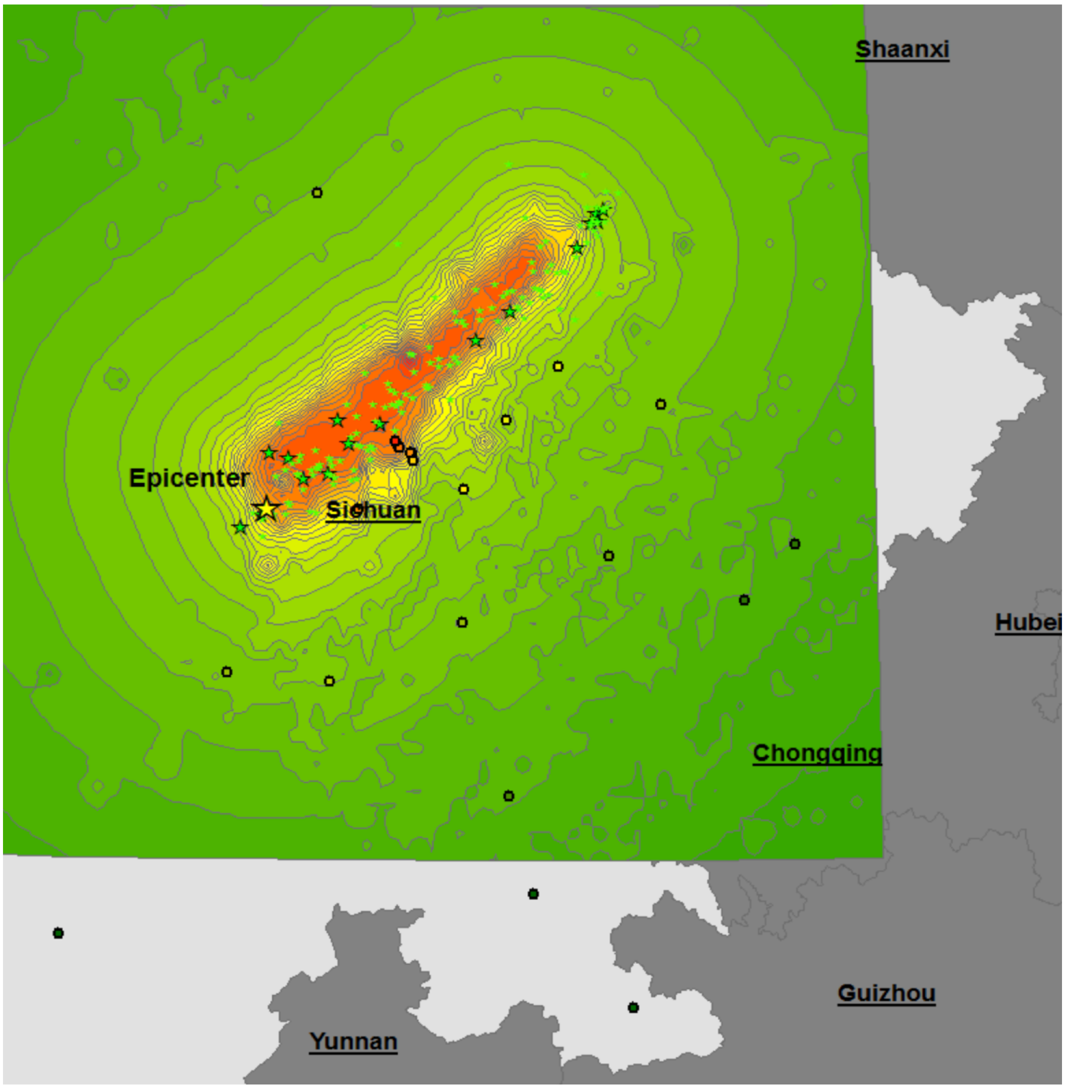

FIGURE 1.2: The Map of the 2008 Sichuan Earthquake Intensity -Epicenter, aftershocks, and sample villages

Sources: Datasets from annual rural panel administered by Chinese Ministry of Agriculture's Research Center for the Rural Economy (2007, 2009, 2010) and Sichuan Rural Household and Migration Survey, Shanghai University of Finance and Economics, and the International Center for Agricultural and Rural Development (2007, 2009, 2010). U.S. Geological Survey.

http://earthquake.usgs.gov/earthquakes/shakemap/background.php

1.3.4 Conclusion

In this chapter, we studied natural disaster as a determinant of self-enforceability conditions. While there is a vast economic literature in social networks spanning game theory, development economics, and behavioral economics, this paper focus on the role of natural disaster in the stability of the informal risk sharing network. In addition, we summarized the impact of natural disaster, particularly the impact on social interactions and cooperative behaviors to build the link between natural disaster and social exchanges. The empirical results of whether natural disaster promote or harm social interactions is mixed, while the theoretical framework has not been developed in previous literature. We also reviewed the determinants of social exchange, cooperation and sharing and concluded four major aspects from previous literature, they are: self-interested motivation, social norms and peer effects, expectation towards future, and outside institutional intervention. Followed by the literature review, we turn to the disaster explored in this paper, the 2008 Sichuan earthquake. We introduced the background information of this earthquake, and described how we collected the three-wave household dataset from both before and after the Sichuan earthquake. The MMI measurement of earthquake intensity is also introduced and visualized by a map together with our sample villages. In the next chapters, we will incorporate our findings in the theoretical model as well as in the empirical estimation.

Chapter 2

Model Specification

2.1 A Model on Risk Sharing in the Wake of a Disaster

In this section, we develop a theoretical model that allows us to evaluate the determinants of social transfers before and after a shock in a small network setting. We consider an infinite horizon, dynamic, discrete game setting. The features that we incorporate into the model include household income, income correlation among all households, household risk aversion rate, time discount factor, and network size. We aim to explore the self-enforcing condition of the risk sharing arrangement (risk sharing network).

We consider discrete time with $t = 0, 1, 2, ...$ A collection of households $i = 1, ..., N$ makes up a friendship/kinship network. N is the network size, and it is different from the concept "network". [1] The income of each household i in the network at each time period is a random variable y_i. We assume that there is no auto-correlation for household income, i.e. the current income is not correlated with past income, and each y_i is identically distributed with mean $\bar{y}$ and variance σ^2. Since members of the network reside in proximate locations, their income realizations are not necessarily independent. Let ρ be the correlation coefficient of the income level for any two households in the network. For simplicity, we furthermore assume that y_i has a two-point support $y_i = \{y^-, y^+\}$ where $y^+ > y^-$, representing periods of good and bad

[1] While *network* is a broad concept in economic theory and other fields (computer science algorithm, etc), we refer to two different concept in our paper. The first one is risk sharing network, which is an informal arrangement in rural China. The second one is network size, which refers to the number of households one can connect to and is regarded as the household characteristic in this paper.

harvest, for example.

The risk preferences of each household can be represented by a von-Neumann Morgenstern utility function $U(y_i)$, which takes the form:

$$U(y_i) = y_i - \frac{r}{2}y_i^2 \tag{2.1}$$

where r denotes the coefficient of absolute risk aversion.

