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Social networks and household financial decisions: evidence from China

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ABSTRACT

Based on three waves of a nationwide household survey in China, we demonstrate that social networks facilitate household financial market participation and risky asset holding. By constructing an index that considers various dimensions of social networks, our extensive empirical analysis suggests that a higher value of the social network index significantly increases the probability of a household's market participation and the fraction of risky assets holding in both formal and informal financial markets. This finding is robust across different waves of survey data; it is also robust to alternative index construction, estimation techniques, and variable definitions. We derive explicit expressions for the coefficients and standard errors of the interaction effects in the Probit and Tobit models and reveal that the impact of social networks is transmitted to household financial decisions through two channels: an information channel and a risk-sharing channel.

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1. Introduction

According to Campbell (2006), one of the main stylized facts of household finance is the phenomenon of “limited participation.” That is, household participation in the financial market is far from universal even among quite wealthy households (Guiso, Sapienza, & Zingales, 2008; Haliassos & Bertaut, 1995; Mankiw & Zeldes, 1991). Limited participation is also clearly observable in developing countries like China. According to the 2015 China Household Finance Survey (CHFS), only 19.1 percent of households participated in the formal financial market and 16.4 percent participated in the informal financial market.¹ For an average Chinese household, risk-free financial assets (e.g., cash and bank deposits) account for 86.7 percent of the total financial assets, and risky financial assets from the formal financial market, mostly common stocks, account for only 7.1 percent. This study explores the drivers of household financial decisions using the household survey data for China.

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¹Consistent with the existing literature, market participation is defined according to whether a household owns risky financial assets. As detailed in section 2.2.1, risky assets from the *formal* financial market include stocks, financial bonds, corporate bonds, funds, derivatives, financial wealth-management products, non-Renminbi (non-RMB) denominated assets, and gold. Risky assets in the *informal* financial market mainly refers to informal lending. See Figure 1 for the structure of household assets.

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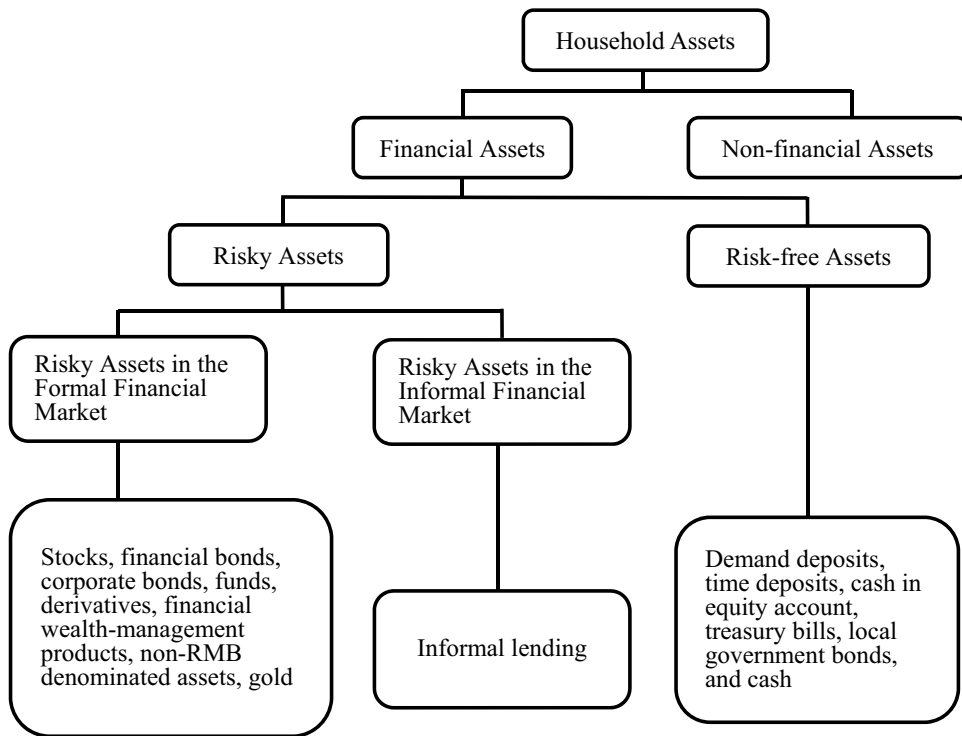


Figure 1. The structure of household assets.

One key question addressed by the household finance literature is the determinants of households' market participation and risky asset holding.² Among social and cultural factors, the impacts of *social capital* on household financial decisions have attracted significant attention. Guiso, Sapienza, and Zingales (2004) use electoral turnout and blood donation to measure social capital and find that the higher the social capital in a region, the higher the households' propensity for stock market investment. Guiso et al. (2008) and El-Attar and Poschke (2011) assert that a lack of trust plays a critical role in explaining the participation puzzle. Georgarakos and Pasini (2011) find that sociability can partly balance the discouragement effect on stockholding induced by low regional prevailing trust.

According to Putnam, Leonardi, and Nanetti (1993), social networks, together with trust and social regulation, constitute the most important elements of social capital. Despite numerous efforts in this area, only a few studies have investigated the effects of social networks on household financial market participation and asset allocation. Among them, researchers reach inconclusive results due to differences in measures of networks, representativeness of data sets, and types of financial markets (*e.g.*, Chai, Chen, Huang, &

²Early studies have shown that demographic characteristics such as wealth, income, and education are critical (Campbell, 2006). Recent studies have demonstrated that other factors are also notable. These factors include Internet (Bogan, 2008), optimism (Puri & Robinson, 2007), attitudes toward risk (Guiso & Paiella, 2008), IQ (Grinblatt, Keloharju, & Linnainmaa, 2011), cognitive abilities (Christelis, Jappelli, & Padula, 2010), financial literacy (Van Rooij et al., 2011), peer-group effects (Brown, Ivković, Smith, & Weisbenner, 2008; Hong, Kubik, & Stein, 2004), and religious beliefs (Guiso, Sapienza, & Zingales, 2003; Kumar, Page, & Spalt, 2011), among others.

Ye, 2018; Liang & Guo, 2015; Liu, Zhang, & Yang, 2014; Wu & Zhao, 2020). How social networks interact with household finance is especially important and relevant in a country such as China, where the formal institution is incomplete and imperfect and social networks serve as an informal institution in shaping households' decisions.

Based on three waves of a nationwide household survey (*i.e.*, the CHFS 2011, 2013 and 2015), we construct a comprehensive index to measure social networks and examine the role of social networks in shaping Chinese households' financial decisions empirically. Our major findings are summarized as follows. First, social networks have significantly positive impacts on household financial market participation and risky asset allocation. The broader the social networks, the more likely a household is to participate in financial markets and the higher proportion a household allocates to risky assets. This finding holds for various robustness checks and does not change as different dimensions of social networks evolve over time. Second, when dividing financial markets into formal and informal markets, we find a consistently positive impact of social networks on household financial decisions in both markets. A broader social network enhances households' willingness to interact with financial intermediaries in the formal market and their borrowing/lending activities with other households or institutes in the informal market. Third, social networks facilitate households' information acquisition, therefore increasing the probability of market participation through an *information channel*. As financial market participation involves a certain fixed cost (Haliassos & Bertaut, 1995), social networks can directly reduce the participation cost by providing households necessary knowledge and important information, complementing recent discussions on the missing role of information sharing on household financial decisions (Wu & Zhao, 2020). Fourth, social networks enhance households' chance of receiving outside aid in the presence of negative shocks (Ambrus et al., 2014; De Weerd & Dercon, 2006), therefore promoting their financial participation and risky asset holding through a *risk-sharing channel*. Although risk aversion discourages households from holding risky financial assets, social networks, as an informal institution, facilitate household risk-management and mitigate the negative impacts of risk aversion on household market participation and risky asset holding.

The major contributions of this study are threefold. First, we use the principal component method to construct a comprehensive index of social networks for three waves of CHFS data and examine its impacts on household financial decisions. This index considers a series of network-related variables that characterize multiple dimensions of social networks. One benefit of using an index to measure social networks lies in its inclusion of various aspects with varying importance. For instance, siblings, gift expenses, and social interactions have all been proposed as measures of social networks (Chai et al., 2018; Liang & Guo, 2015; Wu & Zhao, 2020). Despite their significance and necessity, each individual measure represents one aspect of social networks. With alternative definitions of social networks, researchers have explored the evolution from traditional to modern social networks and obtained conflicting views on the role of social networks (Liang & Guo, 2015; Wu & Zhao, 2020). Rather than debating the relative importance of the competing dimensions of social networks, we focus on the overall function of social networks and their lasting impact on market participation and asset allocation.

Second, this study considers both formal and informal financing in a unified framework. Most of the existing studies on household finance have focused on the formal financial market; few have focused on household interaction with other households or informal financial intermediaries, and even fewer have explored the informal financial market from the perspective of supply of funds.³ Consistent with the formal financing, we approach informal financing from the perspective of the supply of available funds and examines the effects of social networks on household *investments* in the informal financial market.

Third, we extend the existing analysis (e.g., Ai & Norton, 2003) and derive explicitly the expressions for the coefficients and standard error of the interaction effect in the Tobit model. This allows us to empirically examine the transmission channels through which social networks affect household financial decisions. Motivated by the household survey, information acquisition and risk sharing are directly identified as important working channels of social networks. On the one hand, this contributes to the debate about the role of information channel in the formal financial market (e.g., Liang & Guo, 2015; Wu & Zhao, 2020); on the other hand, our analysis shows how the traditional determinants of financial inclusion, *i.e.*, risk attitude, can be affected by social networks.

The remainder of this study is structured as follows. Section 2 introduces model setup, variable definitions, and data sources. Section 3 examines extensively the impacts of social networks on household financial decisions. Section 4 analyzes transmission mechanisms. Section 5 provides concluding remarks.

2. Model and data

2.1. Model

We aim to explore the effects of social networks on household financial decisions from both the extensive and intensive margins. On the extensive margin, we examine how social networks affect households' decisions regarding financial market participation through a Probit model:

$$y_{iv}^* = \beta \cdot network_{iv} + \gamma X_{iv} + \lambda_v + \varepsilon_{iv} \quad (1)$$

$$y_{iv} = 1 \text{ if } y_{iv}^* > 0 \text{ and } y_{iv} = 0 \text{ otherwise.}$$

The dependent variable $y = 1$ denotes the households' observed participation in the financial market. The key explanatory variable, *network*, measures household social networks. The vector X contains control variables including various household characteristics. λ is a provincial dummy and the subscripts i and v denote a variable in the i^{th} household from the v^{th} province. ε is the disturbance term.

On the intensive margin, we examine how social networks affect households' decision regarding risky asset holding through a Tobit model:

³Existing studies on informal financing usually pay attention to the demand for funds. For example, Bloch, Genicot, and Ray (2008) explore how social networks help households obtain informal lending and mitigate liquidity constraints. This partly motivates our work to study formal and informal financial markets in a unified framework. Recently, Chai et al. (2018) study both the supply of and demand for informal financing. They focus on the role of a particular component of social networks, *i.e.*, gift expenses, and adopt an indirect way (via two-step estimations) to test the transmission channels.

$$y_{iv}^* = \beta \cdot network_{iv} + \gamma X_{iv} + \lambda_v + \varepsilon_{iv} \quad (2)$$

$$y_{iv} = y_{iv}^* \text{ if } y_{iv}^* > 0 \text{ and } y_{iv} = 0 \text{ otherwise.}$$

The dependent variable $y = y^* > 0$ denotes the households' observed positive amount of risky asset holding in the financial market. Since many households do not hold risky assets, the observed risky asset holding is censored at zero. We follow the literature and adopt the one-limit version of the Tobit model to explore the impact of social networks on asset allocation. Detailed variable definitions are provided in the next section.

2.2. Data and variables

Data in this study come from three waves of the China Household Finance Survey in 2011, 2013, and 2015. This survey is conducted through the household tracking investigation and has a focus on the household finance. Based on the random stratified sampling, the CHFS collects information of 8,438, 28,141, and 37,289 households in the waves of 2011, 2013, and 2015, respectively.⁴ The coverage of the CHFS survey is nationwide with both rural and urban households: the 2013 and 2015 waves cover all mainland China provinces, except Xinjiang and Tibet. The survey covers family members' demographic characteristics, non-financial assets, financial assets, corresponding liabilities, insurance and social welfare, household expenditures and revenues, etc.

Table 1 summarizes the definitions of all variables and reports their descriptive statistics. In 2015, only 29.8 percent of households participated in financial markets, with the participation rates of 19.1 percent and 16.4 percent in the formal and informal financial markets, respectively. Limited participation in financial markets has been a persistent phenomenon in China. For asset allocation, risky formal financial assets only account for 7.1 percent of total household financial assets in 2015.

2.2.1. Market participation and asset allocation

Figure 1 depicts the structure of household assets, including financial and non-financial assets. Household financial assets are further divided into two groups: risk-free assets and risky assets. The former includes demand deposits, time deposits, cash in equity account, treasury bills, local government bonds, and cash. The latter includes risky assets from both formal and informal financial markets. Risky assets from the formal financial market include stocks, financial bonds, corporate bonds, funds, derivatives, financial wealth-management products, non-RMB denominated assets, and gold. They reflect households' interaction with formal financial intermediaries. Risky assets from the informal financial market mainly refer to informal lending, reflecting households' lending activities with other households or informal financial intermediaries.

