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ARTICLE

The role of the peer effect in forming pension expectations among the middle-aged: existence and mechanisms

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Abstract
Using the instrumental variable approach on nationally representative, individual-level data on middle-aged pension participants in China, this study quantifies the peer effect in the context of forming pension expectations. The study confirms the existence of the peer effect in forming pension expectations in the community. The probability of having optimistic pension expectations significantly increases by 0.309 percentage points if the proportion of optimists in the community increases by 1 percentage point. Moreover, the study explores the channels through which the peer effect operates and finds that the social learning channel dominates the social norms channel. The study also provides empirical evidence that village and township leaders as well as those with old pension program experience are opinion leaders in their peer group. Lastly, we find peer effects in other pension decisions, e.g., contribution size, and the contribution size increases by the proportion of optimists in the community. The study provides policy implications on ways to improve willingness to contribute to pension programs.

Keywords: instrumental variable; peer effect; pension expectations; public pension benefits

JEL Codes: D85; H55; Z13

1. Introduction

Population aging presents enormous challenges to the old-age support system in many countries. To address these challenges, countries spend significant resources on public pension programs (Holzmann and Hinz, 2005; Gruber and Wise, 2009; Bonenkamp *et al.*, 2017). Despite well-designed terms and attractive benefits for participants, public pension programs are often plagued by low enrollment or a low level of voluntary contributions. This dilemma may stem from pessimistic expectations of the future benefits among the public in general (Bissonnette and Van Soest, 2015; Giles *et al.*, 2023). Failure in delivering necessary information about the public pension programs to the public or difficulties in individuals' ability to process such information could explain the limited and insufficient demand for public pensions (Heckman and Smith, 2004; Bhargava and Manoli, 2015; Bai *et al.*, 2021; Giles *et al.*, 2021). Therefore, one way to boost the demand is to facilitate optimistic pension expectations by providing accessible and readily comprehensible information about public pension programs.

Participants can obtain information from two sources, public and private information sources. Public information sources, including annual letters (Dolls *et al.*, 2018), information brochures (Bai *et al.*, 2021), and official account statements (Mastrobuoni, 2011), have been shown to be effective channels in updating participants' information about future pension benefits. These channels help to

release reliable information from the pension management authority; however, building up a massive public information distribution channel (online or by mail) could be time-consuming and costly.

In the meantime, the participants could also obtain information from private sources, for example, peer groups living in the same community. The peers may have more experience in the pension program over a longer period, so that they can provide information on the pension benefits and past changes. They may also help individuals to process and understand the pension benefit formula by sharing personal experiences and cases of acquaintances, especially for those with limited financial literacy (Alessie *et al.*, 2011) or low education levels (Gustman and Steinmeier, 2005). Along this line, peers may also shape an individual's beliefs about the pension system itself regarding whether the benefit estimation is reliable. Private information sources through peers are particularly relevant when public information is scarce and costly and when individuals' perceptions are in a formative stage (Akerlof, 1997; Dahl *et al.*, 2014).

The pension systems in many developing countries are immature and expanding; thus, the public information channel on pension programs is not sufficient to provide updated information conveniently for all participants. Individuals may find it difficult to follow the rules and changes. As a result, individuals rely more often on peers and acquaintances to form their pension expectations. In this context, it is essential to study the role of the peer effect in forming pension expectations. It is well documented that peers may exchange information and imitate others' behaviors, manifesting the peer effect (Manski, 1993, 2000; Chiang and Zheng, 2010; Liu *et al.*, 2014). Economists have investigated the role of the peer effect in various fields of the public interest, such as schooling outcomes (Sacerdote, 2001; Angrist and Lang, 2004; Arcidiacono and Nicholson, 2005; Duflo *et al.*, 2011; Li *et al.*, 2013), welfare program participation (Solon *et al.*, 1988; Dahl *et al.*, 2014; Liu *et al.*, 2014; Cai *et al.*, 2015; Ahn *et al.*, 2023), and insurance purchases (Liu *et al.*, 2014), among others.[1] However, we have not found any literature documenting the peer effect in forming pension expectations. We intend to fill this gap by studying the existence, if any, and mechanisms of the peer effect on pension expectations.