Member households within the network participate in risk sharing. They do so by solving a linear programming problem akin to Townsend (1994), which seeks the Pareto Optimal income allocations such that the weighted average of the household utilities is maximized.

The Baseline Expected Utility

The expected utility of any single household in the absence risk sharing as EU_0 is a function of the mean and variance of the household's random income.

$$EU_0 = EU(y_i) = E(y_i - \frac{r}{2}y_i^2) = \bar{y} - \frac{r}{2}(\sigma^2 + \bar{y}^2) \tag{2.2}$$

Pareto Optimal Income Sharing

At each time period, there can be $n = 0, 1, ..., N$ number of households who face negative income shocks, with $y_i = y^-$. Let $p(n)$ denote the probability that n number of households experience negative income shocks. For any given $n \leq N - 1$, the network of N households can solve a maximizing problem wherein the N households transfer income from the collective pool $\sum_i^n y_i$ to an individual household i in order to maximize the total utility of the network:

$$\max_{s_i} W(n) = \sum_i^N U(y_i + s_i) \tag{2.3}$$

$$\textit{subject to} \quad \sum_1^N s_i = 0$$

$$\sum y_i = ny^- + (N-n)y^+ \tag{2.4}$$

The Lagrangian is given by

$$L = \sum_{i}^{N} U(y_i + s_i) - \lambda \sum_{1}^{N} s_i \tag{2.5}$$

The first order conditions are:

$$\frac{\partial W(n)}{\partial s_i} = 1 - r(y_i + s_i) - \lambda = 0 \;\; \forall i$$

The Pareto optimal transfers s_i depending on the income revelation of household i as a function of n are therefore given by

$$s_i^{+}(y^{+}, n) = \frac{ny^{-} + (N-n)y^{+}}{N} - y^{+} \tag{2.6}$$

$$s_i^{-}(y^{-}, n) = \frac{ny^{-} + (N-n)y^{+}}{N} - y^{-} \tag{2.7}$$

$$s(y_i, n) = \frac{ny^{-} + (N-n)y^{+}}{N} - y_i \tag{2.8}$$

The income inclusive of transfers $y_i + s(y_i, n)$ is $\frac{ny^{-}+(N-n)y^{+}}{N}$. Thus the expected utility of a household in the presence of first best risk sharing is

$$\begin{aligned} EU_N &= E\left(\frac{\sum_{i=1}^{N} y_i}{N} - \frac{r}{2}\left(\frac{\sum_{i=1}^{N} y_i}{N}\right)^2\right) \\ &= \bar{y} - \frac{r}{2}\left(\frac{\sigma^2}{N} + \frac{N-1}{N}\rho\sigma^2 + \bar{y}^2\right) \end{aligned} \tag{2.9}$$

Interpretation of first best

The Pareto optimal transfer for each household $s(y_i, n)$ is given in (2.7), which equals to the difference between the village level mean income $\bar{y}$ and individual i's income y_i. The mean income $\bar{y}$ thus is positively correlated with optimal transfer, while the income variance σ^2, income correlation ρ have no impact on the level of optimal transfer. The network size N is positively related to the optimal transfer. In the first best situation, the individual household income will finally be equalized after the transferring. As a result, the households receiving good income faced a temptation to renege such risk sharing agreement in the absence of an external enforcement.

The welfare gains from risk sharing is:

$$EU_N - EU_O = \frac{r(N-1)(1-\rho)\sigma^2}{2N} \tag{2.10}$$

which is positively correlated with income variance σ^2. The economic implication is that agents facing with larger income uncertainty would benefit more from the risk sharing arrangement. The income correlation coefficient ρ between each household pair is negatively correlated with the welfare gains, which indicates that households with uncommon income patterns have greater gains from forming a risk sharing network. The network size N contributes to welfare gains, which means that the effect is larger is more people participate in the sharing arrangement.

Now let the probability of all N household experience negative income shock be $\bar{p}$ at every period, the discounted expected utility EV_N of a risk sharing network is given by:

$$\begin{aligned} EV_N &= \sum_{t=0}^{\infty}\sum_{i=1}^{N}(\frac{1}{1+R})^t U(y_i + s_i) \\ &= \sum_{t=0}^{\infty}(\frac{1}{1+R})^t N\{\bar{y} - \frac{r}{2}(\frac{\sigma^2}{N} + \frac{N-1}{N}\rho\sigma^2 + \bar{y}^2)\} \\ &= (1+\frac{1}{R})N\{\bar{y} - \frac{r}{2}(\frac{\sigma^2}{N} + \frac{N-1}{N}\rho\sigma^2 + \bar{y}^2)\} \end{aligned} \tag{2.11}$$

2.1.1 Incentive Compatibility

Now let's consider the self-enforceability of the risk sharing arrangement. In the current period, the households with negative income shocks would always choose to participate in the risk sharing arrangement and receive a positive amount of transfer. However, for the households facing positive income shocks, they may have the attempt to renege from the network to avoid a current-period income loss. Suppose a household will face expected utility EU_0 starting from the next period onwards if he renege the risk sharing arrangement. In the repeated games, the household incorporate current period utility and the expected future utility in decision making process.

The optimal transfer in the network would equalize the income among all agents. Thus, households who are lucky enough to earn y^+ have to pay for a negative amount of transfer s_i. Suppose such a household refuses to pay for the transfer and choose to renege such arrangement, then it will face expected utility EU_0 starting from the next period onwards.

The discounted expected utility over the infinite horizon of reneging household from current period onwards at discount rate R, when the probability of N households experience negative income shock is $\bar{p}$ is given by.

$$\begin{aligned} E\widetilde{V}_N &= U(y^+) + \sum_{t=1}^{\infty}(\frac{1}{1+R})^t EU_0 \\ &= y^+ - \frac{r}{2}y^{+2} + \sum_{t=1}^{\infty}(\frac{1}{1+R})^t[\bar{y} - \frac{r}{2}(\sigma^2 + \bar{y}^2)] \\ &= y^+ - \frac{r}{2}y^{+2} + \frac{1}{R}[\bar{y} - \frac{r}{2}(\sigma^2 + \bar{y}^2)] \end{aligned} \tag{2.12}$$

Assume that throughout all the periods, if no one reneges, a network always selects the first best level of transfer. Thus the discounted expected utility over the infinite horizon of non-reneging household at discount rate R is the baseline utility with post-transfer income $y^+ + s^+$ plus the discounted utility of EU_N of each period onwards.

$$\begin{aligned} EV'_N &= U(y^+ + s^+) + \sum_{t=1}^{\infty}(\frac{1}{1+R})^t EU_N \\ &= U(y^+ + \frac{n}{N}(y^+ - y^-)) + \sum_{t=1}^{\infty}(\frac{1}{1+R})^t EU_N \\ &= y^+ + \frac{n}{N}(y^+ - y^-) - \frac{r}{2}(y^+ + \frac{n}{N}(y^+ - y^-))^2 + \frac{1}{R}[\bar{y} - \frac{r}{2}(\frac{\sigma^2}{N} + \frac{N-1}{N}\rho\sigma^2 + \bar{y}^2)] \end{aligned}$$