To measure household financial market participation, we first use a dummy variable according to the survey question of “whether a household holds risky assets”: the dummy variable $y_{iv} = 1$ when a household holds risky assets and $y_{iv} = 0$ otherwise. Next, we define two other dummy variables according to (1) “whether a household holds risky

⁴In our analysis, we delete households with negative income. We also remove households with missing values of *network* index from our sample. Although the wave of CHFS 2017 is also available, some key variables are either missing or redefined in the questionnaire. Our analysis, therefore, did not incorporate CHFS 2017 data.

assets in the *formal* financial market” and (2) “whether a household provides *informal* lending” to characterize household financial market participation in the formal and informal financial markets, respectively.

To measure financial asset allocation, we first calculate the fraction of a household’s risky financial assets out of total financial assets. Then we calculate the fractions of (1) risky assets in the *formal* financial market and (2) risky assets in the *informal* financial market out of total financial assets to proxy risky asset holding in formal and informal financial markets, respectively. These measures permit the analysis of households’ decisions in the overall financial market and different forms of financial markets.

2.2.2. Social networks

Social networks are a broad concept, and how to accurately measure them has been a challenge in economics and sociology. The existing literature has adopted various measurements that differ significantly.⁵ Each measure exhibits its own characteristics and necessity; the relative importance of various measures also changes over time (Liang & Guo, 2015; Liu et al., 2014). Rather than debating the importance of a single dimension, we regard social networks as a multidimensional concept that captures households’ connections from the perspectives of kinship, work, and social interactions. Specifically, using the rich information in the CHFS questionnaires, we consider multiple aspects of social networks as in Du, Guo, and Zhang (2013): number of siblings, job position, type of work unit, communist party membership, gift expenditure, and communication expenditure.

As listed and defined in Table 2, the first variable (the number of siblings) has been widely used to measure blood kinship networks. In the presence of a weak formal institution, borrowing and lending among relatives act as a form of insurance against exogenous shocks. Siblings form a strong tie in social networks based on blood-kinship. The following three variables (job position, type of work unit, and communist party membership) measure the households’ work-related social networks. Job relationships form the basis of interpersonal networks outside the family in modern society. They are inevitably affected by job positions and types. In China, the work-related social networks are further impacted by a person’s political identity, in particular whether a person owns the communist party membership (e.g., Li, Meng, Wang, & Zhou, 2008). The remaining variables measure the household’s social activity expenditures on gift and communication. Incorporating these expenditures reveals the fact that social networks among Chinese households are mostly built on blood kinship, family connections, and geographic connections. Giving gifts and maintaining social interactions constitute a critical means to establish or maintain their household networks, particularly during major holidays (e.g., the Spring Festival, the mid-autumn festival) and significant events (e.g., weddings, funerals). Including expenditures on communications helps incorporate both measures of traditional and modern social interactions (Liang & Guo, 2015; Liu et al., 2014). Based on these variables, we construct an index of social networks (denoted by

⁵For example, Zhang and Li (2003) use the expenditure on gifts and three sets of dummy variables to measure “guanxi”. Peng (2004) measures the kinship networks as the proportion of households that belong to the largest lineage group. Liang and Guo (2015) emphasize the social interactions including face to face and telephone communications and their substitutions to internet. Wu and Zhao (2020) focus on the social networks based on the number of siblings. Researchers tend to focus on different dimensions of social networks to explore their importance.

Table 1. Definitions of variables and summary statistics.

Variable	Definition	Obs	Mean	St.dev
Finance	Whether or not a household participates in financial market	30,082	0.298	0.457
Financeratio	Fraction of risky financial assets out of total financial assets	28,888	0.133	0.263
Formal	Whether or not a household participates in <i>formal</i> financial market	30,082	0.191	0.393
Formalratio	Fraction of risky <i>formal</i> financial assets out of total financial asset	28,888	0.071	0.196
Informal	Whether or not a household has informal lending	30,082	0.164	0.371
Informalratio	Ratio of informal lending to total financial asset	28,888	0.062	0.185
Network	Social network index	30,082	4.003	6.854
Logasset	Household nonfinancial assets in logarithm	30,082	12.532	1.836
Loghhincome	Household income in logarithm	30,082	10.557	1.431
Selfemploy	Whether or not a household owns family businesses	30,082	0.160	0.366
House	number of houses owned by a household	30,044	1.101	0.628
hysize	Household size	30,082	2.973	1.703
Financial literacy	whether or not a family member works in the financial industry	30,082	0.021	0.143
Age	Age of the household head	30,082	52.706	14.109
Female	Whether or not a household head is a female	30,082	0.248	0.432
Edu	Years of education of the household head	30,082	9.684	4.186
Unmarried	Whether or not a household head is single	30,082	0.039	0.193
Riskaverse	Degree of household risk aversion (1–5)	30,082	4.094	1.164
Rural	Whether or not a household resides in the rural area	30,082	0.292	0.455
Localrelative	Number of relatives residing in the local town/city	30,023	2.734	1.076
Information	Degree of concerns for economic and financial information (1–5)	30,053	2.156	1.097

This table reports detailed definitions of variables and their descriptive statistics in CHFS 2015.

Table 2. Definitions of social network related variables.

Variables	Definition
Number of siblings	The number of siblings of the household head and his/her spouse
Job position	The score of job grade is assigned as follows: 1 for group leader (or village cadre); 2 for (vice) chief of section (or town cadre); 3 for (vice) director of a department; 4 for (vice) director of a bureau or higher positions.
Type of work unit	The score of each type is assigned as follows: 6 for government or military; 5 for publicly listed state-owned enterprises; 4 for public institutions; 3 for non-listed state-owned enterprises; 2 for publicly listed non state-owned enterprises; 1 for non-listed private enterprises; 0 for other types of work units.
Party membership	Whether or not one of the family members is a communist party member
Gift expenditure	Expenditure given to non-family members during Chinese New Year, Mid-autumn festival, and other major holidays (including new year's money, birthday money), and during weddings and funerals.
Communication expenditure	Annual family expenditure on communication (e.g., telephone, internet, network fees).

This table shows detailed definitions of variables included in the construction of the *network* index.

network) through the principal component analysis (PCA). This process remains a simple way of transforming the information content in a large number of series into a single principal component and, at the same time, minimizes the potential measurement errors when using an individual variable to measure social networks. In this way, we are able to concentrate on the overall function of social networks for household financial decision-making despite the changing substitution or complementary relationships between the different dimensions of social networks.

Table 3. Principal component analysis.

Panel A: Rotation							
Component	Eigenvalue		Difference		Proportion		Cumulative
Comp1	44.2958		22.2490		0.5619		0.5619
Comp2	22.0468		13.1262		0.2797		0.8416
Comp3	8.9206		5.6757		0.1132		0.9548
Comp4	3.2449		3.0620		0.0412		0.9960
Comp5	0.1829		0.0472		0.0023		0.9983
Comp6	0.1357				0.0017		1
Panel B: Principal Components							
Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Unexplained
Number of siblings	0.0048	0.0041	0.9993	0.0375	−0.0024	0.0007	0
Job position	0.0059	0.0025	−0.0025	0.0834	0.5247	0.8472	0
Type of work unit	0.0341	0.0297	−0.0377	0.9934	−0.0884	−0.0435	0
Party membership	0.0068	0.0020	0.0004	0.0519	0.8467	−0.5295	0
Gift expenditure	0.9895	−0.1415	−0.0031	−0.0304	−0.0057	0.0000	0
Communication expenditure	0.1404	0.9895	−0.0034	−0.0346	−0.0012	0.0003	0

This table reports the results of the benchmark principal component analysis. Panel A reports the variance explained by each component. Panel B reports the loadings of the original variables for each principal component.

Table 3 reports the results of the benchmark PCA. Panel A reports the variance explained by each component. The first component alone accounts for 56.19% of the overall variations of the social network-related variables. Panel B reports that the loadings of the original variables for each principal component. The first component is positively related to all variables considered here, consistent with our expectation. In addition, Panel B shows that the benchmark PCA attributes the largest two loadings to the gift and communication expenditures, reflecting the fact that the Chinese society is indeed based on interpersonal relations.

2.2.3. Control variables

We follow the literature and add a series of control variables related to the whole household or the household head that may affect household financial decisions. The household-level variables include household non-financial assets (a proxy of household wealth), household income, family size, and whether or not being a rural household. Because financial literacy affects households' decisions (Van Rooij, Lusardi, & Alessie, 2011), we define a dummy variable according to “whether a household member works in the financial industry” to control for its impacts. In addition, because of the possible crowding-out effects of non-financial assets on household financial assets, we incorporate a dummy variable of “whether a household owns a business”, as well as the number of houses owned by a household, into our analysis.

To control for the characteristics of the household head, we include age, age squared, gender, years of education, and marriage status. Moreover, households' risk attitude is a critical psychological factor that affects financial investment (Dimmock & Kouwenberg, 2010). Given the same risks and returns of investment, higher risk-aversion reduces the possibility of household financial participation. We control for risk attitude in our estimations.⁶

3. Empirical analysis

In the empirical results reported below, for most of the cases, we only report results based on the 2015 survey data, which has the largest sample size. Using the 2011 and 2013 survey data essentially result in similar findings.

3.1. Social networks and household financial decisions

In this section, we examine the effects of social networks on *overall* financial market participation (*i.e.*, whether a household owns risky assets) and asset allocation (*i.e.*, the fraction of risky assets out of total financial assets). Equation (1) is estimated to examine market participation, and the results are reported in Columns 1 through 2 in Table 4. Equation (2) is then estimated to examine asset allocation, and the results are reported in Columns 3 through 4.

According to Table 4, estimations of the Probit model (Column 1) show that the *network* index is statistically significant and positively promotes household participation in the financial market. With provincial dummies incorporated to account for unobservable regional heterogeneity (Column 2), the results do not change much. Broader social networks enhance a household's possibility of participating in financial markets. Focusing on the specification with provincial dummies and keeping other variables at their sample means, the marginal effect estimations suggest that a one-unit increase in the *network* index is associated with an increase in the probability of household participation by 0.68 percentage points.⁷

Estimations of the Tobit model (Column 3) show that the *network* index is statistically significant and promotes households allocation toward risky assets. With provincial dummies incorporated (Column 4), social networks remain statistically significant at the 1 percent significance level. Broader social networks induce households to adjust their portfolio toward risky financial assets. Specifically, if the *network* index increases by one unit, the fraction of risky assets out of total financial assets increases by 0.58 percentage points.

As for the control variables, our estimations are consistent with the existing literature. Income and wealth (proxied by the non-financial assets) have a positive and significant impact on household financial decisions, suggesting that higher income or greater wealth increases the probability of household participation and the ratio of risky assets in the household portfolio. Control variables, such as more education years, operating a family-owned business, a smaller household size, a lower degree of risk aversion, working in the financial industry, and living in urban area, all positively and significantly contribute to household financial market

⁶In the CHFS questionnaire, the information about risk attitudes is collected by the following question. "If you have an asset, which one of the following investment projects are you likely to choose: (1) projects with higher risks and higher returns; (2) projects with slightly higher risks and slightly higher returns; (3) projects with average risks and average returns; (4) projects with slightly lower risks and slightly lower returns; and (5) projects with no risks at all. We assign a score of 1 to 5 to each of the above five options to construct the variable *riskaverse*."

⁷The estimated marginal effects based on the specifications without provincial dummies are comparable and not reported to avoid repetition.

Table 4. Effects of social networks on household financial market participation and asset allocation.

Variables	Financial Market Participation		Financial Market Asset Allocation	
	(1) Probit	(2) Probit	(3) Tobit	(4) Tobit
Network	0.0204*** (10.9652)	0.0215*** (11.0814)	0.0057*** (8.6475)	0.0058*** (8.5723)
Logasset	0.1176*** (15.1213)	0.0958*** (12.2065)	0.0593*** (14.0470)	0.0494*** (11.5187)
Loghhincome	0.1733*** (19.4975)	0.1661*** (18.8163)	0.0892*** (19.1364)	0.0847*** (18.3936)
Selfemploy	0.1353*** (5.7279)	0.1508*** (6.3309)	0.0506*** (4.2180)	0.0596*** (4.9365)
House	0.0088 (0.5470)	0.0310* (1.8642)	-0.0061 (-0.7939)	0.0033 (0.4272)
hhsz	-0.0460*** (-7.9982)	-0.0441*** (-7.4877)	-0.0257*** (-8.0362)	-0.0243*** (-7.4769)
Age	-0.0945** (-2.2008)	-0.0848* (-1.9558)	0.0343 (1.5368)	0.0382* (1.7021)
Age-sq	-0.0009 (-0.2293)	-0.0025 (-0.6158)	-0.0069*** (-3.2700)	-0.0076*** (-3.5601)
female	0.0228 (1.1368)	0.0184 (0.9101)	0.0165 (1.5783)	0.0143 (1.3716)
Edu	0.0617*** (22.3678)	0.0631*** (22.4703)	0.0300*** (20.1610)	0.0304*** (20.2067)
Unmarried	0.1408*** (2.7945)	0.1168** (2.3221)	0.0413* (1.7936)	0.0347 (1.5136)
Riskaverse	-0.1829*** (-24.5876)	-0.1840*** (-24.4835)	-0.0865*** (-22.3047)	-0.0872*** (-22.4134)
Financial literacy	0.3148*** (5.0747)	0.3300*** (5.2987)	0.1064*** (4.6441)	0.1116*** (4.8992)
Rural	-0.1787*** (-7.5830)	-0.1606*** (-6.7075)	-0.0851*** (-6.2515)	-0.0778*** (-5.6562)
Provincial Dummy	No	Yes	No	Yes
Constant	-3.2426*** (-19.8775)	-2.9032*** (-16.5604)	-1.9233*** (-23.0035)	-1.7204*** (-19.2103)
Observations	30,044	30,044	28,859	28,859
Pseudo R ²	0.2245	0.2310	0.1705	0.1749

This table shows the estimation results from Probit and Tobit regressions of financial market participation and asset allocation on social networks and a series of control variables. In Columns 1 through 2, the dependent variable is a dummy variable, *i.e.*, whether or not a household owns risky financial assets (stocks, financial bonds, corporate bonds, funds, derivatives, financial products, non-RMB denominated assets, gold and informal lending), and the corresponding Probit estimates are reported. In Columns 3 through 4, the dependent variable is the ratio of risky financial assets to total household financial assets, and the corresponding Tobit estimates are reported. The variable age is divided by 10 so that its estimated coefficients are readable. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

participation and risky asset holding. Other variables, including the number of houses and the age, gender, and marriage status of household head, do not have robust impacts on household financial decisions.