The identification of peer effect is proved to be challenging because of two issues. The first is the endogeneity issue, i.e., individuals' behaviors can be affected by his/her peers' behaviors and vice versa. We follow the literature and apply the instrumental variable approach to solve the endogeneity issue (De Giorgi *et al.*, 2010; Imberman *et al.*, 2012; Nicoletti *et al.*, 2018). Specifically, we instrument the pension expectation of the peers with the average health status of peers' parents, relying on the fact that the health status of peers' parents cannot affect individuals' pension expectations directly but only indirectly through pension expectations of their peers. The second issue is related to the definition of the peer network. In general, existing literature pins down an individual's peer network by investigating her/his education experiences, work history, and residence information. As pointed out by Cai *et al.* (2015), individuals living in the same village and community in China interact with each other in daily life, making the village and community a suitable peer network in this context. Therefore, we use communities of residence to define our baseline peer group and discuss other alternative definitions in the robustness tests.

China's Resident Basic Pension (RBP) is a voluntary program to cover urban and rural residents aged 16 and above, who are not students and are not covered by employee basic pension (Huang and Zhang, 2021). For the following three reasons, the RBP program in China is an ideal case to study the peer effect in forming pension expectations. First, although the RBP successfully expanded to provide unified coverage for more than 549 million residents and the coverage rate is 84% in 2022 (the RBP target population is 652 million, i.e., the residents over 16 years old who are not students and not covered by employee basic pension), it suffers from a low level of voluntary contributions associated with the participants' prevailing pessimistic expectations toward future pension benefits. This

[1]Other matters of public interest include employment patterns (Kuroda and Yamamoto, 2013; Godøy and Dale-Olsen, 2018; Nicoletti *et al.*, 2018), investment or saving decisions (Beshears *et al.*, 2015), and risk attitudes (Dohmen *et al.*, 2012; Balsa *et al.*, 2015).

is also the motivation of our research that we focus on the pension expectation attitude toward RBP to provide explanation for low contribution level. Second, the provision of public information has been insufficient, especially in the early phase, making it relevant for individuals to obtain private information from their peers. Third, the Chinese traditional culture values neighborhood and community relationships, which facilitate the role of peers in shaping individuals' pension expectations (Cai *et al.*, 2015).

This study makes two significant contributions to the literature. First, we improve the understanding of the role of the peer effect in the formation of pension expectations among the middle-aged when they are getting close to retirement. Private information from peers can help individuals form pension expectations, whereas the literature mainly focuses on the impact of public information (Mastrobuoni, 2011; Dolls *et al.*, 2018; Bai *et al.*, 2021).

Second, we contribute to understanding the mechanisms through which the peer effect operates. Social learning and social norms are two plausible channels (Manski, 2000; Mas and Moretti, 2009; Liu *et al.*, 2014). Social learning occurs when certain information is transmitted from one individual to another, changing peers' behaviors. Social norms indicate that an individual is inclined to conform to the behaviors of the majority among their peers. We identify the dominant channel of the two in forming the peer effect of pension expectations. The analysis sheds light on ways policy makers could utilize the peer effect to impact residents' pension expectations and contributions.

Using four waves of nationally representative survey data from 2011 to 2018 in China, this study provides evidence of the peer effect in forming pension expectations among middle-aged residents. The probability of being optimistic about pension benefits significantly increases by 0.309 percentage points if the proportion of optimists in the community increases by 1 percentage point. Moreover, we confirm that the peer effect operates through the social learning channel, i.e., transmitting information about the pension program. We also show that village and township leaders and those with old pension program experience are opinion leaders in the peer group. Lastly, we find peer effects in other pension decisions, e.g., contribution size, and the contribution size increases by the proportion of optimists in the community.

The remainder of the paper is organized as follows. Section 2 describes the institutional background of China's public pension system. Section 3 introduces the data set. Section 4 specifies the empirical design. Sections 5 and 6 present the results and additional discussion, respectively, and section 7 concludes.