The risk sharing contract will be self-enforcing if and only if the expected utility of joining the contract is greater than reneging in infinite horizons, that is $EV'_N - E\widetilde{V}_N > 0$, which is known as the incentive compatibility constraint.

$$\begin{aligned} &EV'_N - E\widetilde{V}_N \\ &= \frac{n}{N}(y^- - y^+) - \frac{r}{2}[\frac{N-n}{N}y^+ + \frac{n}{N}y^-]^2 + \frac{r}{2}y^{+2} + \frac{r(N-1)(1-\rho)\sigma^2}{2NR} \\ &= \frac{n}{N}(y^+ - y^-)[ry^+ - \frac{nr}{2N}(y^+ - y^-) - 1] + \frac{r(N-1)(1-\rho)\sigma^2}{2NR} > 0 \end{aligned} \tag{2.13}$$

when $n = N - 1$, the self-enforcement constraint becomes:

$$EV'_N - E\widetilde{V}_N$$
$$= \frac{N-1}{N}(y^+ - y^-)\{\frac{r}{2}[y^+ + y^- + \frac{1}{N}(y^+ - y^-)] - 1\} + \frac{r(N-1)(1-\rho)\sigma^2}{2NR} > 0 \tag{2.14}$$

which is always greater than zero if we require the income y to be large enough. That is, if $N - 1$ households suffered from a negative income shock, then the risk sharing arrangement is self-enforcing.

2.1.2 Interpretation

Now let labor sharing be the primary means of income sharing among the N households because all of them participate in agricultural production. Suppose that a self-enforcing risk sharing arrangement is in place before a disaster. The set of characteristics of households included in our model is $\{\bar{y}, \sigma^2, \rho, r, N, R\}$ the mean income $\bar{y}$, which is mainly determined by agricultural productivity; the household income variance σ^2, determined by weather shocks, pests, and other production shocks; risk aversion rate r, time discount factor R, network size N; income correlation coefficient ρ among households.

Existing literature has explored the impact of earthquake on the above characteristics. People update their perception of risk after experiencing a disaster. Most previous studies have claimed that people are more risk averse if they suffering from a disaster (Cameron and Shah, 2015, Havenaar et al., 2003, Sacco, Galletto, and Blanzieri, 2003), while some other literature found that people were not always more risk averse (Li et al., 2011). For time discount factor, Filipski et al., 2015 investigated that the 2008 Sichuan earthquake has induced a shift in people's time preference, where they put greater preference for the present and "living like there's no tomorrow". This founding is consistent with the adjusting discount rate for uncertainty in cost-benefit analysis. Intuitively, income correlation coefficient within a village ρ would increase if the entire network was impacted by a common shock.

The self-enforcing condition given in (2.15) describes the static relationship of several determinants for such an arrangement to be self-enforcing. The comparative statics provide more information on how the features of household may determine their incentives to participate in the cooperative arrangement. The partial derivatives of the self-enforcing condition (equation 2.12) with respect to the discount factor R and the mean income $\bar{y}$ are negative, while the partial derivatives with respect to network size N, income variance σ^2, risk aversion rate r, and income correlation coefficient ρ are positive. The comparative statics indicate that an decrease in time discount factor, network size, risk aversion rate, and income correlation coefficient would reinforce the self-enforcing condition.

$$\frac{\partial(EV'_N - E\widetilde{V}_N)}{\partial N} > 0, \quad \frac{\partial(EV'_N - E\widetilde{V}_N)}{\partial \sigma^2} > 0 \tag{2.15}$$

$$\frac{\partial(EV'_N - E\widetilde{V}_N)}{\partial \rho} < 0, \quad \frac{\partial(EV'_N - E\widetilde{V}_N)}{\partial r} > 0 \tag{2.16}$$

$$\frac{\partial(EV'_N - E\widetilde{V}_N)}{\partial \bar{y}} < 0, \quad \frac{\partial(EV'_N - E\widetilde{V}_N)}{\partial R} < 0 \tag{2.17}$$

A community shock will act on those factors for all the households simultaneously, shift their incentives to invest in and maintain the social network, and and therefore facilitate the performance of informal risk sharing network in the society.

We will further test the theoretical results using the empirical data from before and after the 2008 Sichuan earthquake. Based on the availability of data and previous literature, we find the proxy for each of those household characteristics. The estimation of income $\bar{y}$ and σ^2 has played a central role in agricultural economics. One of the standard approach is to assume the distribution of income and estimate the parameters based on panel data or cross-sectional/time serious data including output, price, consumption, and other relevant information observed by economists (Lin, Dean, and Moore, 1974,Just, Zilberman, and Hochman, 1983). In this paper, we simply control for the real income and other production-related factors to control income. The risk aversion of various measures have also been an essential part in determining dynamic results of behavior under uncertainty in agricultural economics literature (Bar-Shira, Just, and Zilberman, 1997, Just, Zilberman, and Hochman, 1983). We simply assume that the representative household have the same risk aversion rate, and the risk aversion level would increase in the post-disaster period (Skidmore and Toya, 2002). For the rest three features, income correlation coefficient, time discount factor, and risk aversion rate, we didn't control for them due to the constraint of the data. Our strategy is to check whether the empirical result is consistent with the theoretical prediction. A further discussion is provided in Chapter 3.

Chapter 3

Labor Sharing

3.1 Introduction

In this chapter, we provide empirical results of the impact of natural disaster on labor sharing behavior in the village networks in rural Sichuan, China. This type of reciprocated labor-sharing arrangement is of paramount importance in rural developing areas (Fafchamps and Lund, 2003). It often serves as a substitute for formal contract enforcement for better resource allocation when the formal labor institutions are missing or imperfect. The agricultural labor under such arrangements has been given various names, such as cooperative labor, reciprocal labor, collective labor, exchanged labor, and communal labor (Erasmus, 1956; Moore, 1975; Takasaki 2011). The notion of such reciprocal exchange in agricultural production are rooted in pre-capitalist societies, and is still widely existed in many developing areas.

There are several advantages of such labor arrangements. Firstly, it is one of the primary mechanisms for risk sharing in the rural society(Takasaki et al., 2014, Gilligan, 2004, Barr, Dekker, and Fafchamps, 2012, Fafchamps and Lund, 2003). The cooperative labor helps to smooth out the bottleneck in any seasonal labor shortage, mobilize labor when lacking the cash to hire extra-family labor, and provide protection against health risk since agricultural operations must be done in a timely fashion (Fafchamps and Lund, 2003, Takasaki et al., 2014). Secondly, cooperative labors perform synchronous work faster and are thus more productive than family labors (Takasaki et al., 2014). Through adjustments in labor reciprocity, the labor-sharing arrangements are efficient in increasing production by accomplishment of certain tasks at a lower cost than hired labor (Abizaid et al., 2015). Besides, the sharing arrangements also play social functions by serving as a source of group identify and solidarity (Mitchell, 2006). In conclusion, the households form an informal network arrangement through reciprocal labor sharing.

