Learning from neighbors: Peer effects in Chinese household financial investments[⋆]

Juncong Guo, Xi Qu[*]

Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, 200030, China

Abstract

This paper employs nationally representative survey data from China to examine peer effects in the investment behaviors of Chinese households with respect to wealth management products. Our empirical findings indicate that neighbors' behaviors have a statistically significant impact on investments in these financial products. These peer effects exist at both the extensive and intensive margins, even in situations where households cannot observe their peers' investment behaviors due to incomplete information. Heterogeneity analyses suggest that the underlying mechanism driving these effects may be the spread of financial information and knowledge. Additionally, we observe that the rise in the participation rate in wealth management product investments is linked to a reduction in inequality. Accordingly, our findings propose that policymakers could leverage peer effects from influencers to promote household investments, thereby contributing to the mitigation of inequality.

Keywords: Peer effects, household investments, information learning, inequality, spatial econometrics

JEL classification: D14, D91, G51, C31

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[*]Corresponding author

Email addresses: gjc99@sjtu.edu.cn (Juncong Guo), xiqu@sjtu.edu.cn (Xi Qu)

1. Introduction

Financial decisions often involve intricacies, prompting households to exercise caution in their investment choices. Those with elevated levels of financial literacy or access to information tend to actively engage in financial investments, consequently yielding higher returns. Meanwhile, these households typically possess greater wealth, irrespective of the impact of financial investments. As consequences, the divergence in financial literacy and information may exacerbate wealth inequality.

However, households do not make investment decisions alone. Previous research has demonstrated that individuals and households tend to seek information and advice from peers when making financial investment decisions. Through various forms of social interactions, such as word-of-mouth, households are able to gain a deeper understanding of the risk-return profiles of investment products, thereby informing their decision-making. This process of information acquisition through social interactions may result in the emergence of peer effects. Furthermore, it can also help to narrow the financial information gap and thus may help to reduce wealth inequality.

Many scholars try to explore how peers affect people's financial investment decisions. However, due to the differences in the development of financial markets, the financial asset allocation of residents in different countries is not the same. In developed countries like the United States (U.S.), according to a survey from the Federal Reserve System (Bhutta et al., 2020), in 2019, the three financial assets with the highest household participation rates are retirement savings (50.5%), cash value life insurance (19.0%) and stocks (15.2%)[1]. Accordingly, a substantial body of research has centered on the analysis of investments in these financial assets (e.g. Hong et al., 2004, 2005; Brown et al., 2008; Beshears et al., 2015; Ouimet & Tate, 2020).

In contrast to the U.S., Chinese households demonstrate a preference for wealth management products, typically issued and distributed by banks, securities, or insurance companies. Surveys conducted by the People's Bank of China reveal that nearly half of urban house-

[1]Excluding transaction accounts, which has a 98.2% participation rate.

holds have indicated a willingness to invest in such products since the availability of relevant statistics in 2016. Despite the popularity of wealth management products, their participation rate stands at only 19.3%, as per the 2019 China Household Finance Survey (CHFS) data. This figure significantly diverges from the expressed willingness to invest.

It is noteworthy that mainstream wealth management products in China generally feature low risk and stable returns, making the low participation rate inconsistent with their attractive characteristics. This incongruity underscores the importance of investigating peer effects in wealth management product investments. Such an examination is crucial for policymakers seeking to comprehend the behavioral patterns of household financial investments. If peer effects are identified, the resulting multiplier effect could magnify the impact of policies or shocks, necessitating careful consideration.

Moreover, recognizing the presence of peer effects allows policymakers to leverage influencers who can disseminate information and enhance household financial literacy (Banerjee et al., 2013). This strategy holds potential for promoting a more informed and participatory approach to wealth management product investments among Chinese households.

This study complements three strands of literature. First, we provide a complement to research investigating peer effects in household or individual behaviors or performances. Two of the most widely studied are peer effects in student achievements or behaviors (e.g. Gaviria & Raphael, 2001; Sacerdote, 2001; Zimmerman, 2003; Card & Giuliano, 2013; Bursztyn et al., 2019) and peer effects in consumption (e.g. De Giorgi et al., 2020; Agarwal et al., 2021; Lewbel et al., 2022). For studies in the area of investment or finance, scholars have focused on a wide variety of topics. In regards to peer effects in the participation of retirement savings or retirement plan programs, the empirical findings are inconsistent. While Duflo & Saez (2002, 2003) imply the existence of positive peer effects, Beshears et al. (2015) argue that the presence of peer information on retirement savings decisions has negative effects on nonparticipants. For peer effects in stock market participation or stock purchase, scholars find peers' choices or social interactions have positive effects on individual or household behaviors (Hong et al., 2004, 2005; Brown et al., 2008; Hvide & Östberg, 2015; Girshina et al., 2019; Ouimet & Tate, 2020; Arrondel et al., 2022). For example, Hong et al. (2004) find households that have more interaction with others are substantially more likely to invest in stock market. Brown et al. (2008) directly investigate the effects from peers in the same neighborhood on household stock market participation and find word-of-mouth communication drives peer effects. More recently, Ouimet & Tate (2020) show that people's decisions on employee stock purchase plans can be affected by coworkers. In addition to retirement plans and stock investments, other types of investment or financial behaviors are also be investigated. For example, peer effects in human capital investments (Guo & Qu, 2022), in insurance purchase (Hu, 2022), in refinancing or lending (Banerjee et al., 2013; Maturana & Nickerson, 2019), etc. The existing body of research exploring peer effects predominantly centers on investment instruments within financially advanced countries. This study, in contrast, directs attention to wealth management products that enjoy widespread popularity in China, the world's largest developing country, thereby addressing a notable void in the academic literature. The prevalent utilization of retirement accounts and stock investments provides a compelling rationale for investigating their peer effects within the U.S. and many other developed countries. However, within the Chinese context, these widely embraced wealth management products remain relatively unexplored in scholarly inquiry. To the best of our knowledge, this paper represents the inaugural attempt to scrutinize peer effects in wealth management product investments among Chinese households.

Second, our study complements the studies exploring why an individual or household's behavior is affected by peers. In the literature on peer effects in expenditure decisions (consumption and investments), status seeking, risk sharing, and information spread are three common mechanisms. The mechanism of status seeking is mostly found in peer effects in consumption, as confirmed by a number of empirical studies (Charles et al., 2009; Brown et al., 2011; Kaus, 2013; Bulte et al., 2018; De Giorgi et al., 2020; Agarwal et al., 2021). In contrast, the literature studying peer effects in financial decisions is more supportive of the mechanism of information spread and learning (Hong et al., 2004; Brown et al., 2008; Banerjee et al., 2013; Bursztyn et al., 2014; Maturana & Nickerson, 2019; Ouimet & Tate, 2020). As for risk sharing, where peers help each other to cope with risks, some studies discuss it but do not find significant evidence (e.g. Brown et al., 2011; De Giorgi et al., 2020;

Agarwal et al., 2021). In this paper, we construct several proxies to distinguish between household who are likely to have more information versus less information about financial decision-making. Through a series of heterogeneity analyses, we provide empirical evidence supporting this mechanism of information spread and learning.

Third, this study establishes a connection between peer effects and economic inequality. Some studies have explored the correlation between wealth inequality and financial knowledge. For instance, Peress (2004) observes that the availability of expensive information may intensify wealth disparities. Lusardi et al. (2017) point out that financial literacy plays a pivotal role in determining wealth inequality, estimating that 30%–40% of retirement wealth inequality in the U.S. can be attributed to financial literacy. Moreover, Lei (2019) indicates that affluent individuals have access to more information, enabling them to allocate a higher proportion of their wealth to lucrative assets, thereby augmenting their wealth further. In essence, these studies highlight how information and knowledge disparities contribute to wealth inequality. However, the influence of peer effects and the underlying mechanisms of information dissemination and learning indicate that individuals can acquire information and knowledge from their peers, mitigating information inequality and potentially wealth inequality. This perspective offers valuable insights for policymakers, suggesting that leveraging peer effects in financial investments could serve as a strategy to alleviate inequality under a given income distribution.

To answer questions in the above three strands, we utilize representative survey data from China. The results confirm the existence of peer effects in both extensive margins and intensive margins. And the results are robust when we distinguish between the cases of complete and incomplete information depending on whether households can observe the investment behaviors of other households. Through a comprehensive series of heterogeneity analyses, our findings support that the mechanism behind peer effects is information spread and learning. These heterogeneity analyses indicate that households with more finance-related information are more likely to affect other households in the same neighborhood. Moreover, households characterized by a higher degree of similarity are also inclined to mutually impact each other. These findings suggest that certain households act as influencers, capable of diffusing information and fostering the engagement of other households in investments related to wealth management products. This insight holds implications for policymakers, indicating an opportunity to enlist these influential households to promote the adoption of these stable-return investment products, thereby contributing to the mitigation of economic inequality.

In summary, the contributions of this study are in three aspects. First, this study focuses on household investment behaviors in developing countries, which has been neglected in the literature. We pay attention to wealth management products that are widely popular in China, and investigate peer effects in household financial investments. This helps researchers to understand the differences between developing countries such as China and developed countries such as the U.S., and helps policymakers in China to understand the investment patterns of Chinese households.