3.2. Social networks and formal financial market decisions

This section presents the results of household *formal* financial market decisions. Table 5 reports the estimation results based on the Probit regression (Columns 1 through 2) and Tobit regressions (Columns 3 through 4).

Table 5. Effects of social networks on household *formal* financial market participation and asset allocation.

Variables	Formal Financial Market Participation		Formal Financial Market Asset Allocation	
	(1) Probit	(2) Probit	(3) Tobit	(4) Tobit
Network	0.0108*** (6.6046)	0.0121*** (7.0248)	0.0025*** (5.0273)	0.0027*** (5.2453)
Logasset	0.1694*** (16.3469)	0.1208*** (12.1701)	0.0825*** (14.7642)	0.0563*** (10.7455)
Loghhincome	0.1832*** (15.4665)	0.1638*** (14.4029)	0.1009*** (17.0409)	0.0876*** (15.9212)
Selfemploy	-0.0760*** (-2.6962)	-0.0373 (-1.3036)	-0.0601*** (-4.1707)	-0.0350** (-2.4387)
House	-0.0503*** (-2.8167)	0.0039 (0.2166)	-0.0356*** (-3.9730)	-0.0072 (-0.8321)
hhsz	-0.0649*** (-8.9889)	-0.0573*** (-7.6656)	-0.0364*** (-9.4363)	-0.0316*** (-8.1183)
Age	0.0516 (1.0588)	0.0730 (1.4631)	0.0756*** (3.0514)	0.0829*** (3.3523)
Age-sq	-0.0061 (-1.3559)	-0.0091** (-1.9671)	-0.0052** (-2.2590)	-0.0064*** (-2.7754)
Female	0.1461*** (6.4373)	0.1415*** (6.1098)	0.0805*** (6.9657)	0.0759*** (6.6265)
Edu	0.0956*** (28.0462)	0.1012*** (28.5887)	0.0471*** (26.6022)	0.0485*** (27.2391)
Unmarried	0.1914*** (3.4918)	0.1446*** (2.6309)	0.0725*** (2.8689)	0.0523** (2.1219)
Riskaverse	-0.2559*** (-29.9382)	-0.2633*** (-30.0932)	-0.1215*** (-28.1166)	-0.1231*** (-28.5613)
Financial literacy	0.3302*** (5.4682)	0.3728*** (6.0383)	0.1174*** (4.9275)	0.1354*** (5.7206)
Rural	-0.6852*** (-17.9261)	-0.6648*** (-17.1443)	-0.3572*** (-16.5164)	-0.3402*** (-15.9291)
Provincial Dummy	No	Yes	No	Yes
Constant	-4.9608*** (-24.3818)	-4.1855*** (-19.5724)	-2.8049*** (-28.0305)	-2.2831*** (-22.2611)
Observations	30,044	30,044	28,859	28,859
Pseudo R ²	0.3215	0.3399	0.2872	0.3041

This table shows the estimation results from Probit and Tobit regressions of *formal* financial market participation and asset allocation on social networks and a series of control variables. In Columns 1 through 2, the dependent variable is a dummy variable, *i.e.*, whether or not a household owns risky formal financial assets, and the corresponding Probit estimates are reported. In Columns 3 through 4, the dependent variable is the ratio of risky formal financial assets to total household financial assets, and the corresponding Tobit estimates are reported. The variable age is divided by 10 so that its estimated coefficients are readable. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

According to Table 5, the estimated coefficient of the *network* index on household *formal* financial market participation (Columns 1 and 2) is 0.0108 and 0.0121, without or with controlling for provincial dummies; both are significant at the 1 percent significance level. The marginal effect estimation suggests that with a one-unit increase in the *network* index, the probability of household formal financial market participation increases by 0.2 percentage points.

Columns 3 through 4 examine the impacts of social networks on household asset allocation in the formal financial market. The Tobit regression results show that social networks have statistically significant impacts on asset allocation. The estimated marginal impact of the *network* index is 0.27 percentage points.

The effects of control variables do not change much: the effects of household income, wealth, education years, unmarried household heads, and financial working experience remain positive, and household size, rural household heads, and risk aversion reduce the household participation rate and the ratio of risky assets in the formal financial market. Operating a family-owned business tends to crowd out risky financial assets holding and female household heads become statistically positive.

3.3. Social networks and informal financial market decisions

In this section, we examine the impacts of social networks on household *informal* financial market decisions. A Probit regression and Tobit regression are run based on Equations (1) and (2). The results are summarized in Table 6.

Estimations of the Probit model (Column 1) show that social networks result in a statistically significant increase in household participation in the informal financial market. We incorporate provincial dummies to account for unobservable heterogeneity (Column 2), the results do not change much. Broader social networks enhance a household's possibility to provide informal lending. The marginal effect estimations suggest that with a one-unit increase in the *network* index, the probability of household informal lending increases by 0.36 percentage points.

Estimations of the Tobit model (Column 3) show that the *network* index is statistically significant and positively promotes household asset allocation to risky informal lending. With provincial dummies incorporated (Column 4), social networks remain statistically significant at 1 percent significance level. Broader social networks induce a household to increase its share of informal lending in its asset portfolio.

3.4. Robustness

In addition to the robustness to different waves of survey data, we examine how our findings will change when (i) using alternative measures of social networks and household financial participation and (ii) considering the possible endogeneity problem of social networks.

3.4.1. PCA with categorical variables

Some of the variables used for constructing the *network* index are categorical variables (*i.e.*, job position, type of work unit). The classical PCA may not work properly with categorical variables.⁸ In this section, we use two alternative methods to examine the potential impact of categorical variables.

First, we follow the literature (*e.g.*, Filmer & Pritchett, 2001) and transform each categorical variable into a series of dummies, that is, following a common suggestion that a categorical variable should be treated that way when it is used in regression. It turns out that the resulting index from the PCA looks very similar to the benchmark calculation. Panel A in Table 7 summarizes the estimated results using the alternatively constructed *network* index. Compared to Table 4 through 6, both the coefficient and significance of the *network* index are very close.

⁸We would like to thank an anonymous reviewer for pointing this out to us.

Table 6. Effects of social networks on household *informal* financial market participation and asset allocation.

Variables	Informal Financial Market Participation		Informal Financial Market Asset Allocation	
	(1) Probit	(2) Probit	(3) Tobit	(4) Tobit
Network	0.0163*** (8.4899)	0.0164*** (8.3475)	0.0072*** (7.5797)	0.0073*** (7.8411)
Logasset	0.0333*** (4.5091)	0.0410*** (5.1868)	0.0189*** (3.9879)	0.0262*** (5.1438)
Loghhincome	0.1063*** (12.0920)	0.1122*** (12.4334)	0.0596*** (10.6935)	0.0634*** (11.1438)
Selfemploy	0.3374*** (14.3665)	0.3207*** (13.5191)	0.1786*** (12.2011)	0.1657*** (11.2747)
House	0.0569*** (3.4055)	0.0452*** (2.7196)	0.0290*** (2.9554)	0.0182* (1.8522)
hhszise	-0.0151** (-2.4711)	-0.0193*** (-3.0856)	-0.0088** (-2.1782)	-0.0107*** (-2.6279)
Age	-0.1270*** (-2.6719)	-0.1211** (-2.5276)	-0.0128 (-0.4196)	-0.0117 (-0.3849)
Age-sq	-0.0049 (-1.0777)	-0.0050 (-1.0966)	-0.0094*** (-3.1672)	-0.0091*** (-3.0559)
Female	-0.1106*** (-4.9768)	-0.1036*** (-4.6294)	-0.0685*** (-4.8366)	-0.0623*** (-4.4079)
Edu	0.0093*** (3.2491)	0.0105*** (3.6109)	0.0030 (1.5826)	0.0038** (2.0229)
Unmarried	0.1053** (2.1740)	0.1131** (2.3170)	0.0404 (1.3913)	0.0507* (1.7440)
Riskaverse	-0.0650*** (-8.1250)	-0.0638*** (-7.8909)	-0.0308*** (-5.9676)	-0.0304*** (-5.8642)
Financial literacy	0.0669 (1.1465)	0.0572 (0.9758)	0.0166 (0.4932)	0.0089 (0.2655)
Rural	0.0190 (0.7749)	0.0064 (0.2575)	0.0266 (1.6325)	0.0167 (1.0167)
Provincial Dummy	No	Yes	No	Yes
Constant	-1.7551*** (-10.7458)	-2.0511*** (-11.3439)	-1.1931*** (-11.3389)	-1.4104*** (-12.1793)
Observations	30,044	30,044	28,859	28,859
Pseudo R ²	0.1079	0.1124	0.0817	0.0869

This table shows the estimation results from Probit and Tobit regressions of *informal* financial market participation and asset allocation on social networks and a series of control variables. In Columns 1 through 2, the dependent variable is a dummy variable, *i.e.*, whether or not a household has informal lending, and the corresponding Probit estimates are reported. In Columns 3 through 4, the dependent variable is the ratio of total amount of informal lending to total household financial assets, and the Tobit estimates are reported. The variable age is divided by 10 so that its estimated coefficients are readable. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

Second, we remove job position and type of work unit from the original list of network-related variables and then perform the PCA to construct the *network* index. As suggested by Table 3, both categorical variables have a relatively small loading in the first component; therefore the removal of these two variables should not change the results much. Panel B in Table 7 confirms this conjecture. Our results are robust to the inclusion or removal of the categorical variables.

3.4.2. Alternative measures of household participation

In this section we focus on the impact of using alternatively defined financial assets and financial market participation. First, in the baseline estimations, risky assets in the formal financial market include stocks, financial bonds, corporate bonds, funds, derivatives, financial wealth-management products, non-RMB denominated assets, and gold. Among

Table 7. Robustness (Alternative PCA with categorical variables).

Panel A: Generating dummy variables for each of the categorical variables						
	Overall Financial Market		Formal Financial Market		Informal Financial Market	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Probit	Tobit	Probit	Tobit	Probit	Tobit
Network	0.0214*** (11.0644)	0.0058*** (8.5649)	0.0120*** (6.9948)	0.0027*** (5.2243)	0.0164*** (8.3410)	0.0073*** (7.8362)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,044	28,859	30,044	28,859	30,044	28,859
Pseudo R ²	0.2310	0.1749	0.3398	0.3041	0.1124	0.0869
Panel B: PCA without categorical variables						
	Overall Financial Market		Formal Financial Market		Informal Financial Market	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Probit	Tobit	Probit	Tobit	Probit	Tobit
Network	0.0214*** (11.0640)	0.0058*** (8.5649)	0.0120*** (6.9937)	0.0027*** (5.2238)	0.0164*** (8.3408)	0.0073*** (7.8361)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,044	28,859	30,044	28,859	30,044	28,859
Pseudo R ²	0.2310	0.1749	0.3398	0.3041	0.1124	0.0869

This table shows the estimation results from Probit and Tobit regressions of household financial market participation and asset allocation on social networks and a series of control variables with alternatively defined formal financial assets. In Panel A, the network index is constructed based on the PCA transforming each categorical variable into a series of dummies variables. In Panel B, the network index is constructed based on the PCA by removing categorical variables from the original list of network-related variables. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

financial market participants, most of them only invest in stocks and funds. Other risky assets account for a small fraction.⁹ Based on this observation, we redefine the household participation in the formal financial market in two ways: (1) a household participates in the formal financial market if it holds stocks, funds, financial wealth-management products, or non-RMB denominated assets, excluding bonds, derivatives, and gold; (2) a household participates in the formal financial market if it holds stocks or funds, further excluding financial wealth-management products and non-RMB denominated assets.

Table 8 reports the estimation results. Columns 1 through 2 correspond to the first definition, and Columns 3 through 4 correspond to the second definition. A crosscheck of Table 8 reveals that, under all circumstances, the estimated coefficients of social networks are significantly positive. This suggests that the positive impacts of social networks on household formal financial market participation are robust to redefined measures of formal financial assets.