3.2 Description of Key Variables

Our research interest is to explore the impact of natural disasters on labor sharing arrangements. Thus our key variables include measurement of labor sharing, intensity of earthquake, and other household-level or village level characteristics that are relevant to labor sharing.

3.2.1 Dependent Variable: Measurement of Labor Sharing Arrangement

The data uses categorical measurement for labor-sharing frequency. Farmers are asked to indicate how often they helped their neighbors and friends in the farm work during agricultural harvest season. Score 1 indicated never, 2 indicated sometimes, and 3 indicated very often. We collected information from the year 2007 and 2011, so we have both pre-disaster and post-disaster information for the 2008 Sichuan Earthquake.

We choose this frequency of labor sharing behavior to describe the performance of the sharing arrangement for three reasons. Firstly, our goal is to examine the changes in general networking behavior in the presence of a disaster, instead of focusing on the structure of social pairs (whether it is one sided or reciprocated, etc.). Secondly, the level of behavior is one of the two forms of connectedness in the network theory, it is the implicit consequences of agent's actions on everyone else in the network (Easley and Kleinberg, 2010). Thirdly, the level of behavior is a straightforward question for network density and is available in our data. While there are many other different aspects of network measurement as described in Chapter 1, we believe the level of reciprocal behavior is most appropriate one in this study.

3.2.2 Explanatory Variables: Earthquake Intensity

Our primary proxy for earthquake intensity is the Modified Mercalli Intensity (MMI), which quantifies the observed effects of an earthquake into different levels. It is computed using the MMI map from the United States Geological Survey (USGS) and the geographic information systems software (GIS). We use this measurement across all specifications, and use distance to epicenter for robustness check. As shown in Figure 1.2, there are also many aftershocks scattered near the epicenter which last for almost two years after the 2008 Sichuan Earthquake, we admit that not having controlled for those aftershocks in one shortcoming in this study.

3.2.3 Other Control Variables

We reviewed the determinants of sharing and cooperative behaviors in Chapter 1, and incorporate the relevant features in our theoretical model in Chapter 2. There are many aspects to consider when people make a decision to share or to cooperate, including economic situation, time preference, emotion, status concern, etc. Therefore, we control for standard demographic information, including household size, which is the total number of family members in a household; a dummy variable for household head gender; education years for household head; a dummy variable for household head's party membership; household income (the ln value of total income in RMB), and landownership (acre) in all regressions. Besides, we control for.

3.3 Empirical Results: Labor Sharing in the aftermath of 2008 Sichuan Earthquake

3.3.1 General trend

Figure 3.1 plots the average changes in labor sharing behavior in the sample villages. The twenty one villages out of twenty two samples experienced significant decrease in labor sharing, as shown in the fitted lowess curve. Moreover, the reduction was related to the earthquake intensity. Villages exposed to severe earthquakes tend to show a greater decrease in sharing behavior among the agents.

FIGURE 3.1: Changes in labor sharing behavior and fitted lowess curve over time in areas that were affected and in areas not affected by the 2008 earthquake in Sichuan, China

Notes: The y-axis are the changes in the average frequency of labor-sharing behavior before and after the earthquake. The frequency was measured by a self-reported scale from 1 to 3 (1 means never, and 3 means very often). The x-axis is the MMI earthquake intensity that represents different locations. The size of the dot is proportional to the sample size in each location. The line is the *Lowess Curve* curve with a bandwidth of 0.6.

3.3.2 Identification

Estimation 1: OLS Model

To test the general trend in Figure 3.1 that the severity of earthquake is associated with decreased labor sharing behavior, we regress labor sharing frequency on the interaction of the earthquake intensity and post-disaster dummy. Our identification strategy is similar to the difference-in-difference model, except that our treatment was not binary; we used the continuous measure MMI for earthquake intensity to represent the variation in the treatment. By using panel data, we were able to isolate the exogenous effect of the earthquake by taking the difference before and after the disaster, and compare the differences across households that experienced different levels of earthquakes. Our baseline regression is the Linear Ordinary Least Square:

$$sharing_{vit} = \alpha T_t^{post} + \gamma Intensity_v \times T_t^{post} + x_{vit}\beta + v_{vi} + l_v + \varepsilon_{vit} \quad (3.1)$$

The left-hand side variable, $sharing_{vit}$ is the frequency of labor sharing behavior for household i in period t. T_t^{post} is an indicator variable that equals one for the period after the earthquake, $Intensity_v$ is the earthquake intensity suffered by household i at village v, x_{vit} is time-varying household characteristics that included the household head's gender, age, age squared, party membership, education, household size, and landholdings.

We also include a set of household fixed effect and location fixed effects in equation (3.1). Household fixed effects v_{vi} control for unobserved time-invariant household preference for sharing cooperation. Location fixed effects l_v (twenty-two dummies for each village) control for time-invariant local preference and culture for labor sharing. The term ε_{vit} is unobserved random shocks following normal distributions, which are time varying and location specific. The coefficient α measures the effect of the earthquake and other time trends that were common to all the households (for example, regional changes in agricultural mechanization, labor migration, and other province-level shock for labor sharing activity). And γ is our coefficient of interest that distinguishes the impact of the earthquake (i.e., whether the intensity of the earthquake explains the changes in the left-hand-side in time i compared to the base year). The results are presented in column (1) of Table 2.

Estimation 2: Ordered Logistic Model

Our variable of interest, the frequency of labor sharing behavior, takes discrete values 1, 2, and 3. The survey respondents choose those answers on scale, where 1 indicates "very rare" and 3 indicates "very often". The underlying assumption in the OLS regression is that the distance between the three categories are all equal, which is problematic. Therefore, we use the ordered logistic model to relax this assumption, the identification thus becomes:

$$\boldsymbol{sharing^*_{vit} = \alpha T^{post}_t + \gamma Intensity_v \times T^{post}_t + x_{vit}\beta + v_{vi} + l_v + \varepsilon_{vit}} \tag{3.2}$$

The left-hand side variable $sharing^*_{vit}$ is the latent variable of frequency of labor sharing behavior for household i in period t, which is an exact but unobserved variable. T^{post}_t, $Intensity_v$, x_{vit}, v_{vi}, and l_v are the same with the baseline OLS regression. The random shock ε_{vit} follows a logistic normal distribution. The coefficients α measures common time trends, and γ is our coefficient of interest that distinguishes the impact of the earthquake.

$$C_{vit} = k \ if \ \kappa_{k-1} < sharing^{*}_{vit} < \kappa_k, \ k = 1, 2, 3 \tag{3.3}$$

The thresholds for the frequency are strictly increasing, where 3 indicates very frequent labor sharing behavior, while 1 indicates no sharing, $(i.e. \kappa_{k-1} < \kappa_k$ and $\kappa_0 = -\infty, \kappa_{k+1} = +\infty)$. Therefore, the probability of observing outcome k for household i at time t is given by:

$$\begin{aligned} Prob(C_{vit} = k|\kappa, x_{it}, v_i) = \Lambda(\kappa_k - \rho T_t^{post} - \gamma Intensity_v \times T_t^{post} - x_{it}\beta - v_i) \\ - \Lambda(\kappa_{k-1} - \rho T_t^{post} - \gamma Intensity_v \times T_t^{post} - x_{it}\beta - v_i) \end{aligned} \tag{3.4}$$

where Λ is the logistic distribution function with the form $\Lambda(u) = (1 + exp(-u)^{-1})$. We can assume the time-invariant household heterogeneity v_{vi} to be random. The results are presented in column (2) and column (3) of Table 2.