Second, this paper discusses the role of two types of information in the formation of peer effects. The first type is based on the observability of peers' behaviors. Given the privacy of investment decisions, household may not observe the behaviors of other households. In our models, we consider both cases that households can observe the behaviors of other households (complete information) and households cannot observe the behaviors of other households (incomplete information), and provide the corresponding estimation strategies. To the best of our knowledge, peer effects under incomplete information are rarely explored in the previous literature. The second type of information is related to the mechanism of peer effects. We find the spread of financial information and knowledge matters in the formation of peer effects.

Last, we link investments in wealth management products to inequality. It is shown that there is a positive relationship between participation in these products and the level of household income and wealth, and that increasing participation in wealth management products helps to reduce inequality. This provides a plausible motivation for policymakers to leverage peer effects to promote household participation in wealth management products.

The organization of this paper is as follows. Section 2 introduces the data, the stylized facts on the investment patterns of Chinese households and the variables used in empirical studies. Section 3 builds a conceptual framework to explain why there are peer effects. Section 4 is the econometric strategies we apply, including two cases of complete information and incomplete information. Section 5 presents the main empirical findings, including extensive-margin effects, intensive-margin effects, total effects and robustness checks under incomplete information. Section 6 provides the empirical evidence on the mechanism of the peer effects. In section 7, we further discuss the association between household investment in wealth management products and economic inequality. Finally, section 8 concludes.

2. Stylized facts and variables

2.1. Stylized facts

Our research relies on data derived from four survey waves of CHFS conducted in the years 2013, 2015, 2017, and 2019. The CHFS serves as a comprehensive examination of household financial dynamics from a micro-level perspective. The survey's primary objective is to capture relevant information on household finances. It uses probability proportionate to size sampling framework which ensures the national representation. The dataset encompasses 29 provinces, 367 counties, and more than 1,400 neighborhoods (villages or communities). In aggregate, the sample comprises around 40,000 households and 127,000 individuals.

Based on the available dataset, we can discern the asset allocation of Chinese households, revealing notable distinctions from developed countries like the U.S. Table 1 illustrates the asset allocation patterns of Chinese households in comparison to their American counterparts. Chinese households exhibit a predominant interest in wealth management products, with a participation rate of 14.2%, alongside cash and deposits. However, this percentage is relatively lower than the equivalent figure of U.S. households and closely aligns with the U.S. household participation rate in the stock market (15.2%). In the U.S., aside from transaction assets such as checking and savings, the highest household holdings are observed in retirement plan products, boasting a participation rate of 50.5%. Generally, the rates of financial asset holding in China fall significantly below those observed in the U.S. Therefore, this paper directs its focus on investigating peer effects in the investments of wealth management products, which are the most prevalent financial products among Chinese households.

Table 1: Participation rates of different financial assets

In China		In the U.S.	
Transaction accounts	87.9%	Transaction accounts	98.2%
Time deposits	17.0%	Time deposits	7.7%
Stocks	4.9%	Stocks	15.2%
Funds	1.9%	Funds	9.0%
Bonds	0.3%	Savings bonds	7.5%
Others	0.5%	Bonds	1.1%
Wealth management products	14.2%	Retirement accounts	50.5%
–Traditional	9.6%	Cash value life insurance	19.0%
–Internet	6.6%	Other managed assets	5.9%
		Others	7.4%

Note: China data is derived from the 2019 CHFS, and the U.S. data is sourced from Bhutta et al. (2020). Notably, significant disparities exist between the classification systems adopted in these two nations. In China, transaction accounts include cash and demand deposits. Wealth management product category encompasses both traditional ones dispensed by banks and brokerages, as well as Internet ones (most of them are money market funds) marketed by Internet companies. Funds cover diverse funds apart from those money market funds promoted by Internet companies. In the U. S., transaction accounts constitute checking, savings, and money market deposit accounts, as well as call or cash accounts at brokerages, and prepaid debit cards. Funds encompass various funds apart from money market funds and indirectly held mutual funds.

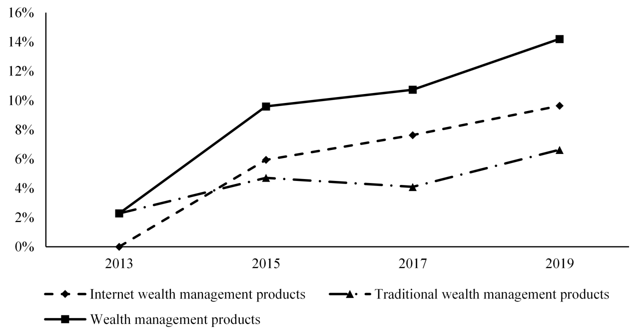
In China, mainstream wealth management products are low-risk financial instruments issued by licensed financial institutions and primarily marketed by banks. Prior to the introduction of new regulations in 2018, these products typically featured principal and income protection, resulting in negligible risk. From the beginning of 2022, the inflexible redemption rules of wealth management products have been completely dismantled. While they no longer offer principal protection, wealth management products in China are generally considered to be among the least risky and most stable financial instruments, second only to time deposits. These properties can explain the higher levels of participation rates of wealth management products among Chinese households compared to other financial instruments.

We then show the evolution of household wealth management product allocation in China. Wealth management products can be divided into two categories based on distribution channels: traditional ones and Internet ones. Figure 1(a) presents the participation rates of wealth management products based on the data we have collected. In 2013 survey, there is no Internet wealth management products available, so all wealth management products are traditional and predominantly sold by banks. However, in mid-2013, China's largest e-commerce platform, Alibaba, launched *Yu'ebao* on its payment software Alipay, primarily selling money market funds. This event led to a significant increase in the participation rate of wealth management products in 2015. In a similar manner, Tencent, China's largest online social networking company, launched a product similar to *Yu'ebao* in 2018, further attracting households to invest in Internet wealth management products. As depicted in the figure, the participation rate of Internet wealth management products has been consistently higher than that of traditional ones since 2015, thereby becoming the dominant factor in the increase of overall wealth management product participation rates.

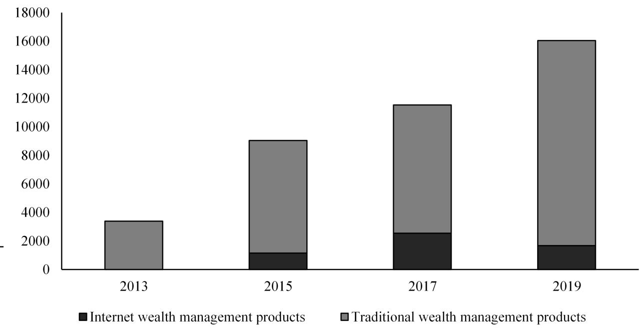
Figure 1(b) displays the mean quantity of Internet and traditional wealth management products possessed per household in China. Notably, while the participation rates for Internet products surpass those of traditional products, the former's average holding amounts are considerably lower, having even decreased in 2019. Figure 1(c) exhibits the mean allocation share of wealth management products relative to the total household assets. Despite experiencing an upward trend, the overall average allocation share remains meager, amounting to less than 1% in absolute terms. Only approximately 1% of households demonstrate significant allocations to wealth management products, as demonstrated in Figure 1(d).

In general, Chinese households not only have a low participation rate for wealth management products, but also a low holding amount and allocation share. This result is reasonable considering that Chinese households invest heavily in real estate (67% of assets are real estate according to 2019 CHFS). However, as the Chinese government put it in 2016, houses are for living in, not for speculation. Real estate investments in many cities of China are no longer lucrative, especially after the COVID-19 pandemic. Thus, it is crucial to encourage households to invest actively in other financial products to preserve and increase their wealth and benefit from the overall economic growth. This is why this paper examines investments in wealth management products and explores the impact of peer groups.