2. Institutional background

RBP in China has expanded rapidly since its establishment and underwent several institutional changes, providing an ideal opportunity to study how people form their pension expectations in a group. In this section, we introduce the institutional background of RBP in China.

The first attempt to provide a pension program for residents in China was in 1991 when the Old Rural Resident Basic Pension (ORRBP) program was established. Due to widespread concerns about its financial sustainability and effectiveness (Cheng *et al.*, 2018), the ORRBP ceased operation in 1999. In 2009, the New Rural Resident Basic Pension (NRRBP) program resumed coverage for rural residents, and the government transferred the balances in the individual pension accounts in ORRBP to those in NRRBP. In 2011, the Urban Resident Basic Pension (URBP) program started to provide coverage for urban residents. Starting in 2014, the two programs, NRRBP and URBP, merged into RBP to provide unified coverage for all residents in China, regardless of rural/urban residence.

For pension contributions, several options are available, ranging from 100 Yuan to 2,000 Yuan per year in 2014,[2] and RBP participants can voluntarily choose an annual amount. In addition to

[2]In 2009, there were five annual contribution options for participants: 100 Yuan, 200 Yuan, 300 Yuan, 400 Yuan, and 500 Yuan per year. In 2014, there were 12 options: 100 Yuan, 200 Yuan, 300 Yuan, 400 Yuan, 500 Yuan, 600 Yuan, 700 Yuan, 800 Yuan, 900 Yuan, 1,000 Yuan, 1,500 Yuan, and 2,000 Yuan per year.

individual contributions, the government also provides subsidies for all participants, but individuals' willingness to contribute to the RBP is still low. According to the China Health and Retirement Longitudinal Study (CHARLS), 72% of participants chose the lowest bracket for their annual contribution in 2018 (100 Yuan per year, equivalent to about $15).

For the pension benefit, all RBP participants with a contribution history of at least 15 years are eligible to receive pension benefits at age 60. The monthly benefits provided by the RBP are the sum of (i) the basic pension benefit (BPB), which the government funds and is subject to periodic adjustment,[3] and (ii) the individual account pension benefit, which equals the individual pension account balance at age 60 divided by a fixed denominator of 139 months.

Even though RBP has achieved great success in universal coverage, the protection it supports remains limited. Based on the CHARLS data, the average annual RBP pension benefit for all age-eligible residents (i.e., residents aged 60 years or over) was only 1,170 Yuan in 2018, accounting for 20% of their total annual retirement income. The low level of voluntary contributions is one of the significant reasons for inadequate protection. CHARLS data indicates that the median (average) contribution level of RBP participants was only 100 (227) Yuan per year in 2018. According to previous studies, residents' limited trust in the pension system and lack of efficient public information transmission channels may be the impact factors (Gustman and Steinmeier, 2005; Dolls *et al.*, 2018; Bai *et al.*, 2021).

We plot the annual individual contribution and the proportion of optimists among pension participants[4] in the community in Figure 1. The figure shows a positive correlation between the two factors, suggesting that the low contribution level is associated with a pessimistic attitude toward future pension benefits. This figure only provides evidence that there may be a correlation relationship between contribution and optimistic pension expectation. However, this figure does not control for other covariates, and we will give a detailed analysis of the effect of average optimistic pension expectation in the community on individual contribution in section 6.4.

Focusing on the peer effect on the formation of pension expectations and its mechanism can help the government understand ways to boost people's expectations, to increase their willingness to contribute to the RBP program.

3. Data

3.1 Data set and sample

We use data from 2011 to 2018 collected by CHARLS. It is a nationwide survey targeting residents aged 45 years and older and their spouses, and the samples were chosen through multistage probability sampling to provide nationally representative panel data (Zhao *et al.*, 2014).[5] CHARLS is a mainstream data source for studies of the aging population in China (Oliveira, 2016; Giles *et al.*, 2023; Zheng *et al.*, 2023).