Second, after discussing the variety of assets, we switch to quantity of assets. In the baseline estimations, a household with *any* positive amount of investment in the formal financial market or informal lending is counted as a market participant. To some extent,

⁹According to the CHFS 2011, the participation rate of Chinese households in the formal financial market is 9.00% (stock market), 4.23% (funds markets), 0.11% (bonds market), 0.01% (derivatives market), 0.87% (financial wealth-management products), 1.22% (non-RMB denominated asset market), and 0.71% (gold market). In 2015, these numbers become 10.26% (stock market), 3.63% (funds markets), 0.04% (bonds market), 0.07% (derivatives market), 4.77% (financial wealth-management products), 0.17% (non-RMB denominated asset market), and 0.51% (gold market).

Table 8. Robustness (Alternative definitions of *formal* financial assets).

	Alternative Definition 1		Alternative Definition2	
	Panel A: Formal Financial Market Participation			
Variables	(1) Probit	(2) Probit	(3) Probit	(4) Probit
Network	0.0105*** (6.4333)	0.0118*** (6.8853)	0.0024*** (4.7984)	0.0026*** (4.9912)
Control Variables	Yes	Yes	Yes	Yes
Provincial Dummy	No	Yes	No	Yes
Observations	30,044	30,044	28,859	28,859
Pseudo R ²	0.3227	0.3417	0.2921	0.3094
	Panel B: Formal Financial Market Asset Allocation			
	(1) Tobit	(2) Tobit	(5) Tobit	(6) Tobit
Network	0.0076*** (4.5635)	0.0086*** (4.7469)	0.0020*** (3.3499)	0.0021*** (3.3035)
Control Variables	Yes	Yes	Yes	Yes
Provincial Dummy	No	Yes	No	Yes
Observations	30,044	30,044	28,859	28,859
Pseudo R ²	0.3287	0.3483	0.3141	0.3312

This table shows the estimation results from Probit and Tobit regressions of household formal financial market participation (Panel A) and asset allocation (Panel B) on social networks and a series of control variables with alternatively defined formal financial assets. In Columns 1 through 2 in Panel A, the dependent variable is redefined as whether or not a household invests in stocks, funds, financial wealth-management products, or non-RMB denominated assets. In Columns 3 through 4 in Panel A, the dependent variable is further redefined as whether or not a household invests in stocks and funds. In Columns 1 through 2 in Panel B, the dependent variable is changed to the share of total financial assets invested in stocks, funds, financial wealth-management products, or non-RMB denominated assets. In Columns 3 through 4 in Panel B, the dependent variable is changed to the share of total financial assets invested in stocks and funds only. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

households with a very small investment amount are not actively participating in the financial market.¹⁰ In this part, we redefine market participation and asset allocation by excluding households with risky assets lower than a certain threshold. We experiment with three thresholds: RMB 5,000, RMB 10,000, and RMB 20,000.¹¹

Table 9 reports the estimation results with redefined financial market participation using three thresholds. A crosscheck indicates that, even with a more precise measure, the estimated impacts of social networks on household financial decisions are significantly positive in all cases. The positive impacts of social networks on household financial decisions are robust to alternative definitions of participation. Measurement errors do not seem to drive the main findings.

¹⁰Such households account for about 0.7–3.1% of all the financial participators. For example, the CHFS 2015 indicates that 25 households (out of all 3,468 stock market participants) have a stock exchange account with a market value less than RMB 1,000; 14 households (out of all 1,227 fund investors) have a fund account with a market value less than RMB 1,000; 161 households (out of all 5,257 informal lenders) have informal lending less than RMB 1,000.

¹¹According to the CHFS 2015, the market values of household stock exchange accounts at different quantiles are as follows: RMB 20,000 (25% quantile), RMB 50,000 (50% quantile), RMB 146,500 (75% quantile). The values of household informal lending at different quantiles are as follows: RMB 6,000 (25% quantile), RMB 20,000 (50% quantile), RMB 50,000 (75% quantile).

Table 9. Robustness (Alternative definitions of financial market participation).

Variables	Overall Financial Market		Formal Financial Market		Informal Financial Market	
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Tobit	Probit	Tobit	Probit	Tobit
Panel A: Households with Investment above RMB 5,000						
Network	0.0196*** (10.8434)	0.0064*** (8.2852)	0.0106*** (6.3539)	0.0027*** (4.7900)	0.0156*** (8.0860)	0.0083*** (7.8062)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,044	28,859	30,044	28,859	30,044	28,859
Pseudo R ²	0.2249	0.1848	0.3353	0.3106	0.1171	0.0942
Panel B: Households with Investment above RMB 10,000						
Network	0.0197*** (10.9955)	0.0067*** (8.1453)	0.0103*** (6.2460)	0.0029*** (4.7405)	0.0163*** (8.1859)	0.0091*** (7.7910)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,044	28,859	30,044	28,859	30,044	28,859
Pseudo R ²	0.2360	0.1948	0.3386	0.3117	0.1278	0.1030
Panel C: Households with Investment above RMB 20,000						
Network	0.0190*** (10.6642)	0.0072*** (7.8392)	0.0098*** (5.9909)	0.0030*** (4.6433)	0.0165*** (8.0979)	0.0102*** (7.6358)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,044	28,859	30,044	28,859	30,044	28,859
Pseudo R ²	0.2501	0.2067	0.3406	0.3109	0.1398	0.1127

This table shows the estimation results from Probit and Tobit regressions of household financial market participation and asset allocation (Columns 1 through 2), formal financial market decisions (Columns 3 through 4), and informal market decisions (Columns 5 through 6) on social networks and a series of control variables with alternative definitions of dependent variable. Only households with investments in the formal or informal financial market above RMB 5,000, RMB 10,000, or RMB 20,000 are included in the sample and analyzed in Panels A, B, and C, respectively. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to [Table 1](#).

3.4.3. Panel data estimations

Despite our efforts to include a list of control variables into the baseline estimations, some unobserved factors may bias our estimates. In this section, we compile the three waves of CHFS data (2011, 2013, and 2015) to obtain a balanced household-level panel data set. The panel data structure allows us to capture the unobserved heterogeneity through individual- and time-specific effects in addition to control variables, hence effectively alleviating the omitted-variable bias. The cost of constructing a panel data set is that the number of households reduces from 30,044 to 4095 in the case of market participation (and from 28,859 to 4944 in the case of asset allocation) in the constructed panel data set.¹²

Equations (1) and (2) are modified as

$$y_{it}^* = \beta \cdot network_{it} + \gamma X_{it} + \alpha_i + \varphi_t + \varepsilon_{it} \quad (3)$$

$$y_{it} = 1 \text{ if } y_{it}^* > 0 \text{ and } y_{it} = 0 \text{ otherwise, for market participation} \quad (4)$$

$$y_{it} = y_{it}^* \text{ if } y_{it}^* > 0 \text{ and } y_{it} = 0 \text{ otherwise, for riskyassetholding} \quad (5)$$

¹²One reason that leads to the drop of the sample size is that the CHFS collects information of 8,438 households in the wave of 2011 before expanding the sample size to more than 37,000 households in 2015.

y_{it} is a binary variable indicating whether household i participates in a risky financial market in year t in the case of the market participation. In the case of asset allocation, y_{it} indicates the nonnegative amount of risky asset holding as a fraction of the total financial asset. α_i denotes individual effects and φ_t is the year fixed effects. ε_{it} indicates the random disturbance term.

Table 10 summarizes the estimation results of two-way fixed effects models.¹³ Columns 1 through 2 report results of overall market participation and risky assets holding. Columns 3 through 4 focus on the formal financial market and Columns 5 through 6 focus on the informal financial market. In general, the coefficient of the *network* index remains positive and statistically significant at the 1 percent significance level in most cases. This suggests that the positive impacts of social networks on households financial market participation and risky asset holding are robust and not driven by the omitted-variable bias.

3.4.4. Instrumental variable estimations

In addition to the omitted-variable bias, reverse causality can also lead to endogeneity issues. In this section, we adopt the instrumental variable estimations to address these problems. Specifically, we use “the number of blood kinships living in the local area” as the instrumental variable for social networks. This variable is not perfect but it is selected for the following reasons. First, it is closely related to social networks. Having more relatives in an area helps households build a broader network. Second, whether a household’s relatives residing in the local area is determined by the relatives themselves,

Table 10. Robustness (Panel data estimations).

Variables	Overall Financial Market		Formal Financial Market		Informal Financial Market	
	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	Tobit	Logit	Tobit	Logit	Tobit
Network	0.0296*** (3.7338)	0.0039*** (28.6443)	0.0084 (1.0228)	0.0011*** (6.6723)	0.0388*** (4.3527)	0.035*** (15.3990)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,095	4,944	2,267	2,919	3,216	3,141
# of Households	1,365	1,648	764	973	1,091	1,047

This table shows the estimation results from Logit and Tobit panel fixed-effects regressions of household financial market participation and asset allocation (Columns 1 through 2), formal financial market decisions (Columns 3 through 4), and informal market decisions (Columns 5 through 6) on social networks and a series of control variables, using the balanced 2011–2015 panel data set. Both year- and individual-specific effects are included in the regression. Fixed effects Tobit estimator follows Honore (1992). The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

¹³As well documented in the literature (e.g., Honore, 1992, 2002; Greene, 2004), the fixed effects Probit and Tobit models cannot be properly estimated by the conventional method of maximum likelihood estimations. The estimator suffers the incidental parameter problem as the cross section dimension increases with the time dimension fixed. As a result, the estimates are in general biased and inconsistent. To explore households’ market participation behavior in the context of panel data, we estimate a fixed effects Logit model as Newey (2007) shows that the conditional maximum likelihood estimator is consistent and asymptotically normally distributed in this case. To explore households’ asset allocation behavior, we resort to a semiparametric fixed effects Tobit estimator proposed by Honore (1992), which is shown to be a consistent estimator with good finite sample properties. Besides, we also perform estimations through the random effects models and the results remain the same qualitatively.

not by the households. Therefore, it can be regarded as a relatively exogenous variable to the determination of a household's financial decisions and affects households financial decisions only through the channel of social networks.¹⁴

Table 11 reports the estimation results with this instrumental variable. Columns 1 through 2 analyze the effects on market participation, and the other two columns examine the effects on asset allocation. Panels A, B, and C explore the effects of social networks on the overall, formal, and informal financial markets, respectively. Because the first stage estimation is the same across the three panels, the results are only reported in Panel A.

Table 11. Robustness (Instrumental variable estimations).

Variables	(1) ivprobit	(2) ivprobit	(3) ivtobit	(4) ivtobit
Panel A Household Financial Market Participation and Asset Allocations				
Network	0.1510** (2.1571)	0.1781** (2.1400)	0.0710* (1.8861)	0.0792* (1.8163)
Control Variables	Yes	Yes	Yes	Yes
Provincial Dummy	No	Yes	No	Yes
Wald test	4.62	5.17	3.94	3.93
[p-value]	[0.032]	[0.023]	[0.047]	[0.047]
F-statistics of the first-stage regression	227.02	87.79	214.33	83.00
Localrelative	0.1337*** (3.76)	0.0119*** (3.36)	0.1312*** (3.57)	0.1170*** (3.18)
Observations	29,987	29,987	28,811	28,811
Panel B Household Formal Financial Market Participation and Asset Allocation				
Network	0.2196** (2.4073)	0.2751** (2.4101)	0.1220** (2.4085)	0.1405** (2.3171)
Control Variables	Yes	Yes	Yes	Yes
Provincial Dummy	No	Yes	No	Yes
Wald test	8.33	10.05	9.89	10.54
[p-value]	[0.004]	[0.002]	[0.002]	[0.001]
Observations	29,987	29,987	28,811	28,811
Panel C Household Informal Financial Market Participation and Asset Allocation				
Network	0.0690 (1.0424)	0.0748 (0.9939)	0.0298 (0.6960)	0.0257 (0.5369)
Control Variables	Yes	Yes	Yes	Yes
Provincial Dummy	No	Yes	No	Yes
Wald test	0.66	0.64	0.28	0.15
[p-value]	[0.415]	[0.425]	[0.594]	[0.698]
Observations	29,987	29,987	28,811	28,811

This table shows the instrumental variable estimation results from IVProbit and IVTobit regressions of household financial market participation and asset allocation (Panel A), formal financial market decisions (Panel B), and informal financial market decisions (Panel C) on social networks and a series of control variables. The number of relatives residing in local area (*localrelative*) is adopted as the instrumental variable. In the two-step IV regressions in Panel B and Panel C, the first-stage regression results are not reported since they are the same as the first-stage estimation results in Panel A. Robust z statistics are reported in parentheses and p-values are reported in square brackets. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

¹⁴In addition to the number of relatives, we also try to use “whether a household head has a local Hukou (a registered permanent local resident)” as an IV for social networks. Households without a local Hukou must rely more on interpersonal communications to establish or strengthen personal networks; moreover, the property of Hukou of the household head is determined by historical and institutional factors, not by the households. It turns out that the results are qualitatively similar.

In Panel A, the Wald test of exogeneity in all cases rejects the null hypothesis of no endogeneity, confirming the endogeneity of social networks. With instrumental variables, the estimated coefficients for the *network* index remain positive and statistically significant for all cases. These results confirm our earlier finding: a wider social network enhances household participation rate in the financial market and induces households to own a higher fraction of risky assets.

Panel B provides a similar and somewhat stronger explanation regarding the formal financial market. In Panel B, the Wald test in all cases rejects the null hypothesis of no endogeneity. All of them report a positive and significant impact of social networks on household financial decisions in the formal financial markets.

Panel C examines the performance of social networks in the informal financial market. The Wald test in all cases fails to reject the null hypothesis of no endogeneity; hence, the analysis related to these columns should be directed to the corresponding columns in Table 6 although all columns here still report a positive (but insignificant) impact of social networks on household financial decisions in the informal financial markets.