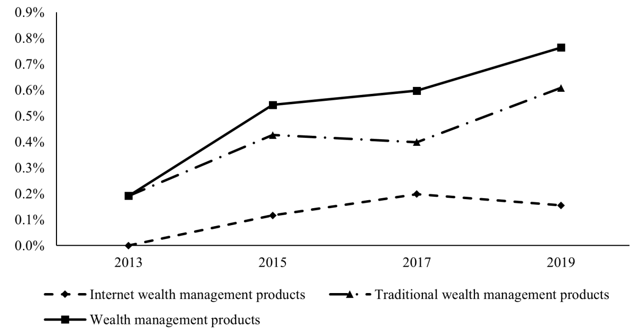
Considering the diversity in financial literacy among households, varying levels of par-



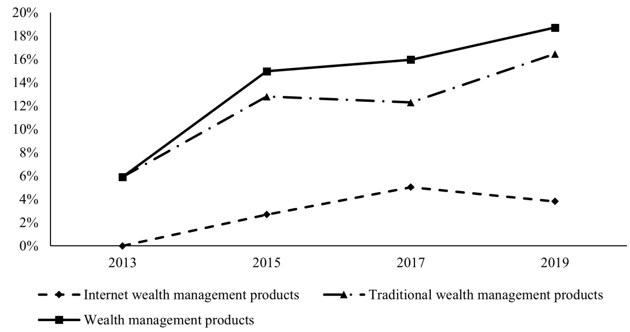
(a) Household participation rates



(b) Average holding value (CNY)

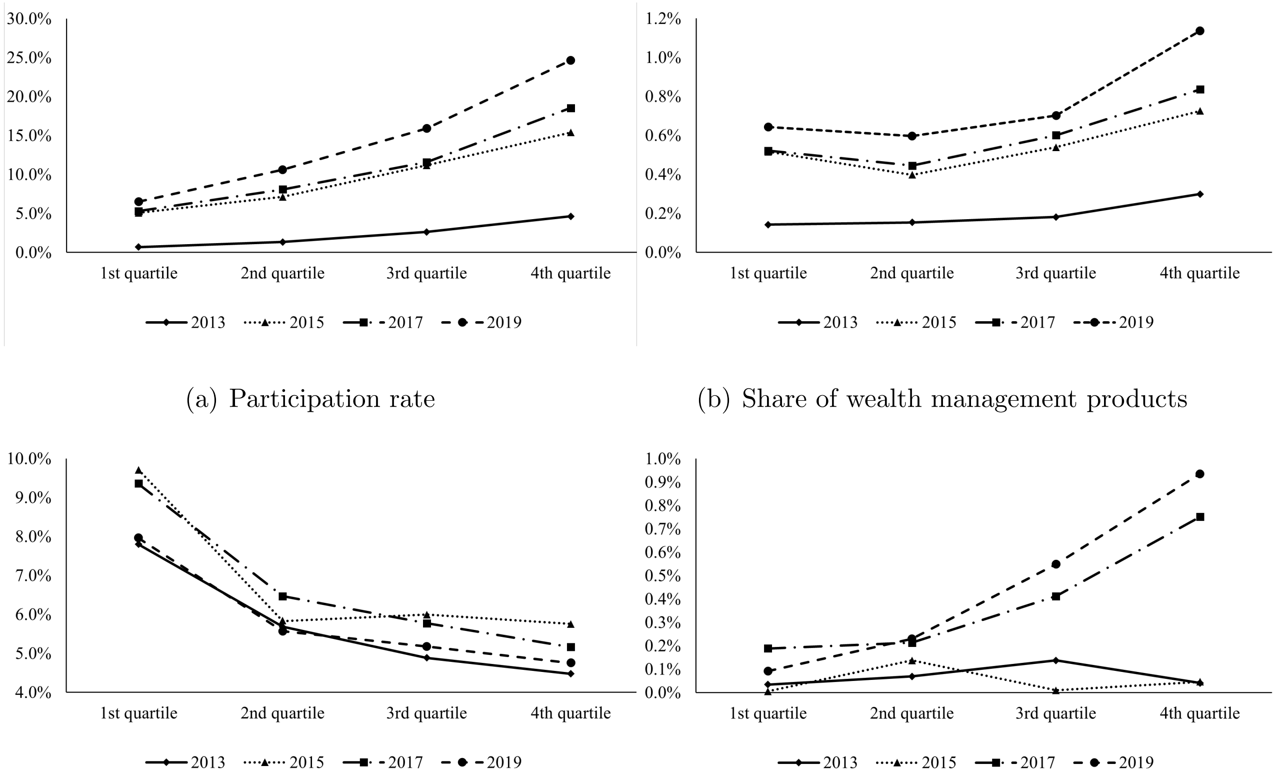


(c) Average allocation share



(d) 99% percentile allocation share

Figure 1: Stylized facts on wealth management products in China



(a) Participation rate

(b) Share of wealth management products

(c) Share of savings

(d) Return/income

Figure 2: Investment patterns for households with different levels of assets

ticipation and allocation in wealth management products can be observed. Households with higher income or wealth tend to possess advantages in accessing financial information and knowledge, leading to a greater allocation of assets toward wealth management products. Given the relatively low risk and stable returns associated with these products, such divergences in asset allocation may contribute to the widening of economic inequality.

Figure 2 illustrates the participation and allocation trends among households with different asset levels. It is evident that wealthier households exhibit higher participation rates and allocate a larger share of their assets to wealth management products. Conversely, they allocate a smaller share of their assets to savings. Additionally, these affluent households realize greater returns from their investments in wealth management products. In essence, a notable portion of their income is derived from returns on these products. The phenomena are even more pronounced in the 2017 and 2019 surveys.

These observed patterns affirm that affluent households tend to accumulate more wealth by investing in a higher value of wealth management products, thereby exacerbating the wealth gap between the affluent and less affluent. Consequently, to mitigate economic inequality, it is advisable for the government to encourage households to engage in the investment of wealth management products in a moderate manner.

2.2. Variables

Utilizing data from four waves of CHFS, we construct both dependent and independent variables, which summary statistics are presented in Table 2. Specifically, Panel A of the table displays the household investment in wealth management products, with an average value of 10.4 thousand CNY. Among these products, traditional wealth management products account for the majority of investments, with an average value of 8.9 thousand CNY (85.6%), while the average investment in Internet wealth management products is a mere 1.5 thousand CNY (14.4%).

Moving on to the control variables, Panel B and Panel C provide summary statistics for various attributes of the households and their heads. The average age of household heads is approximately 54, with over three quarters of these individuals being male, and over 85% being married. Overall, the general health of these individuals is normal and they possess an average of over 9 years of education. The summary statistics of risk preference indicate that Chinese households are generally risk-averse. To further elucidate the economic conditions of these households, household asset and income are collected as shown in Panel C. On average, the total asset of sampled households is 999 thousand CNY, with a total annual income of approximately 83 thousand CNY. The median asset and income levels are found to be substantially lower than their corresponding means, with respective values of 368 thousand CNY and 48 thousand CNY, implying great inequality. Last, for the household size, a typical household has 3 members.

Table 2: Summary statistics of main variables

	Mean	Median	St. dev	Unit
Panel A: Outcome variables	(1)	(2)	(3)	(4)
Wealth management products	10.430	0	79.493	1000 CNY
Internet wealth management products	1.544	0	21.691	1000 CNY
Traditional wealth management products	8.891	0	73.913	1000 CNY
Panel B: Attributes of the heads of households				
Age	54.255	54	14.329	year
Gender (male)	0.765	1	0.424	dummy
Marriage	0.851	1	0.356	dummy
Health condition	3.208	3	1.071	ordinal
Years of schooling	9.247	9	4.173	year
Risk preference	1.790	1	1.129	ordinal
Panel C: Attributes of households				
Asset	998.373	368.300	6,294.886	1000 CNY
Income	82.642	48.035	187.479	1000 CNY
Size	3.315	3	1.618	1

Note: Health condition is measured by a scale from 1 (poor) to 5 (excellent). Years of schooling are translated by education levels according to the following correspondence. Never been to school corresponds to 0 year. Primary school, junior high school, senior high school/ technical secondary school/ vocational high school, junior college/ higher vocational school, undergraduate, master's program, and doctoral program corresponds to 6, 9, 12, 15, 16, 19, and 23 years, respectively. Risk preference is measured by a scale from 1 (low risk/ do not know) to 5 (high risk).

3. Conceptual framework

3.1. Continuous investments

We illustrate the existence of peer effects and their underlying mechanism through a conceptual framework. In the framework, households try to maximize their utility by choosing optimal investment levels. Assuming there is a representative household i that chooses the investment y_i in financial products to maximize

$$V(y_i) = A_i y_i - \frac{y_i^2}{2} + \varepsilon_i,$$

where ε_i a random utility term. The first term $A_i y_i$ captures the expected net return (discount factor adjusted total return minus direct cost) from the investment for the household i. The second term $y_i^2/2$ is the indirect cost of the investment, which reflects the loss of utility from delayed consumption. The net return rate A_i depends on household attributes X_i and household's knowledge and information on financial products. The household can acquire information from its peers' investment behaviors $\bar{y}$, and higher $\bar{y}$ leads to more information and then higher potential return rate A_i. Therefore, $A_i = A_i(X_i, \bar{y})$ with $\partial A_i/\partial \bar{y} > 0$.

For $\bar{y}$, if we assume the household has complete information on peers' investments, in other words, the household can observe the real investment behaviors of its peers, then $\bar{y}$ can be the average investments of peers. However, in reality, households' investment behaviors are unlikely to be fully disclosed to others, and thus household i has only incomplete information about its peers' investments. In this case, $\bar{y}$ can be a rational expectation of peers' investments based on the attributes of peers.

By maximizing $V(y_i)$, we can obtain the optimal investment $y_i^* = A_i$. Hence, we have $\partial y_i^*/\partial \bar{y} = \partial y_i^*/\partial A_i \times \partial A_i/\partial \bar{y} > 0$. It suggests that the representative household's investment will be positively affected by its peers' investments, i.e., positive peer effects. Notice here, although $\bar{y}$ is taken as given when household i makes decisions, within a peer group with n households, investments by different households are simultaneously decided.