[3]The central government sets and funds (or partially funds) the minimum amount of the basic pension benefits. Periodically, the minimum standard is adjusted. It was 55 Yuan per month when the program was first established in 2009, and the monthly benefits increased to 70 Yuan in 2014, 88 Yuan in 2018, and 93 Yuan in 2020. Additionally, the local governments determine the actual amount of basic pension benefits according to the funding resources.

[4]The optimistic pension participants are those who overestimate the pension benefits, and we provide a detailed definition in subsection 3.2.

[5]In the first stage, 150 county-level units were randomly chosen with a probability-proportional-to-size (PPS) sampling technique from a sampling frame containing all county-level units except for Tibet in China. The sample was stratified by region and within region by urban districts or rural counties and per capita statistics on gross domestic product. The final sample of 150 counties fell within 28 provinces. The CHARLS sample used the lowest level of government organization, consisting of administrative villages in rural areas and neighborhoods in urban areas, as primary sampling units (i.e., communities in our analysis). Then CHARLS again applied PPS sampling to select three communities within each county-level unit. In each community, CHARLS conducted mapping and listing operations within each community to obtain the sampling frame (excluding schools, nursing homes, and other no-residence houses) and then randomly selected houses to be interviewed and the household with at least one age-eligible member can be chosen into final sample. All stages of the sampling were conducted by computer to avoid human manipulation.

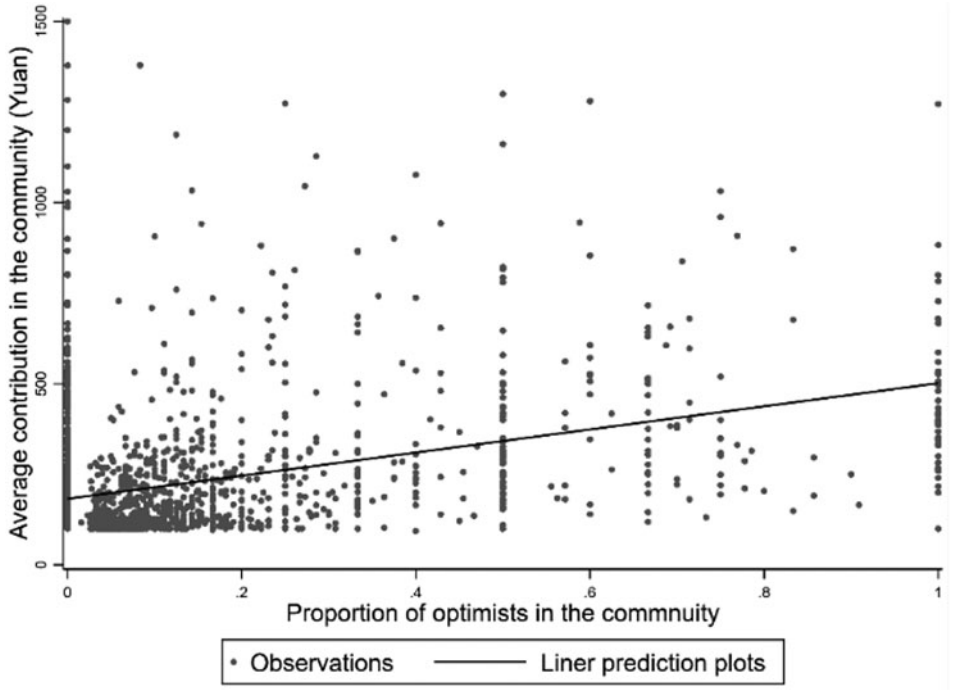

Figure 1. Annual individual contribution and the proportion of optimists in the community. *Data source:* Authors' calculations based on data from the China Health and Retirement Longitudinal Study.

In our context, the middle-aged population has a more extended history of contributing to the RBP, and they pay more attention to changes in the pension benefits given that they are about to retire.

The baseline survey was conducted in 2011 in 150 counties of 28 provinces, covering 17,708 individuals. The second, third, and fourth national surveys in 2013, 2015, and 2018, respectively, aimed to revisit the same respondents sampled in the previous waves. The survey gathered information on individual and household microeconomic behavior and the sociodemographic characteristics of each respondent.

