

A Study on How Social Networks Affect High-Risk Family Investments — Using the CGSS Database as a Sample

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Abstract: Using the 2023 CGSS data, this paper classifies household social networks into kinship-friendship ties and network centrality, and employs a binary logistic model to explore their impacts on household high-risk financial asset allocation. This study further conducts robustness checks, endogeneity mitigation, regional heterogeneity analysis and mediating effect tests. By systematically comparing the heterogeneous influences of diverse social relations from a multidimensional perspective, this paper establishes a streamlined analytical framework for household financial decision-making research.

Keywords: Social Network; Household High-Risk Investment; Network Centrality

1. Introduction

Along with China's financial development, household asset allocation has diversified from pure savings to high-risk financial investment, with growing participation during 2011–2019. Existing studies attribute household risky investment to conventional factors such as income, education and risk preference. As essential informal social mechanisms, social connections reshape investment behaviors by reducing information costs through peer interaction and information sharing. Nevertheless, prior literature emphasizes network scale or individual social ties while neglecting combined effects of relational types and network structures. Addressing this gap, this study empirically examines how kinship ties, friendship ties and network centrality influence household risky investment participation using 2023 CGSS data.

2. Literature Review

Social networks promote household risky investment by facilitating information exchange and risk identification and mitigating market information asymmetry^[1]. From the social capital perspective, sufficient social connections improve information and resource access, thereby encouraging risky asset investment^[2]. Relevant research analyzes network effects on household investment through scale, tie type and structural characteristics. Expanded social networks and frequent interactions help households obtain investment information and participate in financial markets^[3]. Strong ties provide trust and practical experience, whereas weak ties offer heterogeneous investment information^[1]. Based on Burt's structural hole theory, core network members enjoy superior information and resource edges in financial decision-making. Existing studies also confirm that social networks shape investment behavior via risk preference, financial literacy and resource mobilization^[4]. Empirically, social connections significantly raise households' risky asset participation and holdings^[5]. Furthermore, social networks deliver extensive economic benefits, including income growth, resource acquisition and information dissemination^{[6][7]}. Higher network centrality also strengthens individual advantages in income growth, financing access and resource integration^[8].

3. Theoretical Analysis

(1) Trust Transmission and Risk-sharing Mechanism of Kin-friend Social Networks

In China's differential social structure, kinship and friendship ties reduce information frictions and asymmetry via trust and risk sharing, promoting household risky investment. Kinship delivers stable resource support, whereas friendship facilitates financial experience dissemination and behavioral learning. This study thus proposes the following hypotheses:

H1: The kinship-based social network exerts a significant positive effect on household participation in high-risk investment.

H2: The friendship-based social network exerts a significant positive effect on household participation in high-risk investment.

(2) Structural-position Information and Cross-network Resource Integration Mechanism of Social Network Centrality

Social network centrality characterizes households' structural advantages in information acquisition and resource integration. Households with higher centrality connect with more social nodes, obtaining reliable information from strong ties and diverse information from weak ties. Such advantages lower investment uncertainty and barriers, and ultimately raise households' high-risk investment participation. The corresponding hypothesis is proposed below:

H3: Social network centrality has a significant positive effect on household participation in high-risk investment.

This paper constructs a two-mode network based on 2023 CGSS data to visualize the correlation between social relation types and household high-risk investment (see Figure 1). The results show evident heterogeneity: kinship and friendship ties strongly promote risky investment participation, while neighborhood and organizational ties exert weaker positive effects. Overall, all social relations are positively correlated with household risky investment. These findings confirm the impact of social networks on investment behavior and provide intuitive support for subsequent regression analyses.