3.2. Binary investment decisions

The above analysis assumes that the investment is continuous, which can capture both the intensive margin and extensive margin. For the extensive margin reflected by binary investment decisions, we can simply treat binary decisions as continuous and analyze them using the model above. However, if considering household investment y_i is a discrete choice (0 or 1), the problem is to compare $V(1)$ and $V(0)$. Then the probability that the household participates in the investment is $P(y_i = 1) = P(V(1) > V(0)) = F(A_i)$, where $F(\cdot)$ is a distribution function depending on the distribution of ε_i. For example, if ε_i is independently and identically distributed and follows extreme-value distribution, the probability will be

$$P(y_i = 1) = \frac{\exp(A_i - 1/2)}{1 + \exp(A_i - 1/2)},$$

which is a logit-type model. Similar to the case of continuous investment, this probability also increase with A_i and then with peers' decision $\bar{y}$, suggesting positive peer effects.

4. Econometric strategy

4.1. Constructing peer groups

When it comes to the estimation of peer effects, one of challenges is how to define peers. If true links of social networks are observed by researchers, then peers can be defined by these links. However, most surveys provide only classroom or neighborhood identifiers and do not provide specific connections between individuals. Consequently, peers are often constructed based on these identifiers, and investigate peer effects in dormitories (e.g. Sacerdote, 2001; Zimmerman, 2003; Zárate, 2023), classrooms (e.g., Ding & Lehrer, 2007; De Giorgi et al., 2010; Bifulco et al., 2011; Carman & Zhang, 2012; Burke & Sass, 2013; Guo & Qu, 2022), schools (e.g., Gaviria & Raphael, 2001; Hanushek et al., 2003; Burke & Sass, 2013; Boucher et al., 2014) or neighborhoods (e.g., Brown et al., 2008; Agarwal et al., 2021; Lewbel et al., 2022). In this study, we define peers according to the neighborhood identifiers, given that the data used in the empirical analysis is a survey that lacks detailed social network information. In other words, we define households in the same neighborhood as a peer group. In the sample we use in regressions, the average size of a peer group is approximately 17. This group specification is reasonable, since households in the same neighborhood tend to have more opportunities to interact.

We define the peer group by matrix $G = \{g_{ij}\}$, where

$$g_{ij} = \begin{cases} 1 & \text{if households } i \text{ and } j \text{ are in the same neighborhood and } i \neq j \\ 0 & \text{otherwise.} \end{cases}$$

Here a neighborhood is a village in the rural area or a community in the urban area. We then row-normalize G to get $W = \{w_{ij}\}$, where $w_{ij} = g_{ij} / \sum_j g_{ij}$. Row normalization means peers' outcome is a leave-one-out mean.

4.2. Complete information

If households can fully observe the investment behaviors of their peer households, we use spatial econometric models which are widely used to capture peer effects (e.g. Lin, 2010;

Boucher et al., 2014; Patacchini et al., 2017; Guo & Qu, 2022; Grieser et al., 2022a,b). Referring to the discussion in section 3.1, if we assume A_i is a liner function of household attributes and peers' investments, then the model can be constructed as

$$y_{it} = \lambda \sum_{j \neq i} w_{ij} y_{jt} + X_{it}\beta + \alpha_i + v_t + \xi_{it},$$

where i and t indicate household and year; y_{it} is the log investment amount of wealth management products; α_i and v_t indicate household and year fixed effects; ξ_{it} is a random error; X_{it} is control variables shown in Table 2. We include attributes at the household head level (e.g., age, gender, marital status, education, self-reported health status, risk preference) and household level (e.g., income, assets, size). The spatial coefficient λ can capture the peer effects we are interested in.

To address correlated effects (Manski, 1993) which capture the non-randomness of peer group formation and common factors at group levels, at least neighborhood fixed effects need be controlled. Inspired by De Giorgi et al. (2020), we then use first differences to eliminating household (also neighborhood) fixed effects[2]. Consequently, the model can be written as Equation (1),

$$\Delta y_{it} = \lambda \sum_{j \neq i} w_{ij} \Delta y_{jt} + \Delta X_{it}\beta + \mu_t + \varepsilon_{it}, \tag{1}$$

where $\mu_t = \Delta v_t$ and $\varepsilon_{it} = \Delta \xi_{it}$. To further control contextual effects (Manski, 1993) which capture the effects from peers' attributes, we then introduce additional terms respect to peers' attributes and construct the following equation,

$$\Delta y_{it} = \lambda \sum_{j \neq i} w_{ij} \Delta y_{jt} + \Delta X_{it}\beta + \sum_{j \neq i} w_{ij} \Delta X_{jt}\gamma + \mu_t + \varepsilon_{it}, \tag{2}$$

[2]Household heads may change across time, thus the first differences of the attributes of household heads are not necessarily equal to zero and their coefficients can be estimated. Millimet & Bellemare (2023) point out that when household effects are time-invariant, first difference strategy performs similarly to fixed effects strategy. But if household effects vary over time (that is likely to happen when the panel data is not very short), first difference strategy performs better than fixed effects strategy. Therefore, the former is recommended.

where $\boldsymbol{\gamma}$ can capture contextual effects.

The models above can capture both the intensive and extensive margins of the peer effects since the outcome variable is the amount of investments, which is continuous. We also try to separately investigate extensive margins of the peer effects by the following model,

$$D_{it} = \lambda \sum_{j \neq i} w_{ij} D_{jt} + \Delta X_{it}\beta + \sum_{j \neq i} w_{ij} \Delta X_{jt}\gamma + \mu_t + \varepsilon_{it}, \quad (3)$$

where D_{it} is dummy variable to capture households' entry or exit decisions on the investment in wealth management products. To be specific, $D_{it} = 1$ if households participate the investments in year t but not in year $t-1$; otherwise, $D_{it} = 0$. Similarly, for exit decisions, $D_{it} = 1$ if households participate the investments in year $t-1$ but not in year t; otherwise, $D_{it} = 0$. The above models can be estimated through the quasi-maximum likelihood approach (Lee, 2004), which is one of the most commonly used approaches for the estimation of spatial econometric models.

To separate intensive-margin effects from the total effects, we perform the following heterogeneity analysis based on Equation (2),

$$\Delta y_{it} = \lambda_1 \sum_{j \neq i} w_{ij} \Delta y_{jt} + \lambda_2 \sum_{j \neq i} w_{ij} \Delta y_{jt} \times 1(y_{i,t-1} > 0) + \Delta X_{it}\beta + \sum_{j \neq i} w_{ij} \Delta X_{jt}\gamma + \mu_t + \varepsilon_{it}, \quad (4)$$

where $1(y_{i,t-1} > 0)$ is a dummy variable indicating whether household i has already participated in wealth management product investments in the previous period; λ_2 can capture the intensive-margin effects.

4.3. Incomplete information

However, the assumption of complete information may be strong. Peers are defined as neighbors rather than friends, and it is difficult to ensure that neighbors are all in close communication with each other. Furthermore, even among friends, it may be difficult for households to observe the investment behaviors of other households, given the privacy of these behaviors. Therefore, in the incomplete information cases, peer effects stem not from peers' real behaviors, but rather from household rational expectations of peers' behaviors.

For continuous outcome variables, we show that the model is consistent to that of complete information. For ease of illustration, we rewrite Equation (2) in a vector form,

$$\Delta y_t = \lambda W \Delta y_t + \Delta X_t \beta + W \Delta X_t \gamma + \mu_t l + \varepsilon_t,$$

where l is a vector of ones. Then the reduced form of Δy_t is

$$\Delta y_t = (I - \lambda W)^{-1}(\Delta X_t \beta + W \Delta X_t \gamma + \mu_t l + \varepsilon_t),$$

where I is an identity matrix. Given ΔX_t and W, the expectation of Δy_t is

$$E(\Delta y_t | \Delta X_t, W) = (I - \lambda W)^{-1}(\Delta X_t \beta + W \Delta X_t \gamma + \mu_t l). \tag{5}$$

If the information is incomplete and peer effects stem from rational expectations of peers' behaviors, the model becomes

$$\Delta y_t = \lambda W E(\Delta y_t | \Delta X_t, W) + \Delta X_t \beta + W \Delta X_t \gamma + \mu_t l + \varepsilon_t.$$

Then the expectation of Δy_t is

$$E(\Delta y_t | \Delta X_t, W) = \lambda W E(\Delta y_t | \Delta X_t, W) + \Delta X_t \beta + W \Delta X_t \gamma + \mu_t l,$$

and the reduced form of $E(\Delta y_t | \Delta X_t, W)$ is

$$E(\Delta y_t | \Delta X_t, W) = (I - \lambda W)^{-1}(\Delta X_t \beta + W \Delta X_t \gamma + \mu_t l). \tag{6}$$

As we can see, the expectation of Δy_t conditional on ΔX_t and W in Equations (5) and (6) are the same.