Estimation 3: Fixed effects ordered logit (FE-OL)

The *Ordered Logistic Model* does not control for unobserved time-invariant heterogeneity v_{vi} (such as household's farming habit, etc) in the maximum likelihood estimation for three reasons. Firstly, only the difference $v_{ik} = \kappa_k - v_i$ can be identified. Secondly, under fixed time, asymptotic $\kappa_k - v_i$ is biased due to identical parameter problem.(Lancaster, 2000) Thirdly, the bias of estimated coefficients are substantial in short panels (Greene, 2004). Thus we applied the *Fixed-effect Ordered Logistic Model* to control for the individual unobservable heterogeneity.

Therefore, we collapse $sharing_{it}$ to a binary variable and get estimates, since it is feasible to add fixed-effects to a binary model. Our strategy is similar to Mukherjee et al., 2008 that estimators rely on conditional logit estimation of dichotomized ordered responses. We define a variable $d_{it} = I(sharing_{it} > \kappa_k)$, where $I()$ is the indicator function and k is a cutoff point. The probability of observing a sequence of outcomes $d^k_{it} = (d^k_{i1}, d^k_{i2}, ...d^k_{iT})$ conditional on the ones in the sequence is:

$$Prob(d_{it}^{k}|\sum_{1}^{t} d_{it}^{k} = v_i) = \frac{exp(\sum_{1}^{t} d_{it}^{k} x_{it}\beta)}{\sum_{I_{i=B_i}} exp(\sum_{1}^{t} I_{it} x_{it}\beta)} \tag{3.5}$$

where the β_i is the set of all possible outcomes that have same number of ones as d_i^k. Chamberlain, 1979 showed that maximizing the conditional log likelihood gave a consistent estimate of β.

Assume error terms ε_{it} are i.i.d and follow a logistic distribution, then the minimum sufficient statistic for v_i is $\sum_1^t C_{it}^k$. Conditioning on this sufficient statistic, we can get a consistent estimate by maximizing the conditional likelihood function. Therefore, each individual's contribution to the conditional likelihood would not depend on v_i (Chamberlain, 1979).

In an ordered response situation, we can collapse the C_{it} to a binary variable and get estimates using the method above. By minimizing the distance of all those estimates, we are able to get the final estimates, which are unbiased and consistent, as proved by Chamberlain. (Chamberlain, 1979) Therefore the most important step is to choose the cutoff points to collapse the ordered C_{it}. One suggestion is to use all $k-1$ possible cutoff points (Baetschmann, Staub, and Winkelmann, 2011; Das and Van Soest, 1999). Das and Van Soest, 1999 estimated the coefficient $k-1$ times and used the $k-1$ different cutoff in each time (known as DvS estimator, Minimum Distance estimator, or MD estimator). Baetschmann, Staub, and Winkelmann, 2015 first enlarged the dataset where each individual was repeated $k-1$ times, and clustered the standard errors by individual (known as Blow-up and cluster, or BUC estimator). In this paper, we follow the BUC approach. We firstly repeat each household's information twice, therefore each household has two identical observations. Then we collapse the category data of these two observations using different criteria. In one observation 1 is treated as 0, 2 and 3 are treated as 1; while in another observation 1 and 2 is treated as 0, and 3 is treated as 1. We run the fixed-effect logistic regression using this new dataset, and cluster the standard error by households. The results are presented in column (4) of Table 2.

3.3.3 Empirical Results

Table 2 summarizes the results from linear regression and logistic regressions. Household characteristics, including household size, household head gender, household head age, household head education years, party membership, household income, and landownership, are controlled in all the specifications. The coefficients of the interaction term, the intensity and post disaster dummy are significantly negative across all the specifications. Column (1) reports the ordinary least squares (OLS) estimation results with natural village fixed effect and household fixed effect. One degree increase in the earthquake intensity is associated with 0.11 score decrease in labor sharing behavior at 1% significance level.

Column (2) and column (3) report the results from Ordered Logistic regression. Natural village fixed effects are included in (3) to control for village-specific time-invariant factors that might have influenced sharing behavior, such as village history, customs, and village growth potential. The coefficient of the interaction term are both negative and significant, with similar magnitudes. As the magnitude of the coefficients in logistic level are in log-odd form, and does not have a simple interpretation, we examine the significance level. Both the coefficients of the interaction term are significantly below zero, at 1% significant level and 10% significant level.

Column (4) reports the result from Fixed-effect Logistic regression. The number of household reduced from 1420 to 526, since the households who did not change the sharing behavior would be eliminated from the fixed-effect logistic regression. The information loss is huge from this regression, but the remaining 526 households who adjusted their behaviors under the shock of an earthquake are of our primary interest. The coefficient is negative at 5% significance level, and the magnitude is similar to the results from ordered logistic regression. All regression results indicate that one magnitude increase in the earthquake is associated with a lower probability of labor sharing behavior in the farmwork.

TABLE 2: Impacts of earthquake on labor sharing behavior from OLS and Logistic

	(1)	(2)	(3)	(4)
Variables	Linear FE	Logistic	Logistic	Logistic FE
Intensity*year2011	-0.110***	-0.245***	-0.026*	-0.284**
	(0.018)	(0.089)	(0.089)	(0.140)
year2011	0.656***	1.175**	-0.270	0.663
	(0.118)	(0.572)	(0.544)	(0.837)
Constant	1.210***			
	(0.260)			
Observations	2,606	2,606	2,606	1053
Number of id	1,420	1,420	1,420	526
Village FE	NO	No	YES	NO
Household FE	YES	NO	NO	YES

Notes: The dependent variable is labor sharing frequency in 2007 and in 2011. The frequency was measured by a self-reported scale from 1 to 3 (1 means never, and 3 means very often). The controls are village-fixed effects, or/and household fixed-effects, and household characteristics (household size; household head gender, age, education years, party membership; household income, and landownership). Robust errors in parentheses, clustered at the village level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3.4 Robustness checks

The correlation between the shock intensity and the reduced labor sharing behavior doesn't indicate causality. There are multiple potential sources of endogeneity in our estimation. The primary concern with our independent variable is the measurement of shock. If the independent variable, earthquake intensity is not exogenous, the estimation would be biased. Omitted variables may also affect the result. Thus we add additional controls for the labor sharing behavior in the baseline regression, including network size and local employment status. There are also potential correlated unobservables that drive the changes in general social interactions. We will use another reciprocal behavior, gift exchange, as a robustness check.

In this section, we argue that the earthquake intensity is exogenous, and control for

Earthquake Intensity

In this paper, we use the Modified Mercalli Intensity (MMI) as the measurement for the earthquake. The advantage of this measurement has been discussed in Chapter 1. It quantifies the observed effects of an earthquake on the Earth's surface, humans, objects of nature, and man-made structures on a scale (USGS). However, the the inclusion of experienced damage in this measurement is our first worry of endogeneity. It might be correlated with the error term and thus induce estimation bias. We therefore run a robustness check using an alternative measurement for earthquake intensity, the distance to earthquake epicenter.