3.4.5. Summary

In summary, our exercise with instrumental variables confirms earlier findings: social networks have a positive and statistically significant impact on household financial decisions. Together with previous sections, we show that the baseline findings are not qualitatively different when considering alternative measurements, panel estimations, and instrumental variables. Despite the limit of each method above, they jointly provide evidence for the robustly positive impacts of social networks on household financial market participation and risky asset holding. The endogeneity issue caused by omitted variables and reverse causality are not found to change the main results.

4. Transmission mechanisms

Section 3 shows that social networks have positive and robust impacts on household financial participation and risky asset holding. In this section, we examine *through which channels* social networks affect household financial decisions. Before proceeding to formal estimations, we use the stock market as an example and analyze why many households refuse to invest in the stock market.¹⁵ Figure 2 describes possible reasons why households do not invest in the stock market according to CHFS 2015. The top three reasons include (1) limited funds available (42.5 percent), (2) lack of knowledge (35.6 percent), and (3) high risks in the stock market (34.7 percent). When we examine the 2011 and 2013 data, the top three reasons are exactly the same, despite the different order. This finding suggests that households' financial decisions are largely affected by financial constraints, information acquisition, and risk management. It motivates us to consider the following question: is the positive role of social networks on household financial decisions found in section 3 related to the above three factors? In the following sections, we aim to search statistical evidence for transmission channels of financing, information, and risks.

¹⁵Stock market is the most important formal financial market and has the highest households participation rate. It is the focus of many studies in the literature (e.g., Guiso et al., 2008; Hong et al., 2004).

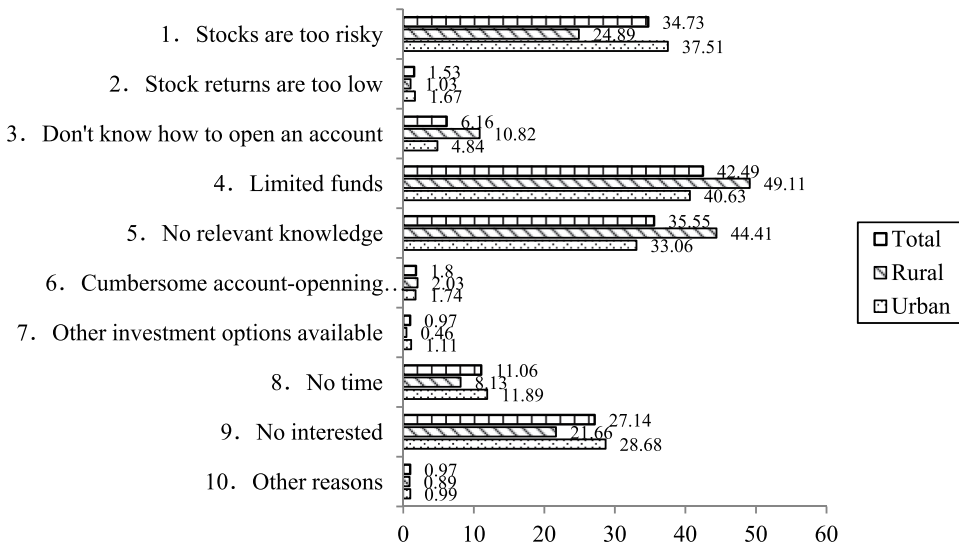


Figure 2. Why households do not invest in the stock market (CHFS 2015). Notes: This figures show the distribution of 10 reasons why rural and urban households do not invest in the stock market in CHFS 2015. Numbers are in percentage.

4.1. Financing mechanism

A prerequisite for households participating in the financial market is the availability of sufficient funds. Credit constraints, however, may dampen the capability of households making risky investment. On the one hand, social networks may reduce households precautionary savings and allow them to invest more (Zhou, 2014); on the other hand, social networks may mitigate asymmetric information and facilitate formal and informal lending to households (Karlan, 2007). In particular, the prevailing informal lending in China is built on mutual trust among relatives and friends. Transactions are regulated by the informal institution on the basis of blood kinship, family connections, and geographic connections. Therefore, members within the network may find obtaining informal financing easier.

Due to the limitation of the available data, we propose a preliminary approach to examine the financing mechanism. If social networks increase household financial participation and risky asset allocation by easing their credit constraints, at least some of the risky assets should be financed by formal or informal lending. Table 12 reports the fraction of households who take a loan or borrow money to finance their risky assets investment. In 2015, among all households purchasing stocks or other risky financial products, only 1.4 percent and 0.3 percent relied on formal or informal lending. Most households use their own funds to make risky investments. For financial derivatives, financial wealth-management products, and non-RMB denominated assets, not a single household takes a loan or borrows money to finance its investment in 2011, and the numbers are close to zero in 2013. This finding suggests that if social networks indeed mitigate household credit constraints, the additional credit might be used for

Table 12. Social networks and the financing mechanism.

Questions in CHFS	Survey Round	Yes	No	Observations
Did your family take a loan or borrow money to buy stock?	2015	1.37%	98.59%	2478
	2013	1.61%	98.39%	1741
	2011	1.94%	98.06%	567
Did your family take a loan or borrow money to buy bonds?	2015	NA	NA	NA
	2013	0.45%	99.55%	220
	2011	3.51%	96.49%	57
Did your family take a loan or borrow money to buy the fund?	2015	NA	NA	NA
	2013	0.81%	99.09%	985
	2011	2.21%	97.79%	317
Did your family borrow money or take loans to purchase financial derivatives?	2015	NA	NA	NA
	2013	2.63%	97.37%	38
	2011	0%	100%	1
Did your family take a loan or borrow money to purchase financial wealth-management products?	2015	NA	Na	NA
	2013	0.34%	99.66%	595
	2011	0%	100%	83
Did you take home loans or borrow money to buy non-RMB denominated assets?	2015	NA	NA	NA
	2013	0%	100%	276
	2011	0%	100%	89
Did your family take a loan or borrow money to buy other financial products (except stocks)?	2015	0.29%	99.71%	4168
	2013	NA	NA	NA
	2011	NA	NA	NA

This table reports the percentage of households who take a loan or borrow money to invest in formal financial markets (e.g., stocks, bonds, fund, financial wealth-management products, non-RMB denominated assets).

consumption smoothing, physical investment, or others, but not for investment in risky financial assets. This observation suggests that the financing mechanism of social networks does not hold, or if it holds, the financing mechanism plays a very limited role.

4.2. Information mechanism

Guanxi (i.e., personal relationships) is a typical and prominent characteristic of the Chinese society. Social networks, interweaved with *Guanxi*, facilitate household information acquisition and asset allocation. Households realize that participation in financial markets is costly (Haliassos & Bertaut, 1995) and that timely communication with other households within their networks may provide valuable information and effectively reduce the participation cost. Hence, social networks may enhance the household participation rate in the financial market.

We test this conjecture formally. If the significant and positive impacts of social networks on household financial decisions indeed function through the information mechanism, households with more information or better access to information are expected to benefit less from social networks. We adopt a variable, *information*, that characterizes “the degree of concern for economic and financial information”.¹⁶ A household more concerned with such information is more likely to be well informed on economic and financial conditions. The variable *information* and its interactive term with social networks are added into Equations (1) and (2). We then run Probit and Tobit regressions based on this equation.

¹⁶The variable *information* measures the respondent's degree of concern for economic and financial information, running from 1 to 5. The higher the measure, the closer attention the respondent pays to economic and financial information.

Table 13. Social networks and the information mechanism.

Variables	Overall Financial Market		Formal Financial Market		Informal Financial Market	
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Tobit	Probit	Tobit	Probit	Tobit
Network	0.0235*** (5.6464)	0.0118*** (6.6350)	0.0218*** (5.7357)	0.0079*** (5.4898)	0.0266*** (6.8154)	0.0141*** (5.8175)
network×Information	−0.0014 (−0.8968)	−0.0022*** (−4.8538)	−0.0042*** (−3.4365)	−0.0019*** (−4.6516)	−0.0037*** (−2.7820)	−0.0024*** (−3.5870)
Information	0.1944*** (18.3404)	0.1001*** (20.1534)	0.2776*** (23.6932)	0.1303*** (23.7277)	0.0972*** (8.7857)	0.0485*** (7.1975)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,015	28,832	30,015	28,832	30,015	28,832
Pseudo R ²	0.2442	0.1860	0.3616	0.3253	0.1156	0.0889

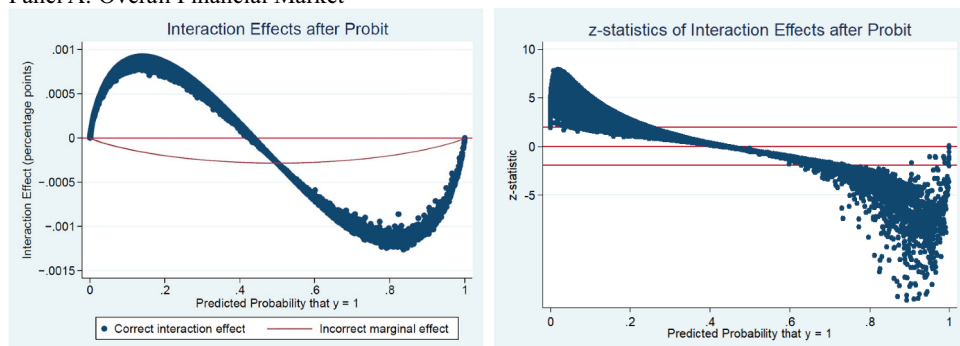
This table shows the estimation results from Probit and Tobit regressions that include information and its interactive term with social networks. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

Table 13 reports the estimation results. Columns 1 through 2 report estimations for the overall financial market, Columns 3 through 4 report the results for the formal financial market, and Columns 5 through 6 report the results for the informal financial market. Two observations prevail. First, all the estimated *information* coefficients are positive and statistically significant at the 1 percent level, suggesting that sensitivity to economic/financial information has positive effects on household financial decisions.

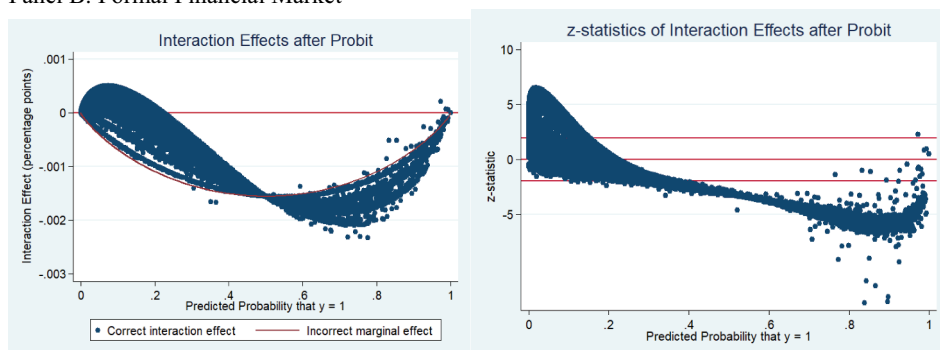
Second, the interactive term of information and social networks tends to be negative and significant. Unfortunately, one cannot interpret the coefficient of the interactive term as the interaction effect in a nonlinear model. As discussed by Ai and Norton (2003) and Norton, Wang, and Ai (2004), the interaction effect in such nonlinear models as the Probit and Tobit models in our case is conditional on the independent variable and may have different signs for different values of independent variables. In the Appendix, we follow Ai and Norton (2003) and derive the coefficients and standard errors of the interaction effect for the Probit model. We then extend their analysis and derive corresponding expressions for the Tobit model. Because of the nonlinearity of our regression models, the interaction effect is conditional on observed covariates, *i.e.*, observation specific. Using the derived expression (A8) in the Appendix, we are able to calculate the interaction effects correctly. Figures 3 and 4 report the estimated interaction effects and z-statistics between social networks and information.

Figure 3 reports the estimated interaction effect against households' probability of participating in different forms of financial markets based on estimates in Columns 1, 3, and 5 of Table 13 and Equation (A8). Each point in the figure corresponds to an estimate conditional on one observation (or one household). The first and second columns show the coefficients and z-statistics, respectively. In all three panels (overall, formal, and informal financial markets), households who tend to invest in the financial market (corresponding to the right part of each scatter plot) exhibit a negative interaction effect. This confirms our conjecture that, on the extensive margin, households with a higher level of information indeed benefit less from social networks because social networks work through information dissemination and acquisition.