We constructed the final sample through the following steps. First, because the minimum eligible age for receiving pension benefits is 60 in the RBP program, we restricted the sample to RBP participants between 45 and 59 years old to focus on near-retirement pension participants (22,800 observations). Second, we excluded respondents without pension expectation information from any peer in the same community,[6] leading to a slightly reduced sample size of 22,628. Third, we excluded observations with missing values of control variables (e.g., gender), resulting in a final sample size of 22,125.

3.2 Definitions of key variables

We examine whether an individual's propensity to be optimistic about future pension benefits varies with that of their community, demonstrating the peer effect. We measure RBP participants' attitudes toward future pension benefits, being optimistic or pessimistic, by comparing their self-reported expected pension benefits and statutory pension benefits.

The expected monthly pension benefit is recorded in CHARLS in Question FN063 as follows, and we convert the value to an annual benefit expectation.

[6]Community refers to a unified body of individuals living together. In urban areas in China, several blocks of streets belong to one community, while in rural area, the unit for a community becomes the village.

FN063. About how much do you expect your benefits to be? (as an amount per month or year or a lump sum?)____ Yuan per month or ____Yuan (Lump sum amount).

This expected monthly pension benefit is a point prediction at the first year to receive the benefit. We understand that this point prediction cannot provide more information about the subjective distribution of the benefit, but it can be regarded as the best prediction (Engelberg *et al.*, 2009).[7] Before answering the expected monthly pension benefit, the respondent must answer questions about the year to start the contribution, annual individual contribution, government subsidy, and the year when he/she expects to receive the pension. The respondent can fully utilize all information answered by himself/herself to anticipate the expected pension benefit.[8]

FN060. In what month and year did you start to pay for your Resident Pension Program?

FN061. Your annual contribution is _____ Yuan, annual subsidy from the collective is _____ Yuan, annual subsidy from the government is ____ Yuan.

FN062. When do you expect to receive pension? At age _____(45..120) years old or in _____ (0..100) years.

We then calculate the statutory pension benefit the participant is entitled to collect at age 60 based on their specific contribution history and the RBP pension benefit calculation rules.[9] In specific, for RBP participants who never participated in ORRBP, the statutory pension benefit ($P_{RBP}^{statutory}$) consists of two parts, namely individual account pension benefit (IPB) and BPB, and the formula to compute the statutory pension benefit is the following:

$$P_{RBP}^{statutory} = \underbrace{\frac{1}{139} \times \sum_{t=Year_c}^{Year_R} \left[Contribution_t \times \prod_{j=t}^{Year_R} (1 + r_j) \right]}_{IPB} + BPB, \tag{1}$$

where $Year_R$ and $Year_C$ refer to the pension eligibility year and the year of beginning participation in the RBP; $Contribution_t$ refers to the contribution level in year t, which includes individual contributions, government subsidies[10], and collective subsidies; r_j refers to the interest rate in year j, which is set as the one-year fixed deposit rate released by the People's Bank of China according to the policy arrangements. The BPB is subject to periodic adjustment. For example, the BPB in Beijing is 310 Yuan per month in 2011 and 850 Yuan per month in 2018. In specific, we assume that the BPB after 2021 in a specific province will increase at the same average growth rate over 2016–2021.

For RBP participants who participated in the ORRBP, the Document No. 32 of the State Council in 2009 documents that the individual pension account balance in the ORRBP can be incorporated into the NRRBP individual pension account. Thus, for these participants, the statutory pension benefit is

[7]Regarding the limitation of the point prediction, Engelberg *et al.* (2009) show that most Survey of Professional Forecasters (SDF) point predictions are within 0.01 of forecasters' subjective means/medians/modes. They also show that the deviations between point predictions and these measures of central tendency tend to be asymmetric, with point predictions tending to give a more favorable view of the economy than do subjective means/medians/modes. According to the CHARLS questionnaire, pension expectation is a point prediction. If individuals think probabilistically and act as SDF suggested in the context of pension expectations, our measure of optimism on pension benefits would slightly deviate from its probabilistic measure. However, as long as the deviations are within a certain extent, as in Engelberg *et al.* (2009), we expect that our main findings would hold when using the probabilistic measure of pension expectations. Nevertheless, we can still conclude that there exists peer effect in forming point pension expectations.