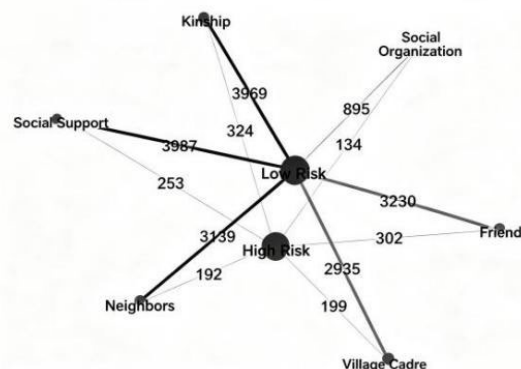


Figure 1: Two-mode network of social network centrality

(3) Mediating Mechanism of Human Capital

Social networks influence household high-risk investment through direct effects and human capital mediation. Social networks boost household educational attainment via information spillovers, normative demonstration and resource support. Improved human capital enhances households' financial cognition, information screening and risk identification abilities, further promoting high-risk investment participation. Accordingly, this study puts forward the following hypothesis:

H4: Social networks exert a significant positive effect on household participation in high-risk investment by influencing human capital.

4. Data, Model, and Variable Selection

(1) Data

This study adopts the 2023 Chinese General Social Survey (CGSS) data released by Renmin University of China's National Survey Research Center. Covering adult residents across China's 31 provincial regions, the dataset contains comprehensive information on individual demographics, social networks and household financial behaviors, providing reliable and representative data for analyzing household social network characteristics and investment decisions.

(2) Model Specification

This paper adopts household high-risk investment (high-risk) as the binary dependent variable. Following mainstream empirical paradigms, the binary Logit model is employed as the baseline specification to examine how multi-dimensional social network characteristics affect household high-risk investment behavior. The models take the logit probability of household high-risk investment participation, $\text{Logit}[P(\text{high-risk}=1|X)]$, as the explained variable. Three progressive Logit regression models are constructed to verify the research hypotheses. The specific model specifications are as follows:

Model 1 (introducing relative relationships)

$$\text{Logit}[P(\text{highrisk} = 1 | X)] = \beta_0 + \beta_1 \text{rel_meet} + \beta_i \text{Control}_i + \varepsilon \quad (1)$$

Model 2 (introducing friend relationships)

$$\text{Logit}[P(\text{highrisk} = 1 | X)] = \beta_0 + \beta_1 \text{rel_friend} + \beta_i \text{Control}_i + \varepsilon \quad (2)$$

Model 3 (introducing social network centrality, full variable model)

$$\text{Logit}[P(\text{highrisk} = 1 | X)] = \beta_0 + \beta_1 \text{net_degree} + \beta_i \text{Control}_i + \varepsilon \quad (3)$$

Where:

$$\text{net_degree} = \text{rel_friend} + \text{rel_neighbor} + \text{rel_meet} + \text{rel_support} + \text{vote} + \text{organization} \quad (4)$$

(3) Variable Selection

▪ Dependent Variable

The dependent variable is whether the household participates in high-risk investment (high-risk). The data come from the indicator "whether the household participates in related investment activities" in CGSS 2023. This paper defines high-risk investments as financial assets with high volatility, such as stocks, funds, bonds, futures, and options.

▪ Explanatory Variables

The frequency of gatherings with non-cohabiting relatives and the frequency of social activities with friends are used to measure relative relationships and friend relationships, respectively. This paper uses variables such as neighborhood interaction, social support, voting participation, and community organization participation to characterize the degree of social network embeddedness. These six binary variables are then summed to construct the social network centrality indicator.

▪ Mediating Variable

This paper selects "the highest educational level of the household head" from CGSS 2023 as the survey indicator.

▪ Control Variables

This paper selects 9 control variables from three dimensions: household head's individual characteristics, household economic characteristics, and household regional characteristics. The details are shown in Table 1 to ensure the clarity and standardization of the variable system.