Panel A: Overall Financial Market



Panel B: Formal Financial Market



Panel C: Informal Financial Market

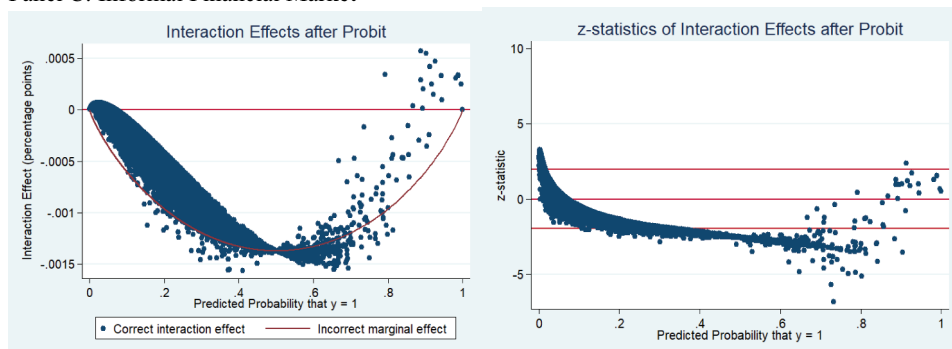
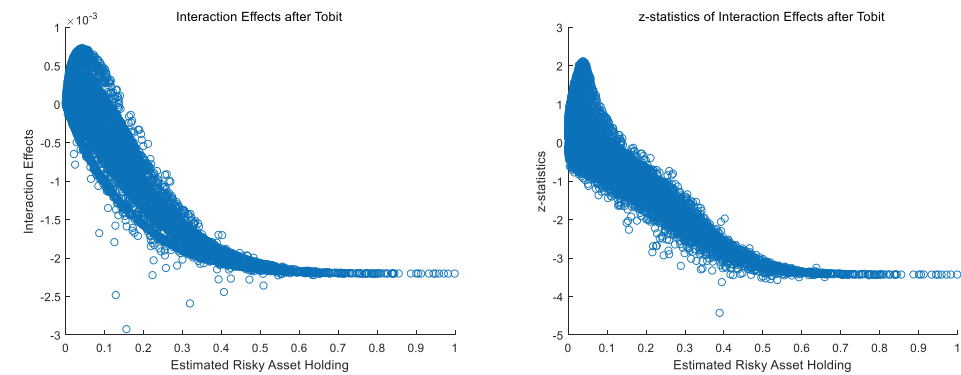


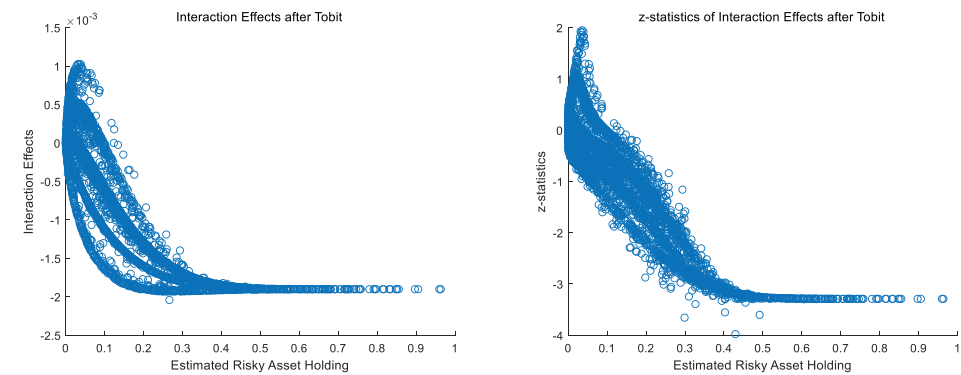
Figure 3. Social network and the information mechanism (Market participation). Notes: This figure shows the calculated interaction effect, how social network affects the marginal impact of information on household financial market participation in the overall, formal, and informal markets, based on estimates in Columns 1, 3, and 5 of Table 13 and Equation (A8) in the Appendix. The first column reports the coefficients and the second column reports the corresponding z-statistics for each observation. The scatter plot is generated by the Stata package described in Norton et al. (2004).

On the intensive margin, Figure 4 reports the estimated interaction effect against households' estimated risky asset holding in different forms of financial markets based on estimates in Columns 2, 4, and 6 of Table 13 and Equations (A18) and (A21) in the Appendix. Similar findings arise. In all three panels (overall, formal, and informal

Panel A: Overall Financial Market



Panel B: Formal Financial Market



Panel C: Informal Financial Market

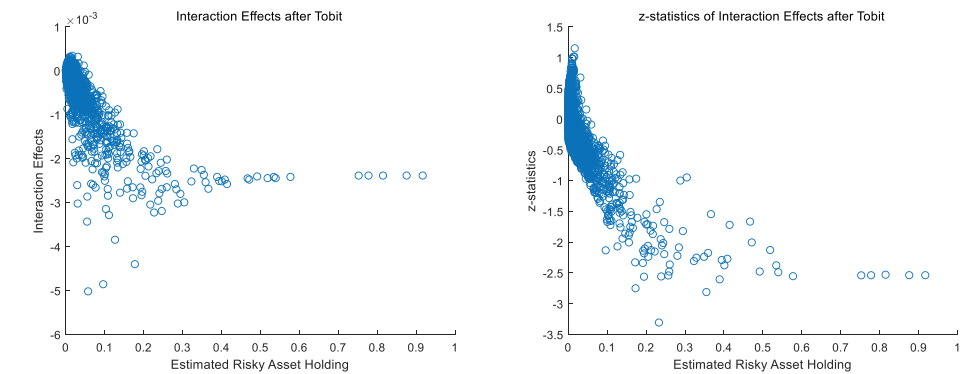


Figure 4. Social network and the information mechanism (Risky asset holding). Notes: This figure shows the calculated interaction effect, how social network affects the marginal impact of information on household risky asset holding in the overall, formal, and informal markets, based on estimates in Columns 2, 4, and 6 of Table 13 and Equations (A18) and (A21) in the Appendix. The first column reports the coefficients and the second column reports the corresponding z-statistics for each observation.

Table 14. Social networks and the risk mechanism (I).

Variables	Overall Financial Market		Formal Financial Market		Informal Financial Market	
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Tobit	Probit	Tobit	Probit	Tobit
Network	0.0187*** (2.6020)	−0.0006 (−0.4292)	0.0090* (1.7109)	−0.0003 (−0.1796)	0.0065 (1.5900)	−0.0009 (−0.6327)
Network × riskaverse	0.0018 (0.2466)	0.0100*** (5.1014)	0.0162*** (2.7622)	0.0110*** (5.7350)	0.0222*** (4.8536)	0.0123*** (4.2926)
Riskaverse	−0.1872*** (−18.2033)	−0.0971*** (−21.8896)	−0.2675*** (−25.1530)	−0.1283*** (−26.0703)	−0.0776*** (−8.1527)	−0.0437*** (−7.6580)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,044	28,859	30,044	28,859	30,044	28,859
Pseudo R ²	0.2310	0.1754	0.3399	0.3042	0.1127	0.0878

This table shows the estimation results from Probit and Tobit regressions with the degree of risk aversion and its interactive term with social networks. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

financial markets), households who tend to hold more risky assets (corresponding to the right part of each scatter plot) show a significantly negative interaction effect. In other words, social networks contribute less to risky asset holding for households with more information, lending support to the information mechanism.

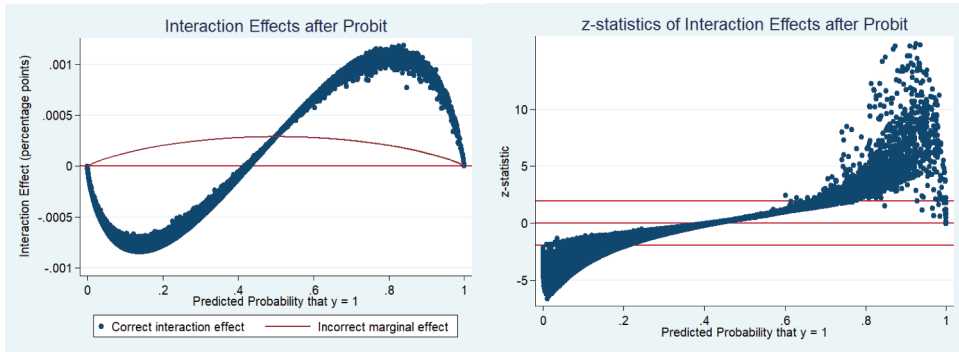
4.3. Risk-sharing mechanism

In the presence of incomplete and imperfect formal financial institutions and social security, households in less developed countries rely more on social networks as informal insurance against natural disasters and diseases (Fafchamps & Gubert, 2007). Households with broader social networks are more likely to receive aid when suffering from negative shocks (Ambrus et al., 2014; De Weerd & Dercon, 2006; Kinnan & Townsend, 2012; Zhou, 2014). Due to social networks' potential role in managing uncertainty, they may also be related to households risk attitude and indirectly affect households financial decisions. We follow two lines to examine the existence of the risk-sharing mechanism.

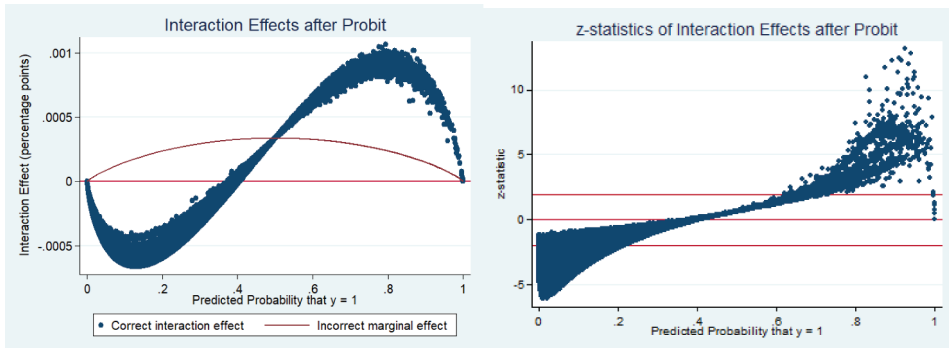
First of all, we follow a direct route to examine the risk mechanism. As mentioned in section 2.2.3 (footnote 6), the available information on household risk attitudes in the CHFS allows us to construct the variable *riskaverse* by assigning a score of 1 to 5 to each of the five options. A higher score of *riskaverse* represents a higher degree of risk aversion. In Equations (1) and (2), we add an interactive term between social networks and households risk attitude (*riskaverse*). Estimation results are reported in Table 14. Several observations are notable. First, as expected, *riskaverse* has significantly negative effects in all cases. More risk averse households are less likely to participate in financial markets and tend to allocate fewer resources to risky assets.

Second, we use the same formula derived in the Appendix to calculate the interaction effect of risk aversion, that is, how social network affects the marginal impact of risk aversion on household financial market participation and risky asset holding. We use the following two figures to report the interaction effect. On the extensive margin, Figure 5

Panel A: Overall Financial Market



Panel B: Formal Financial Market



Panel C: Informal Financial Market

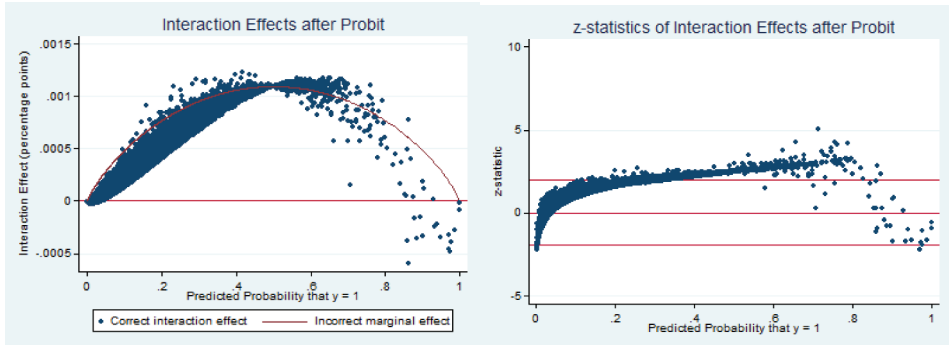
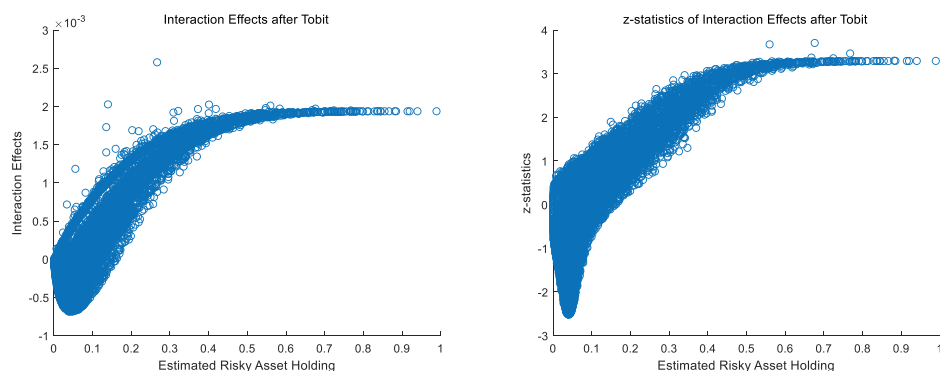


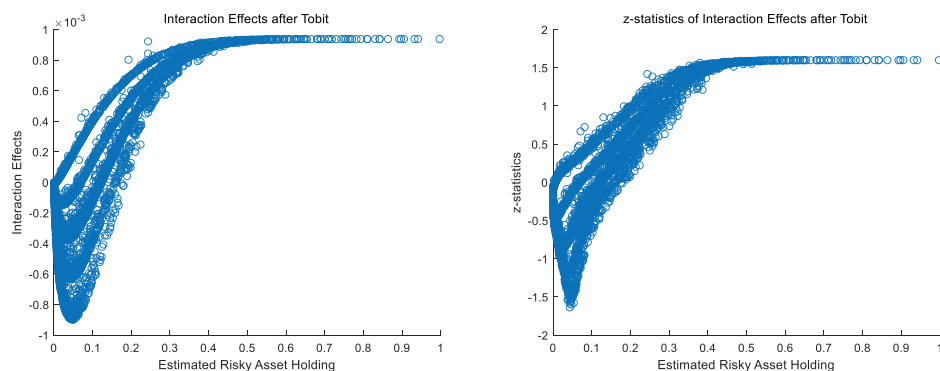
Figure 5. Social network and the risk-sharing mechanism (Market participation). Notes: This figure shows the calculated interaction effect, how social network affects the marginal impact of risk-aversion on household financial market participation in the overall, formal, and informal markets, based on estimates in Columns 1, 3, and 5 of Table 14 and Equation (A8) in the Appendix. The first column reports the coefficients and the second column reports the corresponding z-statistics for each observation. The scatter plot is generated by the Stata package described in Norton et al. (2004).