[8]Regarding whether the respondents will increase or decrease their contributions in the future when they anticipate their future pension benefits, there is no additional information in CHARLS about whether respondents give a constant annual contribution or not. Based on the structure of questionnaire, we assume that respondents form their pension expectations based on current contribution level.

[9]The contribution information (i.e., contribution years, individual contribution level, government subsidy, and retirement year) is recorded in CHARLS. We follow the official document to calculate the statutory pension benefits and the details are included in Appendix A1. Our calculation follows the same strategy as used by the official pension benefits projection website, i.e., http://si.zwfw.mohrss.gov.cn/20635567.jhtml?menuguide=1.

[10]The detailed calculation of the government subsidy is introduced in Appendix A.

the sum of the statutory pension benefit in the ORRBP ($P_{ORRBP}^{statutory}$) and the statutory pension benefit in the RBP, which is computed based on Equation (1). In specific, the $P_{ORRBP}^{statutory}$ is computed using the following formula:

$$P_{ORRBP}^{statutory} = \frac{1}{139} \times \prod_{i=1999}^{Year_R} (1 + r_j) \times \sum_{t=Year_c}^{1999} \left[Contribution_t \times \prod_{j=t}^{1999} (1 + r_j) \right], \tag{2}$$

where $Year_R$ and $Year_c$ refer to the pension eligibility year and the year of beginning participation in the ORRBP, respectively; $Contribution_t$ refers to the contribution level in year t, which includes individual contributions and collective subsidies; and r_j refers to the interest rate in year j, which is set as the one-year fixed deposit rate released by the People's Bank of China according to the policy arrangements.

It is noteworthy we make some assumptions when calculating the statutory pension benefit. For example, we assume that the one-year fixed deposit rate is 1.5% after 2023, since it has remained at this level since 2015.[11] Moreover, we assume that the BPB after 2021 increases at the same average growth rate over 2016–2021 (5-year average growth rate). Following Baldini *et al.* (2019) and Van Duijn *et al.* (2013), we also conduct sensitivity analyses, changing the assumptions on the BPB growth rate and fixed deposit rate[12], and our main findings still hold.

We use the statutory pension benefit as the benchmark to determine whether the respondent holds an optimistic expectation of the pension benefits for two reasons. First, it can represent a rational level of pension expectation since we have made the most of the information respondents could have, while some may be unaware of the compound interest. Second, it can represent the actual pension benefit in the real world for the respondents to a certain extent since there is no significant difference between the statutory pension benefit and the national average pension benefit reported by the Ministry of Human Resources and Social Security in China.[13] Thus, we argue that the statutory pension benefit is an ideal benchmark.

We use the following equation to define the pension benefit bias between the participant's expectation and the statutory amount (Baldini *et al.*, 2019):

$$P_{i,t}^{bias} = \left(\frac{P_{i,t}^{expected} - P_{i,t}^{statutory}}{P_{i,t}^{statutory}} \right) \times 100\%, \tag{3}$$

where $P_{i,t}^{expected}$ is the expected pension benefit for individual i in year t, $P_{i,t}^{statutory}$ is the statutory pension benefit for individual$i$ in year t, and $P_{i,t}^{bias}$ is a percentage measure of the pension benefit bias. The dependent variable, 'optimist (OPT),' indicates whether the individual is optimistic about future pension benefits. Following Baldini *et al.* (2019), the individual is defined as an optimist ($OPT = 1$) if $P_{i,t}^{bias}$ is positive, and a pessimist otherwise ($OPT = 0$). In the robustness tests, we use alternative thresholds, e.g., $P_{i,t}^{bias} > 25\%$, to define an optimist and our main results still hold.