For dummy outcome variables capturing extensive margins, if we use the linear probability model as Equation (3), it is also consistent to that of complete information. However, the predicted values of linear probability models may fall outside the interval from 0 to 1, which defies reality. Referring to the analysis in section 3.2, we then try to use other binary choice models to capture peer effects, as follows[3],

$$P_{it} = \mathrm{P}(D_{it} = 1) = F(\lambda \sum_{j \neq i} w_{ij} P_{jt} + \Delta X_{it}\beta + \mu_t),$$

where $F(\cdot)$ is the logit function for the logit model, or the cumulative distribution function of the standard normal distribution for the probit model; P_{it} is the expected probability of i's choice of $D_{it} = 1$; P_{jt} is household i's rational expectation of its peer's entry probability (Lee et al., 2014). The expected probability P_{it} simultaneously depends on an information set including exogenous attributes ΔX_{it} of all households, peer matrix W and year fixed effects. The rational expectation equilibrium is a vector P_t^*, where $P_t^* = (P_{1t}^*, \cdots, P_{nt}^*)$, such that

$$P_{it}^* = F(\lambda \sum_{j \neq i} w_{ij} P_{jt}^* + \Delta X_{it}\beta + \mu_t), \tag{7}$$

given ΔX_t, W and year fixed effects.

The estimation of Equation (7) is by the nested pseudo-likelihood algorithm (e.g. Chen et al., 2022). The algorithm starts from an initial value $P^{(0)} = (P_1^{(0)}, \cdots, P_t^{(0)}, \cdots, P_T^{(0)})$ where $P_t^{(0)} = (P_{1t}^{(0)}, \cdots, P_{nt}^{(0)})$ and takes the following iterative steps. Step 1: Given $P^{(\tau-1)} = (P_1^{(\tau-1)}, \cdots, P_t^{(\tau-1)}, \cdots, P_T^{(\tau-1)})$, obtain $\hat{\theta}^{(\tau)} = \arg\max \ln L\left(\theta; P^{(\tau-1)}\right)$, where τ denote the τth iteration, $\theta = (\lambda, \beta', \mu_1, \cdots, \mu_t, \cdots, \mu_T)'$, and

$$\begin{aligned}\ln L\left(\theta; P^{(\tau-1)}\right) = &\sum_i \sum_t \left\{ D_{it} \ln F\left(\lambda \sum_{j \neq i} w_{ij} P_{jt}^{(\tau-1)} + \Delta X_{it}\beta + \mu_t\right)\right. \\ &\left. + (1 - D_{it}) \ln \left[1 - F\left(\lambda \sum_{j \neq i} w_{ij} P_{jt}^{(\tau-1)} + \Delta X_{it}\beta + \mu_t\right)\right]\right\}.\end{aligned}$$

[3] $\sum_{j \neq i} w_{ij} \Delta \boldsymbol{X_{jt}}$ is not introduced because introducing it into this model can also bring multi-collinearity problems. We will also provide empirical evidence that contextual effects will not affect the identification of peer effects.

Step 2: Given $\hat{\theta}^{(\tau)}$, update $P^{(\tau)} = (P_1^{(\tau)}, \cdots, P_t^{(\tau)}, \cdots, P_T^{(\tau)})$ according to

$$P_{it}^{(\tau)} = F\left(\hat{\lambda}^{(\tau)} \sum_{j \neq i} w_{ij} P_{jt}^{(\tau-1)} + \Delta X_{it} \hat{\beta}^{(\tau)} + \hat{\mu}_t^{(\tau)}\right).$$

Repeating the steps 1 and 2 until convergence can obtain the final estimated coefficients $\hat{\theta}$.

4.4. Multiplier effects

Peer effects (λ) can amplify or shrink the impact of exogenous shocks on outcome variables, producing multiplier effects, which have policy implications. For example, if there is a positive peer effect, the corresponding multiplier effect can augment the impact of policies, relative to the case where there is no peer effect.

For models of continuous outcome variable or linear probability models like Equations (2) and (3), multiplier effects can be calculated by $(I - \lambda W)^{-1} l$ based their reduced forms (e.g. Equation (5)). Because W is row-normalized, $(I - \lambda W)^{-1} l = l + \lambda l + \lambda^2 l + \lambda^3 l + \cdots = l/(1-\lambda)$. On average, the empirical multiplier effect can be calculated by $1/(1 - \hat{\lambda})$.

Unlike linear probability models, the multiplier effect of non-linear binary choice models (Equation (7)) cannot be calculated directly from $1/(1 - \hat{\lambda})$. We therefore calculate it based on its direct definition, i.e., the mean of $\hat{P}_{it}^* / \tilde{P}_{it}^*$, where $\hat{P}_{it}^*$ is the predicted value of P_{it}^* with peer effects,

$$\hat{P}_{it}^* = F(\hat{\lambda} \sum_{j \neq i} w_{ij} \hat{P}_{it}^* + \Delta X_{it} \hat{\beta} + \hat{\mu}_t),$$

and $\tilde{P}_{it}^*$ is the predicted value of P_{it}^* without peer effects,

$$\tilde{P}_{it}^* = F(\Delta X_{it} \hat{\beta} + \hat{\mu}_t).$$

5. Empirical results

5.1. Extensive-margin effects

We first investigate the extensive margin of peer effects in investing wealth management products, under the assumption of complete information. Household participation decisions in wealth management product markets may be affected by their peers' decisions. The findings presented in Table 3 shed light on the impact of peers' decisions on a household's investment choices in wealth management products. The coefficients of peers' investments in the first row are peer effects (λ, the same below).

In column (1), where contextual effects are assumed to be non-existent ($\boldsymbol{\gamma} = 0$), our results reveal significant peer effects in entry decisions, with a magnitude of 0.127. When incorporating contextual effects, we employ Equation (3) to estimate peer effects and the corresponding results are in column (2). We find that even including the effects from neighboring household attributes, the magnitude of peer effects remains largely unaltered. Furthermore, we extend our inquiry to explore the effects of peers on exit decisions, and our findings, detailed in Appendix A, indicate significantly positive results[4].

Lewbel et al. (2022) notes that using leave-one-out means based on observed households to represent the average of a neighborhood may introduce bias if there is an insufficient number of households that can be observed. In light of this concern, we remove neighborhoods with fewer than 10 and 15 observations in columns (3) and (4), respectively, and re-estimate Equation (3). The findings indicate that the estimated peer effects are similar to those obtained using the full sample in column (2). This suggests that the issue of partially observable peer groups does not significantly impact our estimates, as most neighborhoods have a sufficient number of observations in our sample.

[4]Considering the tiny percentage of households in the sample that exit wealth management product markets, the results may not be representative, and thus we put them in the appendix part.

Table 3: Peer effects in entry decisions of wealth management product investments

	(1)	(2)	(3)	(4)
Peers' investments	0.128***	0.119***	0.136***	0.148***
	(0.016)	(0.016)	(0.017)	(0.020)
Age	-0.001***	-0.001***	-0.001***	-0.001**
	(2.288e-4)	(2.296e-4)	(2.344e-4)	(2.518e-4)
Gender (male)	0.007	0.007	0.007	0.008
	(0.004)	(0.004)	(0.005)	(0.005)
Marriage	0.015***	0.015***	0.014**	0.016**
	(0.006)	(0.006)	(0.006)	(0.006)
Health condition	0.003**	0.003**	0.004***	0.003**
	(0.001)	(0.001)	(0.002)	(0.002)
Years of schooling	0.001*	0.001*	0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Risk preference	0.008***	0.008***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Asset	0.012***	0.012***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Income	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Sizes of household	0.012***	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Multiplier effects	1.147	1.136	1.158	1.174
Contextual effects	No	Yes	Yes	Yes
Observations	38,045	38,045	35,741	30,691

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. Before taking first differences, household asset and income are logarithmic after plus 1 with the unit of CNY. Year fixed effects are controlled in all columns. Columns (1) and (2) use the full sample. Column (3) drops peer groups whose sizes are less than or equal to 10, and column (4) drops peer groups whose sizes are less than or equal to 15. Multiplier effects are calculated by $1/(1-\hat{\lambda})$.

We interpret the coefficients based on column (2) of Table 3. The peer effects in entry decisions is 0.119, corresponding to a multiplier of 1.135. This multiplier implies that policies aimed to encourage households to participate in the investments will be amplified by approximately 13.5% due to the existence of peer effects. This is substantial in magnitude, giving the average participation rate is approximately 14% in data. For the attributes of household heads, we find that the marital status, the health condition and the risk preference have positive while the age has negative impact on the probability of participation in wealth management product investments. For the attributes of households, all the three variables, namely household asset, income and size, have positive impact on the entry decisions. These coefficients of control variables are consistent with intuition.

5.2. Total and intensive-margin effects

For the total effects with complete information, the impact of neighboring households on a household's investment amount are reported in Table 4. In column (1), the results, derived from Equation (1), reveal significant peer effects. Upon introducing contextual effects using Equation (2), the magnitude of peer effects remains consistent. This parallel pattern with the extensive margins suggests that contextual effects do not impede the identification of endogenous peer effects in our context.

In column (2), the observed magnitude of peer effects is 0.093, equivalent to a multiplier effect of 1.1. This implies that policies aimed at encouraging households to increase their investments would experience an augmentation of approximately 10% due to peer effects. This effect size is noteworthy, underscoring the substantial impact of peer dynamics on investment amounts. Furthermore, akin to the approach taken in exploring extensive margins, we exclude neighborhoods with fewer than 10 and 15 households in columns (3) and (4). The results consistently demonstrate the robustness of the estimated peer effects.