Table 1: Definition and Descriptive Statistics of Research Variables

Variable Name	Variable Symbol	Measurement and Assignment Instructions	Mean	Std. Dev.	Min	Max
High-Risk Investment	high-risk	1 = participated in investment; 0 = non-participation	0.0667	0.2495	0	1
Strong Kinship Ties	rel_meet	1 = contact several times a month or more; 0 = otherwise	0.8205	0.3838	0	1

Strong Friendship Ties	rel_friend	1 = meet several times a month or more; 0 = otherwise	0.6750	0.4684	0	1
Neighborhood	Rel_neighbor	1 = participate in neighborhood activities several times a month or more; 0 = otherwise	0.6367	0.4810	0	1
Social Support	rel_support	1 = receive assistance from others; 0 = no access to support	0.8008	0.3994	0	1
Community Voting Participation	vote	1 = participated in community voting; 0 = non-participation	0.5417	0.4983	0	1
Social Organization	organization	1 = participate in community, public welfare or mass organizations; 0 = non-participation	0.1967	0.3975	0	1
Social Network Centrality	net_degree	Sum of rel_meet, rel_friend, neighbor, rel_support, vote and organization (ranging from 0 to 6)	3.6714	1.3695	0	6
Human Capital	edu	1 = primary school and below; 2 = junior high school; 3 = senior high school / technical secondary school; 4 = college; 5 = bachelor's degree; 6 = master's degree and above	2.3097	1.2964	1	6
Household Head Age	age	Actual age of the household head	57.3897	16.2788	21	97
Household Head Gender	male	0 = female; 1 = male	0.4500	0.4975	0	1
Household Head Educational Attainment	edu	1 = primary school and below; 2 = junior high school; 3 = senior high school / technical secondary school; 4 = college; 5 = bachelor's	2.3097	1.2964	1	6

		degree; 6 = master's degree and above				
Marital Status of Household Head	married	0 = unmarried, divorced or widowed; 1 = married or cohabiting	0.7173	0.4503	0	1
Self-reported Health Status	health	1 = poor health; 2 = average health; 3 = good health	2.2626	0.8028	1	3
Political Affiliation of Household Head	politic	1 = mass citizen; 2 = Communist Youth League member; 3 = member of non-Communist parties; 4 = CPC member	1.4000	0.9765	1	4
Logarithm of Annual Household Income	ln_income	Natural logarithm of total annual household income plus one	11.1559	1.9025	5.0173	16.118
Urban-Rural Residence	urban	1 = rural area; 0 = urban area	0.8174	0.3863	0	1
Region	region	1 = Eastern China; 2 = Central China; 3 = Western China	2.0155	0.8337	1	3

5. Empirical Analysis

(1) Regression Analysis of Family and Friends' Social Networks on Household Participation in High-Risk Investments

Logistic regression results in Table 2 demonstrate that the coefficients of kinship and friendship ties are significantly positive. Both types of close social ties effectively promote household risky investment participation. Kinship ties foster trust and information sharing to reduce investment uncertainty, while friendship ties deliver targeted financial information and reshape investment cognition. Notably, friendship ties exert a more pronounced promotional effect than kinship ties.

Table 2 Logistic Regression Results of Social Networks on Household High-Risk Investment

Variable Name	Model 1 Odds Ratio (Robust Std. Err.)	Model 2 Odds Ratio (Robust Std. Err.)
rel_meet / rel_friend	1.769**(0.403)	2.127**(0.382)
Control Variables	Controlled	Controlled
Constant	0.000*** (0.000)	0.000*** (0.000)
Pseudo R ²	0.2357	0.2406

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

(2) Robustness Tests

▪ Core Variable Replacement Test

This study re-estimates regressions after substituting the measurement indicators of core explanatory variables, as shown in Table 3. Kinship ties are redefined as “how many non-cohabiting family members or relatives the respondent contacts per day”; friendship ties are re-measured as “whether the respondent frequently gathers with friends during leisure time over the past year”. Comparisons between baseline regression and robustness test outputs reveal that the coefficients of core explanatory variables remain significantly positive and consistent with baseline findings, which verifies the robustness of core conclusions against alternative variable measurements.

Table 3 Robustness Test with Alternative Core Variable Measurements

Variable Name	rel_meet	rel_friend
rel_meet / rel_friend	1.170*(0.111)	2.952***(0.745)
Control Variables	Controlled	Controlled
Constant	0.000***(0.000)	0.000***(0.000)
Pseudo R ²	0.2339	0.2419

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

▪ Probit Regression Test

This paper did another round of testing with the Probit model to check if our original calculation results are trustworthy, and avoid wrong conclusions caused by picking an unsuitable calculation model, as shown in Table 4. Probit and Logistic are two similar calculation tools used for yes-or-no research questions, but they follow different basic ideas and calculation steps. This paper compared the output numbers from these two tools. The key influencing factors all had the same positive/negative trend and equally obvious effects, matching the initial Logistic test perfectly. This proves our main research conclusion won't change with different calculation tools.