The key independent variable of interest is the proportion of optimists living in the same community (OPT_C). We define a peer group on the basis of communities of residence. It is noteworthy that observable peers are at the community level, and individuals living in the same community interact with each other on a daily basis (Cai *et al.*, 2015). Moreover, as mentioned by existing literature on peer effects, the tautological nature of 'y on y-bar' regressions (i.e., unity peer effect) would appear to be mitigated by replacing full group means with leave-out means (Townsend, 1994; Sacerdote,

[11]Available in https://ycharts.com/indicators/china_deposit_interest_rate.

[12]In the robustness test, we assume that the one-year fixed deposit rate after 2023 is 1% and 2% instead of 1.5% in our baseline model. Moreover, we assume that pension benefit after 2021 increases at the same average growth rate over 2018–2021 (3-year average growth rate) instead of the average growth rate over 2016–2021 (5-year average growth rate).

[13]See Appendix A2 for the detailed analysis.

2001; Duflo *et al.*, 2011; Imberman *et al.*, 2012; Carrell *et al.*, 2013; Angrist, 2014)[14]. Therefore, we use the leave-out mean, that is, the group average that excludes the residential household, to capture the peer effect more precisely.

3.3 Summary statistics

We control for individual and household characteristics when investigating the peer effect of pension expectations. Individual characteristics include self-reported depression, ORRBP enrollment, medical insurance enrollment, age, sex, marital status, residence type, hukou status,[15] education level, living arrangement, and individual annual income. The household control variables include the number of household members, children, and house ownership.

Table 1 presents the definitions of all the variables, and Table 2 provides summary statistics for each of the four waves of the survey. As shown in Table 2, the mean value of *OPT* is less than 13% in all waves, suggesting that most respondents are pessimistic about future pension benefits. We also observe an increasing trend in the proportion of optimists over time, from 6.09% in 2011 to 12.9% in 2018. Both the expected and statutory pension benefits also increased over this period.

4. Empirical design

We use the following regression equation to investigate whether individuals' attitudes toward future pension benefits are influenced by other residents in the community:

$$\begin{aligned} Probit(OPT_{i,c,t}) &= \Phi^{-1}(OPT_{i,c,t}) \\ &= \alpha + \beta OPT\_C_{i,c,t} + \gamma X_{i,c,t} + \lambda Z_{c,t} + \varphi Province_c + \phi Year_t + \varepsilon_{i,c,t} \end{aligned} \tag{4}$$

The dependent variable $OPT_{i,c,t} = 1$ if the individual i living in community c is optimistic about her/his future pension benefits (i.e., overestimates the benefits) in year t, and 0 if she/he does not overestimate the pension benefits. The variable $OPT\_C_{i,c,t}$ reports the proportion of optimists living in the community c where individual i lives in year t. Specifically, $OPT\_C_{i,c,t} = \sum_{j \in c \setminus h_i} OPT_{j,c,t}/(N_{c,t} - N_{h_i,t})$, in which $N_{c,t}$ and $N_{h_i,t}$ refer to the numbers of residents in community c and household h_i, respectively.

The control variables $X_{i,c,t}$ include individual and household characteristics, such as self-reported depression, ORRBP enrollment, medical insurance enrollment, age, male, marital status, and so on. $Z_{c,t}$ contains variables indicating contextual effects, i.e., an individual's propensity to behave in some way varies with exogenous characteristics of the peer groups (Manski, 2000). Specifically, $Z_{c,t}$ is the subset of $X_{i,c,t}$, including the leave-out mean of age, gender, marital status, education, and individual annual income in the community. We also control for province fixed effects, $Province_c$, and year fixed effects, $Year_t$. We employ a probit model for Equation (4) as our baseline regression. The estimation of β represents the peer effect of pension expectations at the community level.

Estimation of the peer effect is difficult because of endogeneity problems caused by simultaneity or omitted explanatory variables (Manski, 1993; Dahl *et al.*, 2014; Liu *et al.*, 2014; Cai *et al.*, 2015; Nicoletti *et al.*, 2018). First, individuals' behaviors can be affected by their peers and vice versa, which leads to the simultaneity problem. So the estimated peer effect may be misleading. Second, there may be omitted explanatory variables that affect both individuals' and peers' behaviors. For example, an unobserved local official information campaign may change residents' attitudes toward pension benefits in the same community.