The distance to epicenter has been widely used in the evaluation of earthquake impact (Filipski et al., 2015). It is easy to compute and is a fully exogenous proxy for damages. The estimation result using this measurement is shown in table 4, column (4). The impact is very similar to MMI estimation, where people living closer to the epicenter significantly decreased their labor sharing activities.

The endogeneity could also be caused by the self-selected migration and people's previous knowledge about disasters. Such beliefs shift the expectation towards future, and thus bring pre-determined heterogeneity in different areas. To relieve this worry, we examined the earthquake record in Sichuan area, and found no history of huge earthquake in the past three decades (USDG). Therefore, it is reasonable to assume that people's belief about the arrival of future shocks are the same before the 2008 earthquake.

The third potential source of endogeneity is the unobservable geology and topography in local area. The geographical conditions are not only relevant to earthquake intensity, but also impact the crop diversity, locations of households, cultivation system, and thus determine the habit of sharing and cooperation in the farming activities. (Abizaid et al., 2015) To solve this problem, we firstly conduct a baseline regression to check whether sharing activities differ across locations before the earthquake happens. The significant correlation between labor sharing and earthquake intensity indicates that there's indeed baseline difference in sharing activity across villages. This could be caused by geographical conditions, culture, or some other unobservable location-specific conditions. Our hypothesis is that geographical condition in different areas have parallel time trend, thus we could successfully control for unobservable geology and topography using the difference-in-differences method in our specification. The alternative hypothesis is that geology and topography have involved differently in the earthquake area and the non-earthquake areas. For example, the shock may have exerted different impacts on soft soils v.s solid soils, and thus induce some different changes in agricultural behavior. In this case, we argue that such changes are also caused by the earthquake. We admit that an instrumental variable is desired to support this argument, and this is one of the shortcomings of this study.

TABLE 3: Robustness Check of Earthquake Intensity and Labor Sharing Behavior

	(1)	(2)	(3)	(4)
Year	Year 2007	Year 2011	Year 2007	Year 2011
MMI	-0.0721***	-0.0797***		
	(0.0130)	(0.0127)		
ln(distance)			0.232***	0.236***
			(0.0371)	(0.0371)
Constant	2.408***	2.368***	0.692***	0.767***
	(0.0875)	(0.0868)	(0.184)	(0.185)
R-squared	0.023	0.027	0.027	0.030

Notes: The dependent variable is labor sharing frequency.. The frequency was measured by a self-reported scale from 1 to 3 (1 means never, and 3 means very often). The independent variables are different measurement for earthquake intensity, i.e. Modified Mercalli Intensity, and the ln of distance to earthquake epicenter. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Alternative Job Opportunities

The general labor market trend (employment status) and spatially correlated location-specific employment shocks impact labor sharing behavior. The formal labor hiring mechanism, and the availability of non-rural job opportunities in local areas reduce the incentive of labor sharing participation (Faas, 2012). This source of correlation could be partly controlled for by including time fixed effects that picks up the common trend in local labor market. We first summarize the labor components in the sampled villages, trying to describe the general labor structure in the observed periods. Takasaki et al (2012) shows that family, hired, and cooperative labor are perfect substitutes, even though the latter two are more productive. Faas, 2012 also points out that labor employment is negatively associated with participation in labor groups based on reciprocity (mingas). We thus summarize the household labor status in Table 3.

TABLE 4: Summary Statistic of Number of Family Labors

Variables	Mean	Std. Dev.	Min	Max	Obs
Year = 2007					
Intrafamily labor	2.817	1.251	0	9	1,581
Agricultural labor	1.865	1.067	0	9	1,581
Migrant worker	0.663	0.993	0	4	1,581
Year = 2009					
Intrafamily labor	2.755	1.336	0	9	1,553
Agricultural labor	1.883	1.128	0	9	1,553
Migrant worker	0.608	1.003	0	5	1,553
Year = 2011					
Intrafamily labor	2.762	1.386	0	9	1,530
Agricultural labor	1.750	1.091	0	9	1,530
Migrant worker	0.627	0.982	0	5	1,530

As shown in the table, in the observed period, the number of family labor (total number, number of agricultural labor, and number of migrant worker) are stable. Unfortunately, due to the constraint of our data, we could not present the information of hired labor or cooperative labor due to huge measurement errors. But the existing evidence about intra-family labors have shown that family labor supply is seemingly exogenous to the changes in labor sharing, and thus help us to rule out the channel that reduced sharing is caused by labor shortage due to the mortality or hurt during the disaster. It is therefore reasonable to assume that the formal/informal labor market structure, rather than number of available labors, has changed. We further explore this channel by controlling for formal and informal labor market information in local areas in the regression.

TABLE 5: Robustness Check: Employment Status and Labor Sharing

	(1)	(2)	(3)	(4)
Variables				
Intensity*year2011	-0.383***	-0.386***	-0.387**	-0.386**
	(0.125)	(0.127)	(0.152)	(0.152)
year2011	1.361*	1.365*	1.087	1.073
	(0.780)	(0.785)	(0.983)	(0.985)
Village labor price		0.0139		0.0129
		(0.0136)		(0.0132)
Employment status			0.000317	-0.000129
			(0.00138)	(0.00151)
Observations	1053	1053	1053	1053
Number of id	526	526	526	526
Village FE	NO	NO	NO	NO
Household FE	YES	YES	YES	YES

Notes: The dependent variable is labor sharing frequency in 2007 and in 2011. The frequency was measured by a self-reported scale from 1 to 3 (1 means never, and 3 means very often). The controls are village-fixed effects, or/and household fixed-effects, and household characteristics (household size, household head gender, education, party membership, household income, and landownership). Robust errors in parentheses, clustered at the village level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The additional control variables include non-farm job employment status (proxied by the average number of hired labor in the household besides i in the village) and hired labor price (proxied by the average village level wage). We choose these two variables based on the availability of our data. The regression results are presented in Table 4. The coefficients of the interaction term remain stable, and the coefficient of additional controls is not significant. We find little evidence that local employment status significantly affect labor sharing behavior.

Network Size

It has been well addressed that peers exert enormous influence on human behavior. The peer influence is even more significant in cooperative behaviors, where at least two parties have to join the interactions. Jackson (2010) provides a foundation for understanding the impact of social network structure on behaviors, which allows us to examine the behavioral changes where individuals make decisions after information updating or contagion. In this context, the labor sharing behavior could be characterized as a semi-anonymous graphical game, where an individual's choice is mainly influenced by the relative group of people. Therefore, the number of anonymous people who participate in labor sharing effect one's stochastic decision. People rely on narrow and denser networks within a kin group than wide cross group networks for stronger reciprocity in labor sharing (Takasaki et al., 2014), since individuals with larger networks are more likely to receive support from formal institutions (Faas, 2012).