Table 4: Peer effects in investment amount in wealth management products

	(1)	(2)	(3)	(4)
Peers' investments	0.097***	0.093***	0.096***	0.093***
	(0.016)	(0.016)	(0.018)	(0.021)
Age	-0.009***	-0.009***	-0.010***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Gender (male)	0.042	0.044	0.050	0.075
	(0.057)	(0.057)	(0.059)	(0.064)
Marriage	0.115*	0.112*	0.092	0.101
	(0.067)	(0.067)	(0.069)	(0.074)
Health condition	0.007	0.011	0.016	0.011
	(0.017)	(0.017)	(0.018)	(0.020)
Years of schooling	0.019**	0.019**	0.020**	0.018*
	(0.008)	(0.008)	(0.009)	(0.010)
Risk preference	0.122***	0.119***	0.124***	0.131***
	(0.020)	(0.019)	(0.022)	(0.025)
Asset	0.175***	0.176***	0.172***	0.174***
	(0.011)	(0.011)	(0.011)	(0.012)
Income	0.058***	0.057***	0.062***	0.066***
	(0.007)	(0.008)	(0.008)	(0.008)
Sizes of household	0.054***	0.049***	0.050***	0.059***
	(0.015)	(0.015)	(0.015)	(0.017)
Multiplier effects	1.108	1.103	1.106	1.102
Contextual effects	No	Yes	Yes	Yes
Observations	37,980	37,980	35,671	30,604

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. Before taking first differences, the dependent variable, asset and income are logarithmic after plus 1 with the unit of CNY. Results in Appendix B show that the estimated peer effects are robust to the unit of the dependent variable. Year fixed effects are controlled in all columns. Columns (1) and (2) use the full sample. Column (3) drops peer groups whose sizes are less than or equal to 10, and column (4) drops peer groups whose sizes are less than or equal to 15. Multiplier effects are calculated by $1/(1-\hat{\lambda})$.

The coefficients of control variables still do not conflict with intuition. In reference to the coefficients of household heads' attributes, it is observed that as the age of household head increases, the investment in wealth management products decreases. One plausible explanation for this phenomenon is that older individuals may possess limited financial literacy or exhibit more conservative attitudes towards investments. Gender, marital status, and health conditions of the household head do not significantly impact investments in wealth management products. However, educational attainment exerts a positive influence, as each additional year of schooling increases investment amounts by 1.9%. Moreover, risk preference also plays a key role, as household heads with higher risk preference tend to invest more. Regarding household-level attributes, it is not surprising that asset, income, and household size all have positive impacts on investment levels.

We then try to separate intensive-margin effects form the total effects by adding an interactive term (Equation (4)). As shown in the second row of Table 5, those households that already participated in wealth management product investments in the previous period are more affected by their peers, implying that the intensive margin is larger than the extensive margin.

Table 5: Peer effects in investment amount: separate intensive-margin effects

	(1)	(2)	(3)	(4)
Peers' investments	0.102***	0.093***	0.099***	0.101***
	(0.015)	(0.014)	(0.016)	(0.019)
Peers' investments	0.263***	0.266***	0.327***	0.334***
$\times 1(y_{i,t-1} > 0)$	(0.071)	(0.071)	(0.079)	(0.087)
Contextual effects	No	Yes	Yes	Yes
Observations	37,980	37,980	35,671	30,604

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. Before taking first differences, the dependent variable, asset and income are logarithmic after plus 1 with the unit of CNY. Results in Appendix B show that the estimated peer effects are robust to the unit of the dependent variable. Year fixed effects are controlled in all columns. Columns (1) and (2) use the full sample. Column (3) drops peer groups whose sizes are less than or equal to 10, and column (4) drops peer groups whose sizes are less than or equal to 15.

5.3. Robustness checks under incomplete information

We then relax the assumption of complete information and investigate the peer effects under incomplete information. Panels A and B of Table 6 show the results on extensive margins by Equation (7). Instead of focusing on all wealth management products, we separately investigate the peer effects of two categories, Internet and traditional wealth management products, reporting in columns (2) and (3) of the table. In column (4), we list the peer effects in the investments of stocks, bonds and funds.

The results of extensive margins in Panels A and B indicate that peer effects in entry decisions on all wealth management products and on traditional wealth management products are significant. But for Internet wealth management products, the magnitude is slightly smaller and the significance is weaker. When examining entry decisions concerning investments in stocks, bonds, and funds, the peer effects lose their statistical significance, which may be owing to the higher risk of these products. In addition, the robustness of these findings is maintained across various binary choice models. Whether employing the logit model or the probit model, the significance of coefficients and the scale of multiplier effects exhibit consistent patterns. Furthermore, comparing with the multiplier effects under complete information, the scale of multiplier effects under incomplete information are larger but not substantially different.

Table 6: Robustness checks: alternative models and outcomes

	(1) All products	(2) Internet	(3) Traditional	(4) Stocks et al.
Panel A: Extensive-margin effects by the logit model				
Peers' investments	3.298***	2.484*	3.600***	2.330
	(0.530)	(1.328)	(1.099)	(1.831)
Multiplier effects	1.373	1.210	1.292	1.146
Observations	38,045	35,055	24,977	27,277
Panel B: Extensive-margin effects by the probit model				
Peers' investments	1.880***	1.400**	1.917***	1.534*
	(0.284)	(0.634)	(0.597)	(0.787)
Multiplier effects	1.437	1.248	1.329	1.214
Observations	38,045	35,055	24,977	27,277
Panel C: Total effects				
Peers' investments	0.093***	0.048***	0.063***	0.085***
	(0.016)	(0.017)	(0.019)	(0.023)
Multiplier effects	1.103	1.050	1.068	1.093
Observations	37,980	35,105	24,953	26,080

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. The types of financial products in columns (1)–(4) are wealth management products, Internet wealth management products, traditional wealth management products, and stocks+bonds+funds, respectively. Household attributes and year fixed effects are controlled in all panels. Contextual effects in Panel C are controlled. Neighborhoods where no one invests in corresponding financial products are removed. In Panels A and B, multiplier effects are calculated by the mean of $\hat{P}_{it}^{*}/\tilde{P}_{it}^{*}$. In Panel C, multiplier effects are calculated by $1/(1-\hat{\lambda})$.

For the total effects from intensive and extensive margins, as shown in columns (2) and (3) of Panel C, peer effects are robust and consistent across both categories of wealth management products. In column (4), we find positive peer effects in the investment amount of stocks, bonds, and funds.

Combining the results of peer effects in entry decisions, we summarize that households exercise caution in determining participation in high-risk investment vehicles, such as stocks, and exhibit independence from peer behaviors. Conversely, peer effects play a role in their decisions to engage in low-risk investment options, such as wealth management products.

Once households initiate investments in financial products, the amount of their investments can be affected by peer behaviors, irrespective of the product's risk level.

6. Heterogeneity and mechanism

We first conduct a series of cross-sectional heterogeneity analyses to investigate the potential impact of several household attributes on peer effects, namely gender, age, residence location, and education of household heads. We try to uncover possible mechanisms from these heterogeneity analyses. The results are reported in Table 7. As we can see in column (1), household investment behaviors are less affected by peers' investment behaviors when the household head is male. In column (2), we observe that household heads over 60 years old invest less and are less affected by peers. This age heterogeneity may be due to the fact that older individuals have less interaction with others and receive less information on financial products. The results in column (3) indicate that peer effects of rural households are insignificant or even negative, which may because rural households are less likely to communicate about financial products. Column (4) shows that households with lower educated heads invest less in wealth management products and are less susceptible to peer effects. The reason behind this may be similar to the reason for the age heterogeneity. Individuals with low education are more conservative or have less financial literacy and are less likely to learn about finance through social interactions. These heterogeneity phenomena are similar for extensive-margin effects and total effects and imply that the formation of peer effects may be closely related to the spread of information and social learning.

Ouimet & Tate (2020) argue that households with more information on finance may be more likely to affect and be affected by others. To verify this argument, we divide households into two categories based on different criteria, namely, high information households and low information households. The first criterion is based on the industry in which the heads of households work. If the head of a household works in financial industry, he/ she is likely to be exposed to more financial-related information and thus his/ her household is classified as a high information household; the other households are classified as low information households. Second, some heads of households are more interested in finance and

Table 7: Cross-sectional heterogeneity in peer effects

	(1) Male	(2) Old age	(3) Rural area	(4) Low education
Panel A: Extensive-margin effects				
Peers' investments	0.181***	0.140***	0.152***	0.143***
	(0.042)	(0.023)	(0.018)	(0.035)
Peers' investments× *Heter*	-0.085*	-0.047	-0.289***	-0.103**
	(0.049)	(0.036)	(0.030)	(0.041)
Heter	0.012**	-0.055***	-0.011***	-0.070***
	(0.006)	(0.004)	(0.004)	(0.005)
Observations	38,045	38,045	38,045	38,045
Panel B: Total effects				
Peers' investments	0.155***	0.143***	0.120***	0.168***
	(0.037)	(0.022)	(0.019)	(0.036)
Peers' investments× *Heter*	-0.083*	-0.125***	-0.192***	-0.155**
	(0.047)	(0.037)	(0.023)	(0.042)
Heter	0.104*	-0.266***	-0.010	-0.406***
	(0.055)	(0.040)	(0.037)	(0.046)
Observations	37,980	37,980	37,980	37,980

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. The variable *Heter* is a dummy of whether the head of household is male, a dummy of whether the head of household is older than 60 years old, a dummy of whether the household from rural area, and a dummy of whether the head of household has less than 12 years of schooling for columns (1)–(4), respectively. Household attributes, year fixed effects and contextual effects are controlled in all columns.

economy, and thus have more information and their households are defined as high information households[5]. Third, high-income households tend to be more exposed to financial information, so we define the top 25% of households in the neighborhood in terms of income as high information and the rest as low information. Fourth, heads of households with a higher risk preference are also likely to be more receptive to financial information and are therefore classified as high information households based on this criterion[6].