Table 4 Probit Regression Results

Variable Name	rel_meet	rel_friend
rel_meet / rel_friend	0.291** (0.110)	0.375*** (0.087)
Control Variables	Controlled	Controlled
Constant	-4.482***(0.354)	-4.589***(0.353)
Pseudo R ²	0.2369	0.2416

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

(3) Endogeneity Tests

▪ Omitted Variable Bias Test

Potential omitted variables may interfere with the correlation between social connections and household risky investment. To address this issue, this study incorporates household internet usage indicators into the baseline model for robustness testing (see Table 5). The results show that all social connection types still exert significant positive effects on risky investment participation, with negligible changes in effect magnitude and significance level. This further validates the credibility of the core research findings.

Table 5 Regression Results Controlling for Omitted Variable Online (Odds Ratios)

Variable Name	rel_meet	rel_friend
rel_meet / rel_friend	1.634***(0.376)	2.030***(0.367)
online	2.014***(0.388)	1.986***(0.383)

Control Variables	Controlled	Controlled
Constant	0.000*** (0.000)	0.000*** (0.000)
Pseudo R ²	0.2413	0.2460

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

■ Instrument Variable Test

This paper used the IV-Probit model to fix possible data bias problems in Table 6. This paper took each family's self-judged social standing as the auxiliary variable for this test. The testing results show that even after removing bias interference, all kinds of social connections still push families to invest in risky assets, and this rule is almost the same as the original test result. This means our core conclusion won't easily shift. Besides, researchers did the Wald inspection to check bias. The output figures tell us there's no obvious bias trouble inside this research model.

Table 6 IV-Probit Regression Results

Variable	rel_meet	rel_friend
rel_meet/rel_friend	2.0678** (0.8964)	2.2205*** (0.4022)
Control Variables	Controlled	Controlled
Constant	-0.7572 (2.5152)	-3.6447* (1.9575)
Wald χ^2	1217.19***	2768.08***

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

(4) Regression Analysis of Social Network Centrality on Household High-Risk Investment Participation

Following the analysis of kinship and friendship ties, this study further examines the effect of social network centrality on household investment. Logistic regression results show that the odds ratio of network centrality is significantly greater than 1, indicating that households with higher social network centrality are more willing to engage in high-risk investment and verifying the validity of Hypothesis H3. This study also adopts the Probit model for robustness testing (see Table 7). The consistent positive and significant coefficients across regressions confirm the stable promotional effect of social network centrality on household risky investment, demonstrating the reliability of core findings.

Table 7 Regression Results of the Impact of Social Network Centrality on High-Risk Investment

Variable Name	Logistic Regression Odds Ratio (Robust Std. Err.)	Probit Regression Coefficient (Robust Std. Err.)
net_degree	1.961*** (0.399)	0.078*** (0.025)
Control Variables	Controlled	Controlled
Constant	0.001*** (0.001)	-3.517*** (0.477)
Pseudo R ²	0.2413	0.2414

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

This paper further quantifies the effect of social network centrality on household risky investment decisions. Empirical results suggest that, holding other factors constant, each one-point increase in social centrality raises households' risky investment willingness by 0.8%. Households with higher social centrality acquire financial information and social resources more efficiently through interpersonal connections, which enhances their risk tolerance and investment willingness. This finding verifies that individuals' structural positions in social networks exert a direct influence on their financial decision-making.

(5) Mediating Effect Analysis

In Table 8, this paper uses the three-step check method from Baron and Kenny to see if personal education level acts as a middle link here. The first model shows the full influence people's social contacts have on risky investing. The second model checks how these social ties raise people's education level. The third model looks at the direct impact of social connections on risky investing when researchers account for education differences. This paper also runs Bootstrap checks to confirm this middle link really works and isn't just a coincidence.