The previous literature haven shown that network size plays a key role in reciprocal labor sharing. Therefore, We add network size as an additional control in the regression. Our proxy for network size is the number of players in one of the important social entertainment, Majiang game. Majiang (or mah-jongg) is a four-player pastime popular in Sichuan province and in East Asia. The 2007 and 2011 surveys asked the frequency that household members play Majiang, the number of regular Majiang partners, and the relationship with major partner. We use the number of players in one's Majiang game as a proxy for network size. In addition, we also use relationship with Majiang players as the proxy for social distance with friends. The seven types of relationships include: 1, close relative; 2, other relative; 3, neighbour; 4, college; 5, comrade-in-arms; 6, teacher or student; and 7, business partner. We assume the order corresponds to the order of social distance. The results are presented in column (1) to (3) of Table 6. The coefficient of the interaction term remain similar, and the coefficients of network size and social distance are not significant, indicating that none of these factors impact labor sharing behaviors.

TABLE 6: Robustness Check: Network Size

Variables	(1) FE-OL	(2) FE-OL	(3) FE-OL
Intensity*year2011	-0.383***	-0.376***	-0.378**
	(0.125)	(0.127)	(0.125)
year2011	1.361*	1.307*	1.319
	(0.780)	(0.786)	(0.782)
Network Size (number of Majiang players)		0.591	
		(0.0150)	
Social Distance (with Majiang players)			0.166
			(0.989)
Observations	1053	1053	1053
Number of id	526	526	526
Village FE	NO	NO	NO
Household FE	YES	YES	YES

Notes: The dependent variable is labor sharing frequency in 2007 and in 2011. The frequency was measured by a self-reported scale from 1 to 3 (1 means never, and 3 means very often). The controls are village-fixed effects, or/and household fixed-effects, and household characteristics (household size, household head gender, education, party membership, household income, and landownership). Robust errors in parentheses, clustered at the village level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Different cut-off points in FE-OL

We also check the robustness of our main identification, the Fixed Effect Ordered Logistic Model. Other suggestions for the cut-off points involve using the different cut-offs for each individual that can minimize the individual's Hessian matrix (Ferrer-i-Carbonell & Frijters 2004), or use the individual mean or median. The regression results using these different cut-off points are shown in table 7. The relationship between labor sharing activity and earthquake intensity are still significant across different cut-off points.

TABLE 7: Robustness Check, cut-off points in Fixed Effects Ordered Logit Model

	(1)	(2)	(3)	(4)	(5)	(6)
Cut-off points	1	1	2	2	mean	mean
Intensity*year2011	-0.427***	-0.360**	-0.667***	-0.127	-0.323***	-0.226*
	(0.123)	(0.174)	(0.172)	(0.232)	(0.124)	(0.132)
Year2011	2.162***	1.358	2.835***	-0.391	1.200*	0.797
	(0.793)	(1.019)	(1.069)	(1.360)	(0.717)	(0.769)
Constant	3.024		-8.124**		-1.602	
		(2.297)		(3.315)		(1.319)
Observations	2,966	346	2,966	212	2,966	508
Number of id	1,689	173	1,689	106	1,689	254
Village FE	YES	NO	YES	NO	YES	NO
Household FE	NO	YES	NO	YES	NO	YES

Notes: The dependent variable is labor sharing frequency in 2007 and in 2011. The frequency was measured by a self-reported scale from 1 to 3 (1 means never, and 3 means very often). The controls are village-fixed effects, or/and household fixed-effects, and household characteristics (household size, household head gender, education, party membership, household income, and landownership). Robust errors in parentheses, clustered at the village level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3.5 Robustness Check 2: Gift exchange

In this section, we present the results of the reciprocated gift-exchange behavior in the aftermath of the earthquake. The purpose is to examine the response of informal credit market to community shock as a robustness check, which is a robustness check for informal labor market.

The economic meaning of gift exchange behavior has been investigated extensively in the field of economics, psychology, finance, sociology, and anthropology. Gift exchanges are a good supplement to formal mechanisms, such as legal contracts, which allow individuals to trade with each other with a lower transaction cost (Wilfred and Albert, 2009). Larsen and Watson (2001) described gifts as an investment between donor and recipient, and gifts with a greater value contribute to a "more substantial investment". The motives of donors and recipients could be distinguished as consummatory motives and instrumental motives (Portes, 1998). The former refers to a social norm of sharing, and the latter refers to access to resources that is forced by mutual obligations and trust, and such enforceable rules could be regarded as an informal contract in rural communities where the credit market is imperfect or missing. The motivation is similar to labor sharing behavior, to the extent that expected self-interested motivation help to form an informal self-enforcing contract.

In China, presenting gifts at weddings, funerals, birthdays, and other social events has been a traditional custom for thousands of years. Gift exchange is frequently embedded in a network that is formed by kin, political, or religious relations, and is of great importance in maintaining the relationship (Guanxi) in rural societies. It is has been extensively addressed that people even sacrifice their basic food consumption or get into debt to afford the heavy gift spending and to strengthen the social connections. (Chen & Zhang, 2012a, 2012b; Young & Young, 2007)

General trend

Figure 3.2 describes the gift-giving behavior for households in and out of the earthquake area in 2007, 2009, and 2011. The gift-giving frequency is the times per year that the household present a gift to friends or relatives in their social network. Figure 2 shows that the gift-giving behavior in the non-earthquake areas was almost double of that in the earthquake areas in the baseline time. This means that some pre-determined heterogeneities existed in the two areas and, therefore, the natural experiment might not have been randomized. Many factors could have contributed to the baseline difference in people's gift exchange behavior, for example, (1) village size, in a large network the social interactions are more than in a small network; (2) transportation conditions and geographical conditions; (3) culture. We would future apply village-level fixed-effect to solve this endogeneity problem in the econometric regression.

Figure 2 presents the village-level average changes of gift-exchange frequency in the observed period. The average social interactions did not change sharply immediately after the earthquake in 2009, with a parallel time trend in the two areas. In 2011, gift-giving frequency in the earthquake area dropped by approximately 16.7%, while the number went up by 8% in the non-earthquake area. Figure 3 shows that the average gift expenditure increased from 2007 to 2011, but the increase was even sharper in the non-effected areas.