Table 8 reports whether high information households are more affected by their peers,

[5]The level of concern for finance and economy is measured by a scale from 1 (very concerned) to 5 (never concerned). Households with heads answering less than or equal to 2 to this question are defined as high information and other households are defined as low information.

[6]Risk preference is measured by a scale from 1 (low risk/ do not know) to 5 (high risk). Households with heads answering greater than 3 to this question are defined as high information and other households are defined as low information.

based on four different definitions. Results in columns (1)–(4) show that high information households are likely to participate more and invest more in wealth management products. For the heterogeneity in peer effects, most coefficients of interaction terms are insignificant. Notably, only households displaying a heightened emphasis on financial and economic news appear to be more prone to peer effects, as observed in column (2) of Panel B. Conversely, at extensive margins, households with higher incomes exhibit an even lower susceptibility and diminished impact in response to the entry decisions made by their peers. To summarize, these findings suggest that households possessing informational advantages do not necessarily experience a greater impact from their peers. This observation aligns with expectations, given that these households possess a greater ability to make independent investment decisions and are less inclined to seek input from their peers.

Table 8 investigates heterogeneity in peer effects by categorizing focal households into two groups based on their information levels: high and low. In Table 9, we further explore the heterogeneous peer effects on focal households by categorizing peer households into these two groups. The findings reveal that, for both extensive and intensive margins, the impact of high information peers surpasses that of low information peers. This trend remains consistent across various high-information definitions. Upon examining the t-test results, columns (2) and (3) reveal significant heterogeneity. Peer households with a heightened interest in finance and the economy, as well as those with higher income levels, contribute to more pronounced peer effects. In contrast, peer households falling outside these categories exhibit minimal or negligible peer effects.

The results presented above support our assertion that households possessing greater financial knowledge have a heightened impact on other households, implying a mechanism of information spread. Comparison between Tables 8 and 9 also reveal that it is not whether households themselves have more information, but whether their peers have more information that matters.

To explore more on the mechanism, we conduct supplementary analyses focusing on the homophily of peers, a crucial factor in social interactions (Currarini et al., 2009). Peers exhibiting higher homophily, i.e., those sharing more similar attributes, are more inclined to

Table 8: Heterogenous peer effects of households with high information

	(1) Financial industry	(2) Highly concern on finance and economy	(3) Top 25% income	(4) High risk preference
Panel A: Extensive-margin effects				
Peers' investments	0.119***	0.097***	0.146***	0.118***
	(0.016)	(0.016)	(0.018)	(0.017)
Peers' investments	-0.081	0.180**	-0.089**	-0.026
× High information	(0.269)	(0.090)	(0.053)	(0.089)
High information	0.127***	0.043***	0.099***	0.058***
	(0.031)	(0.010)	(0.007)	(0.011)
Observations	38,045	37,962	38,045	38,045
Panel B: Total effects				
Peers' investments	0.093***	0.066***	0.074***	0.087***
	(0.016)	(0.016)	(0.017)	(0.016)
Peers' investments	-0.010	0.253***	0.090	0.055
× High information	(0.295)	(0.089)	(0.055)	(0.096)
High information	0.852***	0.300***	0.620***	0.202**
	(0.317)	(0.090)	(0.060)	(0.102)
Observations	37,980	37,897	37,980	37,980

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. High information is defined by a dummy variable indicating whether the household head works in financial industry, whether the household head is highly focused on finance and economy, whether the household's income ranks in the top 25% of the neighborhood, or whether the household head has high risk preference in columns (1)–(4), respectively. Household attributes, year fixed effects and contextual effects are controlled in all columns.

engage in communication. This, in turn, facilitates the diffusion of information and enhances the social learning process.

We introduce several proxies to measure homophily. The first and the second are household income and assets. Households sharing similar income or wealth levels are inclined to engage in more interactions, fostering increased opportunities for information exchange, particularly in areas such as financial literacy and knowledge of financial products. The third is the age of the household head. Households headed by individuals with similar ages are more likely to share common topics of communication, facilitating the exchange and acquisition of information. The fourth proxy combines data on income, assets, and the age of household heads, providing a comprehensive measure of homophily among households.

Table 9: Peers with high information v.s. Peers with low information

	(1) Financial industry	(2) Highly concern on finance and economy	(3) Top 25% income	(4) High risk preference
Panel A: Extensive-margin effects				
High information peers	0.645	0.474***	0.469***	0.342**
	(0.464)	(0.143)	(0.087)	(0.136)
Low information peers	0.111***	0.077***	0.011	0.095***
	(0.017)	(0.021)	(0.038)	(0.021)
T-tests	0.257	0.011	0.000	0.098
Observations	38,045	37,962	38,045	38,045
Panel B: Total effects				
High information peers	0.384	0.410***	0.344***	0.198
	(0.389)	(0.119)	(0.066)	(0.120)
Low information peers	0.089***	0.056***	0.016	0.082***
	(0.017)	(0.019)	(0.025)	(0.018)
T-tests	0.455	0.006	0.000	0.368
Observations	37,980	37,897	37,980	37,980

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the neighborhood level. P-values of testing the difference between peer effects from high information peers and peer effects from low information peers are reported. Neighborhoods where no one invests in wealth management products are removed. High information is defined by a dummy variable indicating whether the household head works in financial industry, whether the household head is highly focused on finance and economy, whether the household's income ranks in the top 25% of the neighborhood, or whether the household head has high risk preference in columns (1)–(4), respectively. Household attributes, year fixed effects and contextual effects are controlled in all columns.

Based on the four proxies mentioned earlier, we categorize the original peers (i.e., other households in the same neighborhood) into two groups: the top 10 peers exhibiting the highest degree of homophily with the focal household, and the remaining peers. Table 10 presents the results corresponding to these four homophily proxies in columns (1)–(4). The outcomes indicate that the effects from the remaining peers are either weak or statistically insignificant. Notably, peer effects predominantly emanate from households that share a higher degree of similarity or homophily with the focal household, both in terms of extensive and intensive margins. This observation further substantiates the proposed mechanism related to the spread of information and learning.

The preceding discussions indicate that households possessing superior information tend to exert a notable influence, resulting in heightened peer effects on other households. Accordingly, policymakers aiming to promote household investment in wealth management products may find it more effective and less costly to primarily focus on these informed households. Additionally, it is crucial to recognize that the scope for peer effects is circumscribed, with significant impacts observed primarily among households sharing similar characteristics and displaying high homophily. This consideration is pivotal for policymakers seeking to broaden the reach and effectiveness of their initiatives. For instance, in order to broaden the impact of influencers, policymakers might choose influencers from various types of households. In the absence of such diversity among influencers, their interactions may be confined to a homogenous group, making it challenging for their influence to extend beyond that particular demographic.

Table 10: More similar peers v.s. other peers

	(1)	(2)	(3)	(4)
	Income	Asset	Age	Income & asset & age
Panel A: Extensive-margin effects				
The 10 most similar peers	0.155***	0.165***	0.145***	0.132***
	(0.013)	(0.013)	(0.014)	(0.014)
Other peers	-0.012	-0.020	-0.003	0.009
	(0.014)	(0.014)	(0.014)	(0.015)
T-tests	0.000	0.000	0.000	0.000
Observations	30,691	30,691	30,691	30,691
Panel B: Total effects				
The 10 most similar peers	0.084***	0.093***	0.067***	0.059***
	(0.015)	(0.015)	(0.016)	(0.016)
Other peers	0.007	0.002	0.022	0.030*
	(0.015)	(0.015)	(0.015)	(0.016)
T-tests	0.000	0.000	0.044	0.216
Observations	30,604	30,604	30,604	30,604

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. P-values of testing the difference between the two coefficients of peer effects are reported. Neighborhoods where no one invests in wealth management products are removed. Peer groups whose sizes are less than or equal to 15 are dropped. Household attributes, year fixed effects and contextual effects are controlled in all columns.

The analyses above confirm the mechanism of social learning. We also try to rule out the effects of social norms, which may also drive positive correlation among neighbors.

Households may conform to a common social norm or consensus of their reference group, resulting in similar behaviors and outcomes clustering. Given potential household heterogeneity, some may be more inclined to conform to norms and thus more susceptible to peer influence. Therefore, we use two provincial-level metrics to perform heterogeneity analyses. The first is the number of Confucian temples in the provinces where the households reside, which may serve as an indicator of adherence to norms since Confucian culture emphasizes obedience to rules. The second is whether the provinces where the households reside are in south China. Households in south China are often perceived to be more cooperative and thus more likely to develop consensus or norms. Results in Appendix C show that all coefficients respect to heterogeneity are insignificant, which does not support the mechanism of social norms.