reports the estimated interaction effect (both coefficients and z-statistics) against households' probability of participating in different forms of financial markets, based on estimates in Columns 1, 3, and 5 of Table 14 and Equation (A8). In all three panels, households that tend to participate in the financial market exhibit a significantly positive

Panel A: Overall Financial Market



Panel B: Formal Financial Market



Panel C: Informal Financial Market

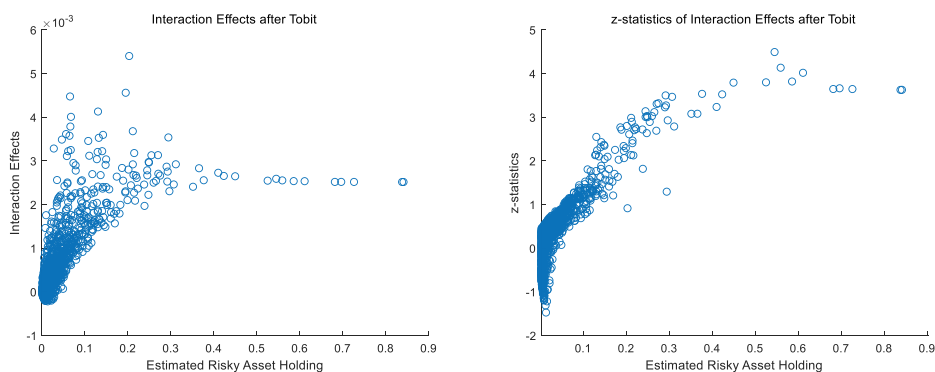


Figure 6. Social network and the risk-sharing mechanism (Risky asset holding). Notes: This figure shows the calculated interaction effect, how social network affects the marginal impact of risk-aversion on household risky asset holding in the overall, formal, and informal markets, based on estimates in Columns 2, 4, and 6 of Table 14 and Equations (A18) and (A21) in the Appendix. The first column reports the coefficients and the second column reports the corresponding z-statistics for each observation.

interaction effect, suggesting that social networks dampen the negative impacts of risk aversion on household financial decisions in both formal and informal financial markets. It provides supportive evidence for the existence of the risk-sharing mechanism.

Table 15. Social networks and the risk mechanism (II).

Variables	(1) oprobit	(2) oprobit	(3) ologit	(4) ologit
Network	−0.0055*** (−5.7658)	−0.0058*** (−5.9167)	−0.0088*** (−5.4015)	−0.0096*** (−5.6587)
Logasset	−0.0589*** (−10.8016)	−0.0590*** (−10.4024)	−0.1075*** (−11.3962)	−0.1047*** (−10.6201)
Loghhincome	−0.0423*** (−7.3227)	−0.0471*** (−8.0072)	−0.0785*** (−7.9255)	−0.0868*** (−8.6557)
Selfemploy	−0.1017*** (−5.6627)	−0.0942*** (−5.1872)	−0.1797*** (−5.9199)	−0.1695*** (−5.5095)
House	−0.0136 (−1.1393)	−0.0159 (−1.2944)	−0.0164 (−0.8250)	−0.0232 (−1.1146)
hhsiz	−0.0117** (−2.5758)	0.0037 (0.7871)	−0.0172** (−2.2591)	0.0089 (1.1391)
Age	0.4259*** (13.0388)	0.3910*** (11.9282)	0.7552*** (13.3902)	0.6925*** (12.2679)
Age-sq	−0.0192*** (−6.2508)	−0.0167*** (−5.3993)	−0.0347*** (−6.5193)	−0.0300*** (−5.6303)
Female	0.0738*** (4.6974)	0.0801*** (5.0726)	0.1284*** (4.8934)	0.1397*** (5.2845)
Edu	−0.0316*** (−15.2715)	−0.0334*** (−15.9358)	−0.0590*** (−16.6854)	−0.0619*** (−17.3473)
Unmarried	−0.1644*** (−4.7976)	−0.1367*** (−3.9572)	−0.2695*** (−4.6483)	−0.2280*** (−3.8897)
Financial literacy	−0.3772*** (−10.4146)	−0.3638*** (−9.8898)	−0.6428*** (−10.3222)	−0.6228*** (−9.7311)
Rural	−0.0243 (−1.3391)	−0.0119 (−0.6467)	−0.0279 (−0.9152)	−0.0100 (−0.3260)
Provincial Dummy	No	Yes	No	Yes
Observations	30,044	30,044	30,044	30,044
Pseudo R ²	0.0673	0.0742	0.0734	0.0807

This table shows the estimation results from ordered Probit and ordered Logit regressions of household degrees of risk aversion on social networks and a series of control variables. The dependent variable is *riskaverse* that measures the degree of risk attitude of a household. A higher score of *riskaverse* indicates a higher degree of risk aversion. The variable age is divided by 10 so that its estimated coefficients are readable. Robust z statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance at 1, 5, and 10 percent level, respectively. For detailed definitions of variables, please refer to Table 1.

On the intensive margin, Figure 6 reports the estimated interaction effect against households' estimated risky asset holding in different forms of financial markets, based on estimates in Columns 2, 4, and 6 of Table 14 and Equations (A18) and (A21). As expected, in the overall, formal, and informal financial markets, households who tend to hold more risky assets (corresponding to the right part of the scatter plot) show a significantly positive interaction effect. In other words, the negative impacts of risk aversion on households' risky asset holding are dramatically mitigated by social networks, a result confirming the risk-sharing mechanism.

The second line we follow amounts to testing whether social networks are directly related to household risk attitude. We take *riskaverse* as the dependent variable and explore whether it is affected by social networks while controlling for other variables.

Because of the nature of an ordinal dependent variable, the estimations are conducted through an ordered Probit model and an ordered Logit model. The estimation results are reported in Table 15. Social networks are significantly negatively related to risk attitude in all cases: households with more social networks tend to be less risk averse. It holds for

estimations (1) with or without control variables; (2) with or without provincial dummies; and (3) using a Probit model or a Logit model. In addition, if we recall the estimation results reported in Table 4 through 6, risk aversion always negatively affects households' decisions on financial market participation and risky asset holding, consistent with the literature (*e.g.*, Barberis, Huang, & Thaler, 2006). Our test therefore supports the view that social networks could alleviate the negative impacts of risk aversion on household financial decisions, providing supportive evidence for the presence of a risk-sharing mechanism.

5. Concluding remarks

In this study we investigate the effects of social networks on household financial market participation and asset allocation using a nationally representative household survey in China. By constructing an index that captures households' connections from the perspectives of kinship, work, and social interactions, we find a robust and positive impact of social networks. Households with a broader social network are more likely to participate in financial markets and hold a higher fraction of risky assets, both in the formal and informal financial markets. This finding is robust across different waves of survey data spanning from 2011 to 2015. It is also robust to alternative index construction, estimation techniques, and variable definitions.

Two mechanisms are identified from social networks to household financial decisions. First, social networks directly help households obtain necessary knowledge and important information, reducing the participation cost and increasing the probability of participation. Second, as an informal institution, social networks promote household risk sharing and indirectly affect household market participation and risky asset holding.

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Disclosure statement

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References

- Ai, C., & Norton, E. (2003). Interaction terms in logit and probit models. *Economics Letters*, 80(1), 123–129.
- Ambrus, A., Mobius, M., & Szeidl, A. (2014). Consumption risk-sharing in social networks. *American Economic Review*, 104(1), 149–182.
- Barberis, N., Huang, M., & Thaler, R. (2006). Individual, monetary gambles, and stock market participation: A case for narrow framing. *American Economic Review*, 96(4), 1069–1090.
- Bloch, F., Genicot, G., & Ray, D. (2008). Informal insurance in social networks. *Journal of Economic Theory*, 143(1), 36–58.
- Bogan, V. (2008). stock market participation and the Internet. *Journal of Financial and Quantitative Analysis*, 43(1), 191–211.
- Brown, R., Ivković, Z., Smith, P., & Weisbenner, S. (2008). Neighbors matter: Causal community effects and stock market participation. *The Journal of Finance*, 63(3), 1509–1531.
- Campbell, Y. (2006). Household finance. *The Journal of Finance*, 61(4), 1553–1604.
- Chai, S., Chen, Y., Huang, B., & Ye, D. (2018). Social networks and informal inclusion of the People's Republic of China (ADB Working Paper 802). Tokyo: Asian Development Bank Institute.
- Christelis, D., Jappelli, T., & Padula, M. (2010). Cognitive abilities and Portfolio choice. *European Economic Review*, 54(1), 18–38.
- De Weerd, J., & Dercon, S. (2006). Risk-sharing networks and insurance against illness. *Journal of Development Economics*, 81(2), 337–356.
- Dimmock, G., & Kouwenberg, R. (2010). Loss-aversion and household Portfolio choice. *Journal of Empirical Finance*, 17(3), 441–459.
- Du, Z., Guo, J., & Zhang, L. (2013). Guanxi and income inequality (Southwestern University of Finance and Economics Working Paper).
- El-Attar, M., & Poschke, M. (2011). Trust and the choice between housing and financial assets: Evidence from Spanish households. *Review of Finance*, 15(4), 727–756.

- Fafchamps, M., & Gubert, F. (2007). The formation of risk sharing networks. *Journal of Development Economics*, 83(2), 326–350.
- Filmer, D., & Pritchett, L. (2001). Estimating wealth effects without expenditure data or tears: An application to educational enrollments in States of India. *Demography*, 38(1), 115–132.
- Georgarakos, D., & Pasini, G. (2011). Trust, sociability, and stock market participation. *Review of Finance*, 15(4), 693–725.
- Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal*, 7(1), 98–119.
- Grinblatt, M., Keloharju, M., & Linnainmaa, J. (2011). IQ and stock market participation. *The Journal of Finance*, 66(6), 2121–2164.
- Guiso, L., & Paiella, M. (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association*, 6(6), 1109–1150.
- Guiso, L., Sapienza, P., & Zingales, L. (2003). People's opium? Religion and economic attitudes. *Journal of Monetary Economics*, 50(1), 225–282.
- Guiso, L., Sapienza, P., & Zingales, L. (2004). The role of social capital in financial development. *American Economic Review*, 94(3), 526–556.
- Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *The Journal of Finance*, 63(6), 2557–2600.
- Haliassos, M., & Bertaut, C. (1995). Why do so few hold stocks? *The Economic Journal*, 105(432), 1110–1129.
- Hong, H., Kubik, J., & Stein, J. (2004). Social interaction and stock market participation. *The Journal of Finance*, 59(1), 137–163.
- Honore, B. E. (1992). Trimmed lad and least squares estimation of truncated and censored regression models with fixed effects. *Econometrica*, 60(3), 533–565.
- Honore, B. E. (2002). Nonlinear models with panel data. *Portuguese Economic Journal*, 1(2), 163–179.
- Karlan, S. (2007). Social connections and group banking. *The Economic Journal*, 117(517), 52–84.
- Kinnan, C., & Townsend, R. (2012). Kinship and financial networks, formal financial access and risk reduction. *American Economic Review*, 102(3), 289–293.
- Kumar, A., Page, J., & Spalt, O. (2011). Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics*, 102(3), 671–708.
- Li, H., Meng, L., Wang, Q., & Zhou, L. (2008). Political connections, financing and firm performance: Evidence from Chinese private firms. *Journal of Development Economics*, 87(2), 283–299.
- Liang, P., & Guo, S. (2015). Internet access and stock market participation—an empirical study in China. *Journal of Comparative Economics*, 43(4), 883–901.
- Liu, Z., Zhang, T., & Yang, X. (2014). Social interaction and stock market participation: Evidence from China. *Mathematical Problems in Engineering*, 2014, Article ID 906564.
- Mankiw, G., & Zeldes, S. (1991). The consumption of stockholders and nonstockholders. *Journal of Financial Economics*, 29(1), 97–112.
- Newey, W. (2007). Course materials for 14.386 new econometric methods, Spring 2007. MIT OpenCourseWare. Massachusetts Institute of Technology. Retrieved October 5, 2021, from <http://ocw.mit.edu>
- Norton, E., Wang, H., & Ai, C. (2004). Computing interaction effects and standard errors in logit and probit models. *The Stata Journal*, 4(2), 154–167.
- Peng, Y. (2004). Kinship Networks and entrepreneurs in China's transitional economy. *American Journal of Sociology*, 109(5), 1045–1074.
- Puri, M., & Robinson, D. (2007). Optimism and economic choice. *Journal of Financial Economics*, 86(1), 71–99.
- Putnam, R., Leonardi, R., & Nanetti, R. (1993). *Making democracy work: Civic tradition in Modern Italy*. Princeton: Princeton University Press.
- Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2), 449–472.