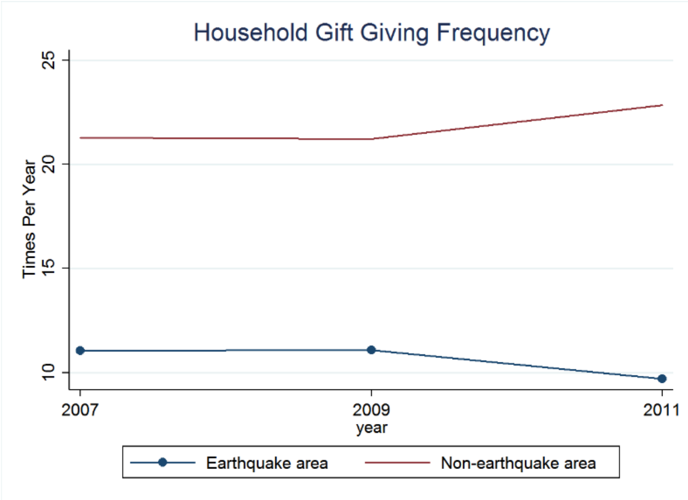

FIGURE 3.2: Frequency of household gift-giving over time in areas that were affected and in areas not affected by the 2008 earthquake in Sichuan, China

Regression result

Our main strategy follows the standard difference in differences (DID) estimation. We examined the changes in reciprocal behaviors in the aftermath of the 2008 Sichuan earthquake. The difference between our strategy and the standard DID estimation is that we used the continuous measure of the intensity of the treatment (earthquake), and we attempted to capture more of the variations in the data.

$$g_{vit} = \alpha + \rho T_t^{post} + \gamma Intensity_v \times T_t^{post} + x_{vit}\beta + v_{vi} + \varepsilon_{vit} \qquad (3.6)$$

where the outcome variable g_{vit} refers to the frequency of gift exchange behaviors for individual i in year t in village v. The variable T_t^{post} is an indicator variable that equals to one for periods after the earthquake, its coefficient ρ measures the effect of the earthquake and other time trends that are common to all the households. $Intensity_v$ is the earthquake intensity in village v. β, the key parameter of interest, captures the impact of earthquake intensity on behavioral changes in terms of gift-exchange and labor sharing.

The equation also includes fixed effects for individuals and years, v_{vi} and T_t^{post}, respectively. The vector x_{vit} includes other household-level characteristics that might affect the outcome variables, which include household size, household head gender education, party membership, household income, and landownership.

TABLE 8: Impacts of earthquake on gift exchange frequency from OLS

Explained variable	(1)	(2)	(3)	(4)
Intensity*year2009	-0.889***	-1.009***	-0.854***	-0.962***
	(0.147)	(0.149)	(0.147)	(0.148)
Intensity*year2011	-0.347***	-0.407***	-0.250*	-0.267**
	(0.131)	(0.133)	(0.135)	(0.135)
Year 2009 dummy	6.200***	6.880***	5.945***	6.558***
	(0.948)	(0.961)	(0.951)	(0.956)
Year 2011 dummy	1.980**	2.361***	1.243	1.328
	(0.886)	(0.898)	(0.903)	(0.906)
Observations	3,674	3,674	3,312	3,312
R-squared		0.030		0.034
Number of id	1,394	1,394	1,155	1,155
Village FE	YES	NO	YES	NO
Household FE	NO	YES	NO	YES

Notes: The dependent variable is times of presenting a gift per year. The controls are village-fixed effects, or/and household fixed-effects, and household characteristics (household size, household head gender, education, party membership, household income, and landownership).Robust errors in parentheses, clustered at the village level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We continue to control for income, recovery resources, income inequality to rule out alternative explanations. Table 3 summarizes the results. The recovery resources from various sources (government, private firms, and NGOs) in the aftermath of earthquake could be one of the alternative impact pathways that impact gift exchange frequency. The estimates coefficients on recovery resources is significant and negative, implying that households that received more alternative sources exhibited less willingness to send gifts. Column (2) through column (4) in Table 3 further control for mortality rate during the earthquake. The results are significantly negative. Losing a family member could prompt depression, which contributes to less social activities. Moreover, losing a child may lower the optimal long-term investment, which leads to less social gift-giving as social investment. Column (3) through column (4) control for income inequality (measured by Gini index), which has been discussed as one reason for booming social spending (Chen & Zhang, 2012b). The significant result shows that income disparity accounts for social exchanges.

TABLE 9: Robustness checks of impacts of earthquake on gift exchange frequency from OLS

Explained variable				
	(1)	(2)	(3)	(4)
Intensity*year2009	-0.873***	-0.977***	-0.929***	-0.094
	(0.133)	(0.146)	(0.148)	(0.151)
Intensity*year2011	-0.373***	-0.366***	-0.224	-0.052
	(0.129)	(0.129)	(0.146)	(0.140)
Year 2009 dummy	6.156***	6.683***	6.542***	0.339
	(0.888)	(0.938)	(0.941)	(0.983)
Year 2011 dummy	2.105**	2.098**	1.492	0.338
	(0.867)	(0.867)	(0.919)	(0.878)
Recovery resources	-0.012**	-0.011**	-0.013***	-0.014***
	(0.005)	(0.005)	(0.005)	(0.005)
Mortality		-0.077*	-0.088**	-0.044
		(0.044)	(0.045)	(0.043)
Number of social events				
Income Inequality			-3.516**	-0.174
(Gini index)			(1.518)	(1.461)
Peer effect				1.091***
				(0.071)
Observations 3,674	3,674	3,674	3,674	3,674
R-squared	0.030	0.030	0.034	0.034
Number of id	1,394	1,394	1,394	1,394
Village FE	NO	NO	NO	NO
Household FE	YES	YES	YES	YES

Notes: The dependent variable is times of presenting a gift per year. The controls are village-fixed effects, or/and household fixed-effects, and household characteristics (household size, household head gender, education, party membership, household income, and landownership). Robust errors in parentheses, clustered at the village level. Significance levels are indicated by *** p < 0.01, ** p < 0.05, * p < 0.1.

3.3.6 Conclusion

In Section 3.3.3, we examined two potential channels for the reduced labor sharing behavior as proposed by our model. The result shows that network size and alternative income have little impact on labor sharing. Therefore, we turn to the other channels proposed in the model, they are, risk aversion rate, income correlation coefficient, and time discount factor. Firstly, it is widely recognized that people become more risk aversion in the aftermath of a natural disaster (De Weerdt, 2002,Skidmore and Toya, 2002). Our model proposed that the self-enforcing condition would be re-enforced if people are more risk averse. The inconsistency indicated that risk aversion rate is not the potential channel. Secondly, using the similar argument, we concluded that income correlation coefficient is not the channel, since an earthquake should have increased the correlation coefficient and thus improved the self-enforcing condition. But the empirical regression provides opposite result. Thirdly, people's beliefs towards the future is found to be the potential mechanism. Our first hypothesis is that the earthquake shifted people's discount factor and put more weight on the present. As a result, the self-enforcing condition of labor sharing arrangement bread down. This hypothesis is consistent with the result in Filipski et al.,(2015), where based on the same dataset they found that the 2008 Sichuan earthquake induced people's time preference characterized by a carpe diem attitude toward spending.

3.4 Summary

This paper examines whether the social network as an informal risk-sharing contract is self-enforcing and the determinants of self-enforcing condition before and after a shock. We firstly presented a theoretical framework to analyze how networks operate, and included six features in the model as the determinants for self-enforcing condition. The results show that the society has not reached the efficient coordination level because many individuals refuse to enter the risk sharing network in the post-disaster period. We also provide empirical evidence using a three-year panel data collected in rural Sichuan, China from both before and after the 2008 Sichuan earthquake. The econometric results indicate that people are less willing to invest in and maintain the social network if they suffered heavily from the earthquake. The potential mechanism is that people's time preference changed in the aftermath of a disaster where they they put less weight on the future. While the other features, network size, income, income correlation coefficient, and risk aversion rate are insignificant or contradict to our theoretical hypothesis.

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