7. Financial investments and inequality

The stylized facts presented in Section 2 suggest that households with higher wealth invest more in wealth management products and subsequently realize greater returns, thereby exacerbating wealth disparities. Consequently, a potential policy avenue for ameliorating inequality involves fostering increased household participation in wealth management products. This section aims to furnish suggestive evidence regarding the correlation between inequality levels and the participation rate, as well as the allocation share of these products. Our analyses are conducted at the neighborhood level, and the results are detailed in Table 11.

To quantify inequality, we employ two Gini indexes calculated at the neighborhood-year level, focusing on household income and assets, respectively. Columns (1) and (2) of in Table 11 reveal an inverse relationship between the participation rate and inequality. Specifically, a 1 percentage point rise in wealth management product participation corresponds to a reduction in the Gini index by 0.07–0.16 percentage points.

Examining the impact of allocation share relative to total household assets, the coefficient in column (2) is positively significant, but the interaction term in row 3 is negative. This implies that in high-participation scenarios, encouraging households to increase their allocation to wealth management products can mitigate inequality. This finding is consistent with the argument in Favilukis (2013) that increased stock market participation will cause a fall in wealth inequality. Columns (3) and (4) introduce lagged terms of independent variables to address potential endogeneity concerns. Remarkably, the negative coefficients of the participation rate persist, underscoring the robustness of our findings.

In summary, our results suggest that promoting household participation in wealth management products holds promise for reducing inequality given the current income distribution system. This observation offers a rationale for pertinent policy initiatives. Furthermore, the amplifying effects of peer influence and underlying information-learning mechanisms, as discussed earlier, can enhance the efficacy of such policies, fostering greater household engagements.

Table 11: The effects of wealth management product investments on inequality

	(1) Gini of income	(2) Gini of asset	(3) Gini of income	(4) Gini of asset
Participation rate	-0.080***	-0.162***		
	(0.029)	(0.029)		
Allocation share	-0.044	1.188***		
	(0.369)	(0.395)		
Participation rate	0.009	-0.022**		
× allocation share	(0.010)	(0.009)		
Lagged participation rate			-0.062	-0.110***
			(0.049)	(0.042)
Lagged allocation share			0.048	-0.826
			(0.721)	(0.595)
Lagged participation rate			0.018	0.026
× lagged allocation share			(0.024)	(0.021)
Observations	5,150	5,235	3,355	3,402

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhood-level mean of household attributes, year and neighborhood fixed effects are controlled in all columns. All independent variables in columns (3) and (4) are lagged. The units of Gini indexes, participation rate and allocation share are 100%.

8. Conclusion

This study investigates peer effects on investments in wealth management products, a widely embraced financial tool among Chinese households. Leveraging data from four waves of the CHFS, we define peer groups at the neighborhood level, while accounting for correlated and contextual effects. Our findings reveal the presence of peer effects in household investments in wealth management products, significant at both extensive and intensive margins. The observed effects magnify the influence of a policy or an exogenous shock by 10%–14% compared to a scenario devoid of peer effects. This pattern is robust even when we consider households have incomplete information on their peers' investment behaviors.

Additionally, our research employs various heterogeneity analyses to underscore the robustness of evidence, suggesting that the primary mechanism driving these peer effects is the dissemination of information and learning. Suggestive evidence supports the notion that increasing household participation rates can mitigate inequality. These discoveries carry substantial implications for policymakers. On the one hand, our study proposes that interventions aimed at enhancing participation and investment levels in wealth management products should be directed toward influential households within neighborhoods, thereby amplifying the broader impact of these policies. On the other hand, fostering appropriate investment among non-affluent households can enable them to accrue returns from these financial products, contributing to a reduction in wealth disparities.

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Appendix A. Peer effects in exit decisions

We also investigate the peer effects in exit decisions by Equation (3), where $D_{it} = 1$ if households participate the investments in year $t-1$ but not in year t; otherwise, $D_{it} = 0$. The results in Table A.12 show positive peer effects, which are consistent with the peer effects in entry decisions.

Table A.12: Peer effects in exit decisions of wealth management product investments

	(1)	(2)	(3)	(4)
Peers' investments	0.197***	0.187***	0.206***	0.212***
	(0.015)	(0.015)	(0.015)	(0.016)
Age	3.479e-4*	3.261e-4*	3.280e-4*	3.853e-4*
	(1.843e-4)	(1.840e-4)	(1.894e-4)	(2.084e-4)
Gender (male)	0.004	0.004	0.004	0.004
	(0.003)	(0.003)	(0.004)	(0.004)
Marriage	0.004	0.005	0.005	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Health condition	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Years of schooling	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Risk preference	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Asset	-0.003***	-0.003***	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Income	-0.003***	-0.003***	-0.003***	-0.003***
	(4.224e-4)	(4.261e-4)	(4.440e-4)	(4.603e-4)
Sizes of household	0.003***	0.002**	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Multiplier effects	1.246	1.229	1.260	1.269
Contextual effects	No	Yes	Yes	Yes
Fixed effects	Year	Year	Year	Year
Observations	38,230	38,230	35,960	30,996

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. Before taking first differences, household asset and income are logarithmic. Year fixed effects are controlled in all columns. Columns (1) and (2) use the full sample. Column (3) drops peer groups whose sizes are less than or equal to 10, and column (4) drops peer groups whose sizes are less than or equal to 15. Multiplier effects are calculated by $1/(1-\hat{\lambda})$.

Appendix B. Robustness checks for different scales of the outcome variable

In our data, many households invest zero in wealth management products and thus their $I_{it} = 0$. For continues outcomes, we apply "log-like" transformation to address these zeros before taking first differences, i.e., $y_{it} = \ln(1 + I_{it})$, and then $\Delta y_{it} = y_{it} - y_{i,t-1} = \ln(1 + I_{it}) - \ln(1 + I_{i,t-1})$. However, this may make the estimated coefficients sensitive to the unit of investment amount (Chen & Roth, 2024). In other words, using different a in $\ln(1 + aI_{it})$ may get different estimated peer effects. We then perform robustness checks under different a using CNY as the original unit. As we can see in Table B.13, the coefficients of peers' investment are robust to a large a. It implies that for our spatial econometric models, when we use a small unit to get a large value of the outcome variable, the estimated spatial coefficients of interest are not sensitive to the units of outcomes.

The intuition behind it is that in our models, the outcome variable is constructed by taking first differences. So for a enough large a, the coefficient of λ will not significantly affected by the size of a since $\ln(1 + aI_{it}) \approx \ln(aI_{it}) = \ln a + \ln I_{it}$ and then $\Delta y_{it}(a) = \ln(1 + aI_{it}) - \ln(1 + aI_{i,t-1}) \approx \ln I_{it} - \ln I_{i,t-1}$, which is free of a for positive I_{it} and $I_{i,t-1}$. If one of them is zero, e.g. $I_{i,t-1} = 0$, then $\Delta y_{it}(a) \approx \ln I_{it} + \ln a$ and increases with a. However, in our spatial econometric models as follows, the outcome variable appears on both the left and right sides of the equation, so the effects of a will be cancelled out to a large extent.

$$\Delta y_{it} = \lambda \sum_{j \neq i} w_{ijt} \Delta y_{it} + \Delta \boldsymbol{X_{it}\beta} + FE + \varepsilon_{it},$$

For a extremely small a, $1 + aI_{it}$ will dominated by 1, and then $\Delta y_{it} \approx 0$ and the coefficient of λ will be unstable. In our main regressions, we choose $a = 1$ and use CNY as the unit of investments to ensure aI_{it} large enough, so the estimated peer effects are not arbitrary, as suggested by the results in Table B.13.

Table B.13: Peer effects in investment amount with different scales

	(1)	(2)	(3)	(4)	(5)
	a=1	a=10	a=100	$a=10^4$	$a=10^8$
Peers' investments	0.093***	0.089***	0.086***	0.081***	0.076***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Contextual effects	Yes	Yes	Yes	Yes	Yes
Observations	37,980	37,980	37,980	37,980	37,980

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Before taking first differences, the dependent variable is the natural logarithms of one plus a times household investment amount (CNY). $a = 1$ is used in our main regressions.

Appendix C. Check the mechanism of social norms

Table C.14: Heterogeneity analyses based on metrics related to social norms

	(1)	(2)	(3)	(4)
	Extensive-margin effects		Total effects	
Peers' investments	0.134***	0.114***	0.103***	0.074***
	(0.021)	(0.022)	(0.022)	(0.023)
Peers' investments× Confucian	-0.008		-0.005	
	(0.007)		(0.007)	
Peers' investments× South		0.010		0.037
		(0.036)		(0.032)
Observations	38,045	38,045	37,980	37,980

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the neighborhood level. Neighborhoods where no one invests in wealth management products are removed. Household attributes, year fixed effects and contextual effects are controlled in all columns. *Confucian* denotes the number of Confucian temple at provincial levels and *South* denotes whether the province is in the south China.