- Wu, X., & Zhao, J. (2020). Risk sharing, siblings, and household equity investment: Evidence from Urban China. *Journal of Population Economics*, 33(2), 461–482.
- Zhang, X., & Li, G. (2003). Does Guanxi matter to nonfarm employment? *Journal of Comparative Economics*, 31(2), 315–331.
- Zhou, W. (2014). Brothers, household financial markets and savings rate in China. *Journal of Development Economics*, 111, 34–47.

Appendix. Interaction in the Probit and Tobit Models

To examine the transmission mechanism of social networks on household financial decisions, we resort to the interaction between social networks and channel variables. However, the interaction term should be interpreted differently in nonlinear models (e.g., Probit and Tobit models) compared to linear models. In particular, the coefficient of the interactive term alone cannot be interpreted directly as the interaction effect in Probit or Tobit models (Ai & Norton, 2003; Norton et al., 2004).

Ai and Norton (2003) provide a theoretical analysis to the interaction effect in Probit and Logit models. Norton et al. (2004) further devise a Stata package to calculate the correct interaction effect and the corresponding standard errors. To examine the interaction effect concerning market participation (a Probit model), we can employ their package to calculate the interaction effect and examine whether social networks affects the marginal impact of information (or risk aversion) on household market participation. To examine the interaction effect concerning risky asset holding (a Tobit model), there does not exist a similar package, to the best of our knowledge. We follow the spirit of Ai and Norton (2003) and derive explicit expressions for the coefficients and standard errors of the interaction effect in this case.

In this Appendix, we first replicate Ai and Norton (2003) for the case of the Probit model and then provide the detailed expressions regarding the interaction effect for the Tobit model.

The Probit Model

Consider a Probit model in a latent variable form

$$y_j^* = \beta_1 x_{1j} + \beta_2 x_{2j} + \beta_{12} x_{1j} x_{2j} + X\beta + \varepsilon_j \quad (\text{A1})$$

The observed variable $y_j = 1$ if $y_j^* > 0$ and $y_j = 0$, otherwise. x_1 and x_2 stand for the two variables of interest and X represents other control variables. The random error term ε follows a normal distribution $\varepsilon \sim N(0, \sigma^2)$. This model specification features the interaction of x_1 and x_2 explicitly. In our case, x_1 is the social network variable and x_2 refers to a channel variable (e.g., an information or risk aversion variable). y characterizes the household financial decision on the extensive margin, that is, whether households participating in the financial market. Ai and Norton (2003) derived how to calculate the interaction effect in this case.

We first define the following notations:

$$u_j \equiv \beta_1 x_{1j} + \beta_2 x_{2j} + \beta_{12} x_{1j} x_{2j} + X\beta$$

$$I_j \equiv [x_{1j}, x_{2j}, X], \text{ the information set}$$

$$\theta \equiv [\beta_1, \beta_2, \beta_{12}, \beta]'$$

$$\phi(y) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}y^2\right), \text{ the density function}$$

$$\Phi(y) = p(y_j \leq y) = \int_{-\infty}^y \phi(y) dy, \text{ the distribution function}$$

where $\phi(y)$ and $\Phi(y)$ denote the probability density function (PDF) and cumulative distribution function (CDF) of a standard normal distribution, respectively.

With these notations, the conditional expectation of y_j can be written as

$$E(y_j|I_j) = p(\varepsilon_j > -u_j) = \Phi\left(\frac{u_j}{\sigma}\right) \quad (\text{A2})$$

The partial impact of x_1 can be derived as

$$\frac{\partial E(y_j|I_j)}{\partial x_{1j}} = \phi\left(\frac{u_j}{\sigma}\right) \frac{\beta_1 + \beta_{12}x_{2j}}{\sigma} \quad (\text{A3})$$

The *interaction effect*, i.e., the impact of x_2 on the above marginal impact of x_1 , is

$$\begin{aligned} \mu_{12}(\theta, I_j) &= \frac{\partial}{\partial x_{2j}} \left(\frac{\partial E(y_j|I_j)}{\partial x_{1j}} \right) = \frac{\partial^2 E(y_j|I_j)}{\partial x_{1j} \partial x_{2j}} \\ &= \phi'\left(\frac{u_j}{\sigma}\right) \frac{\beta_2 + \beta_{12}x_{1j}}{\sigma} \frac{\beta_1 + \beta_{12}x_{2j}}{\sigma} + \phi\left(\frac{u_j}{\sigma}\right) \frac{\beta_{12}}{\sigma} \end{aligned} \quad (\text{A4})$$

Since we have

$$\phi(y) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}y^2\right) \quad (\text{A5})$$

The first and second order derivatives take the following formulations

$$\phi'(y) = -y\phi(y) \quad (\text{A6})$$

$$\phi''(y) = -\phi(y) + y^2\phi(y) \quad (\text{A7})$$

Then Equation (A4) becomes

$$\begin{aligned} \mu_{12}(\theta, I_j) &= \frac{\partial^2 E(y_j|I_j)}{\partial x_{1j} \partial x_{2j}} \\ &= \frac{1}{\sigma} \phi\left(\frac{u_j}{\sigma}\right) \left[\beta_{12} - \frac{(\beta_2 + \beta_{12}x_{1j})(\beta_1 + \beta_{12}x_{2j})}{\sigma^2} u_j \right] \end{aligned} \quad (\text{A8})$$

The Tobit Model

Consider a Tobit model in a latent variable form

$$y_j^* = \beta_1 x_{1j} + \beta_2 x_{2j} + \beta_{12} x_{1j} x_{2j} + X\beta + \varepsilon_j \quad (\text{A9})$$

The observed variable $y_j = y_j^*$ if $y_j^* > 0$ and $y_j = 0$, otherwise. In our case, y characterizes the intensive margin of household financial decisions, that is, the percentage of households' risky assets holding out of their total financial assets. The other notations have the same meanings as in the Probit model.

The conditional CDF of y_j , given $y_j > 0$ and the information set I_j , can be written as:

$$H(y|y_j > 0, I_j) = p(y_j \leq y|y_j > 0, I_j)$$

$$= \frac{p(0 < y_j \leq y|I_j)}{p(y_j > 0|I_j)}$$

$$= \frac{\Phi\left(\frac{y-u_j}{\sigma}\right) - \Phi\left(-\frac{u_j}{\sigma}\right)}{\Phi\left(\frac{u_j}{\sigma}\right)} \quad (\text{A10})$$

The corresponding density function of y_j is:

$$h(y|y_j > 0, I_j) = \frac{\partial H(y|y_j > 0, I_j)}{\partial y} = \frac{\phi\left(\frac{y-u_j}{\sigma}\right)}{\sigma\Phi\left(\frac{u_j}{\sigma}\right)} \quad (\text{A11})$$

Now define a dummy variable $D_j = 1$ if $y_j > 0$ and $D_j = 0$ if $y_j = 0$. Then we have the following expression:

$$p(D_j = 1|I_j) = p(y_j > 0|I_j) = p(\varepsilon_j > -u_j|I_j) = \Phi\left(\frac{u_j}{\sigma}\right) \quad (\text{A12})$$

Given I_j and $D_j = 1$ ($y_j > 0$), the conditional expectation of y_j is

$$E(y_j|I_j, D_j = 1) = \int_0^\infty yh(y|y_j > 0, I_j)dy = \frac{1}{\sigma\Phi\left(\frac{u_j}{\sigma}\right)} \int_0^\infty y\phi\left(\frac{y-u_j}{\sigma}\right)dy \quad (\text{A13})$$

Let $z = \frac{y-u_j}{\sigma}$. With (A6), the above expression can be simplified as:

$$\begin{aligned} E(y_j|I_j, D_j = 1) &= \frac{1}{\sigma\Phi\left(\frac{u_j}{\sigma}\right)} \int_{-\frac{u_j}{\sigma}}^\infty (u_j + \sigma z)\phi(z)\sigma dz \\ &= u_j + \frac{\sigma\phi\left(\frac{u_j}{\sigma}\right)}{\Phi\left(\frac{u_j}{\sigma}\right)} \end{aligned} \quad (\text{A14})$$

Using (A12) and (A14), we derive the conditional expectation of y_j :

$$\begin{aligned} E(y_j|I_j) &= p(D_j = 1|I_j) \cdot E(y_j|I_j, D_j = 1) + p(D_j = 0|I_j) \cdot 0 \\ &= u_j\Phi\left(\frac{u_j}{\sigma}\right) + \sigma\phi\left(\frac{u_j}{\sigma}\right) \end{aligned} \quad (\text{A15})$$

The partial impact of x_1 can be derived as

$$\frac{\partial E(y_j|I_j)}{\partial x_{1j}} = (\beta_1 + \beta_{12}x_{2j}) \left[\Phi\left(\frac{u_j}{\sigma}\right) + \frac{u_j}{\sigma}\phi\left(\frac{u_j}{\sigma}\right) + \phi'\left(\frac{u_j}{\sigma}\right) \right] \quad (\text{A16})$$

The interaction effect, *i.e.*, the influence of x_2 on the above marginal impact of x_1 , can be derived as

$$\begin{aligned} \mu_{12}(\theta, I_j) &\equiv \frac{\partial}{\partial x_{2j}} \left(\frac{\partial E(y_j|I_j)}{\partial x_{1j}} \right) = \frac{\partial^2 E(y_j|I_j)}{\partial x_{1j} \partial x_{2j}} \\ &= \beta_{12}\Phi\left(\frac{u_j}{\sigma}\right) + \left[\beta_{12}\frac{u_j}{\sigma} + \frac{2}{\sigma}(\beta_1 + \beta_{12}x_{2j})(\beta_2 + \beta_{12}x_{1j}) \right] \phi\left(\frac{u_j}{\sigma}\right) \\ &\quad + \left[\beta_{12} + (\beta_1 + \beta_{12}x_{2j})(\beta_2 + \beta_{12}x_{1j})\frac{u_j}{\sigma} \right] \phi'\left(\frac{u_j}{\sigma}\right) \\ &\quad + (\beta_1 + \beta_{12}x_{2j})(\beta_2 + \beta_{12}x_{1j})\frac{1}{\sigma}\phi''\left(\frac{u_j}{\sigma}\right) \end{aligned} \quad (\text{A17})$$

Using (A6) and (A7) the above expressions can be simplified as:

$$\begin{aligned}\mu_{12}(\theta, I_j) &= \frac{\partial^2 E(y_j | I_j)}{\partial x_{1j} \partial x_{2j}} \\ &= \beta_{12} \Phi\left(\frac{u_j}{\sigma}\right) + \frac{(\beta_1 + \beta_{12} x_{2j})(\beta_2 + \beta_{12} x_{1j})}{\sigma} \phi\left(\frac{u_j}{\sigma}\right)\end{aligned}\quad (\text{A18})$$

Following Ai and Norton (2003), we apply the Delta method to find the asymptotic distribution of the estimated interaction effect

$$\hat{\mu}_{12}(\hat{\theta}, I_j) \xrightarrow{d} N\left(\mu_{12}(\theta, I_j), \delta(\theta, I_j)' \Omega_{\theta} \delta(\theta, I_j)\right) \quad (\text{A19})$$

where

$$\begin{aligned}\delta(\theta, I_j) &\equiv \frac{\partial \mu_{12}(\theta, I_j)}{\partial \theta} \\ &= \left[\frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_1}, \frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_2}, \frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_{12}}, \frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta'} \right]'\end{aligned}\quad (\text{A20})$$

The asymptotic variance of $\hat{\mu}_{12}(\hat{\theta}, I_j)$ is estimated consistently by

$$\hat{\sigma}_{12}^2(\hat{\theta}, I_j) = \hat{\delta}(\hat{\theta}, I_j)' \hat{\Omega}_{\theta} \hat{\delta}(\hat{\theta}, I_j) \quad (\text{A21})$$

where $\hat{\Omega}_{\theta}$ is the consistent covariance estimator of $\hat{\theta}$. The specific expression for each element of $\delta(\theta, I_j)$ in (A20) is given by

$$\begin{aligned}\frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_1} &= \frac{1}{\sigma} \phi\left(\frac{u_j}{\sigma}\right) \left[\beta_2 + 2\beta_{12} x_{1j} - (\beta_1 + \beta_{12} x_{2j})(\beta_2 + \beta_{12} x_{1j}) \frac{x_{1j} u_j}{\sigma^2} \right] \\ \frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_2} &= \frac{1}{\sigma} \phi\left(\frac{u_j}{\sigma}\right) \left[\beta_1 + 2\beta_{12} x_{2j} - (\beta_1 + \beta_{12} x_{2j})(\beta_2 + \beta_{12} x_{1j}) \frac{x_{2j} u_j}{\sigma^2} \right] \\ \frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_{12}} &= \phi\left(\frac{u_j}{\sigma}\right) + \frac{1}{\sigma} \phi\left(\frac{u_j}{\sigma}\right) \left[-(\beta_1 + \beta_{12} x_{2j})(\beta_2 + \beta_{12} x_{1j}) \frac{x_{1j} x_{2j} u_j}{\sigma^2} \right] \\ \frac{\partial \mu_{12}(\theta, I_j)}{\partial \beta_m} &= \frac{x_m}{\sigma} \phi\left(\frac{u_j}{\sigma}\right) \left[\beta_{12} - (\beta_1 + \beta_{12} x_{2j})(\beta_2 + \beta_{12} x_{1j}) \frac{u_j}{\sigma^2} \right]\end{aligned}$$

where β_m denotes the coefficient corresponding to the control variable x_m contained in X