Table 8 Mediation Effects of Social Networks on High-Risk Investment via Human Capital

Variable	Model 1	Model 2	Model 3	Bootstrap	Mediation Effect Share
rel_meet	2.265*** (0.496)	0.183*** (0.035)	1.946*** (0.442)	0.157 [0.103, 0.218]	34.1%
Human Capital	—	—	2.374*** (0.143)	—	—
Goodness-of-Fit	R ² =0.131	R ² =0.468	R ² =0.221	—	—
rel_friend	2.566*** (0.439)	0.204*** (0.030)	2.216*** (0.395)	0.176 [0.117, 0.236]	33.6%
Human Capital	—	—	2.366*** (0.143)	—	—
Goodness-of-Fit	R ² =0.138	R ² =0.470	R ² =0.226	—	—
net_degree	0.0117*** (0.0026)	0.0403*** (0.0099)	0.0102*** (0.0025)	0.0015*** [0.0008, 0.0023]	12.82%
Human Capital	—	—	0.0461*** (0.0032)	—	—
Goodness-of-Fit	R ² =0.1330	R ² =0.4671	R ² =0.2243	—	—
Control Variables / Regional Fixed Effects	Controlled	Controlled	Controlled	—	—

Notes: Robust standard errors are reported in parentheses; *p<0.1, **p<0.05, ***p<0.01.

This paper ran a mediation test to figure out how social networks affect high-risk investments through human capital. Here's what researchers found: Both family ties and friend ties clearly help people build up their human capital, and more human capital makes households much more likely to invest in risky assets. When researchers control for human capital, the direct effects of those networks are still positive and statistically strong (at the 1% level). Bootstrap checks confirm that these indirect effects are real, and they make up about 34.1% and 33.6% of the total impact. That means human capital only partly explains the link—it's a partial mediator, not the whole story. Once researchers include human capital in the model, centrality still has a clear positive direct effect, so part of its influence works through human capital. Taken together, our mediation results back up Hypothesis H4.

6. Conclusions, Recommendations and Prospects

(1) Research Conclusions

This paper examines the effects of social networks (kinship ties, friendship ties, and network centrality) on household risky investment behavior. Three core conclusions are drawn from the empirical analysis. First, social networks significantly encourage high-risk investment participation. Both kinship and friendship ties positively affect investment decisions, and the impact of friendship ties is stronger. Trust-based social interaction reduces investment uncertainty via experience sharing and behavioral imitation. Second, higher social network centrality facilitates information and resource acquisition,

further promoting household risky investment. Third, human capital represented by education and financial literacy mediates the network-investment nexus. Social networks enhance households' willingness for risky investment by improving household heads' financial cognition and information processing ability, highlighting the essential value of financial literacy in household investment decisions.

(2) Policy Recommendations

This study proposes targeted policy implications for households, financial institutions and regulators. Households should rationally leverage social networks for low-cost financial information acquisition and refrain from blind investment herding. Improved financial literacy and information discrimination support rational investment, while high-centrality households should verify financial information before sharing to prevent misleading perceptions. Financial institutions can develop social network-oriented differentiated services and utilize interpersonal referrals to cut customer acquisition costs. With digital technology, they can identify high-influence customers for personalized services and strengthen risk control over network-spread financial information risks. Regulators need to standardize financial information disclosure and scale up investor education to improve market transparency. Community policy outreach, differentiated regional supervision and real-time risk monitoring systems are essential to mitigate social network-related financial risks.

(3) Limitations and Future Research Directions

This study's reliance on 2023 CGSS cross-sectional data limits its ability to capture dynamic changes in household social networks and investment behaviors. Additionally, its indicators lack refined measurements of network intensity, relational closeness and interpersonal trust, while ignoring investment scale and asset allocation structures. Future research can employ panel data to identify causal effects and dynamic trends, alongside refined network measurement tools to enhance empirical accuracy. Despite these limitations, this paper provides updated evidence for the social network impacts on household risky investment. Further studies with improved data and methods can offer more credible guidance for household asset allocation and financial market stability.

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