[14]Specifically, Townsend (1994) documents that the average consumption variable should not include the consumption of the specific household to avoid spurious correlation of the left- and right-hand-side variables and avoid biasing the coefficient on average consumption toward unity.

[15]Hukou is a household registration system used in mainland China. It is a legal document issued by the Chinese government to record basic information about the household's population and used as an identity certificate for residents.

Table 1. Variable definitions

Variables		Definition
Dependent variable		
OPT		Dummy variable that equals 1 if the individual is an optimist about pension expectation; 0 otherwise.
Independent variable		
OPT_C		Proportion of optimists in the community in which the respondent lives.
Pension benefits		
Expected pension benefit		Self-reported expected annual pension benefit.
Statutory pension benefit		Statutory pension benefits calculated based on the contribution information and institutional arrangements.
Control variables		
No depression		Dummy variable that equals 1 if the self-reported depression scale using the Center for Epidemiologic Studies Depression Scale (CESD-10) is less than 20, corresponding to no depression; 0 otherwise.
ORRBP enrollment		Dummy variable that equals 1 if once enrolled in ORRBP; 0 otherwise.
Health insurance		Dummy variable that equals 1 if the respondent enrolled in public health insurance programs; 0 otherwise.
Age		Age of the respondent.
Male		Dummy variable that equals 1 if male; 0 otherwise.
Married		Dummy variable that equals 1 if married; 0 otherwise.
Urban resident		Dummy variable that equals 1 if the respondent lives in an urban area; 0 otherwise.
Urban hukou		Dummy variable that equals 1 if the respondent is registered with urban hukou; 0 if the respondent is registered with rural hukou.
Education	No formal education	Categorical variable that equals 1 if no formal education; 0 otherwise.
	Can read and write	Categorical variable that equals 1 if can read and write; 0 otherwise.
	Primary school	Categorical variable that equals 1 if primary school; 0 otherwise.
	Secondary school and above	Categorical variable that equals 1 if secondary school and above; 0 otherwise.
HH size		Number of household members.
Number of children		Number of children born or adopted by the family, including young and adult children.
Rely on children for old-age support		Dummy variable that equals 1 if the individual believes she/he will rely mainly on children for old-age support; 0 otherwise. The original question in the survey is a single-choice question: 'Who do you think you can rely on financially for old-age support?' The choices include children, savings, pension, or labor income after retirement, commercial annuity, and other.
Living with the elderly		Dummy variable that equals 1 if at least one of the household members living together is age 60 years or older; 0 otherwise.
Individual annual income		Individual annual income in the past year (in Yuan). It includes income from self-employed agricultural work, self-employed non-agricultural work, and employed work.
House ownership		Dummy variable that equals 1 if the individual owns property, 0 otherwise.

Following the mainstream literature, we use the instrumental variable (IV) method to solve the potential endogeneity problem in estimating the peer effect.[16] Two types of IV are commonly used. The first type is the predetermined characteristics of peers in the past (De Giorgi *et al.*, 2010; Imberman *et al.*, 2012), for example, using lagged test scores to instrument current scores. The second type of IV is the average characteristics of the peers of peers (Case and Katz, 1991; Sacerdote, 2001; Nicoletti *et al.*, 2018), for example, using the average academic behaviors of peers' parents to instrument peers' behaviors (Case and Katz, 1991; Sacerdote, 2001).

Here, we use the average health status of peers' parents, defined by $\overline{Unhealthy}_{i,c,t} = \sum_{j \in c \setminus h_i} Unhealthy_{j,c,t}/(N_{c,t} - N_{h_i,t})$, as an IV for peers' attitudes toward future pension benefits. The rationale is as follows. For a given individual, her/his peers' parents' health status should not impact the individual's attitude directly. It can only make an impact by changing the peers'

[16]The related literature includes the following: Bayer *et al.* (2008); Carrell *et al.* (2008); Conley and Udry (2010); De Giorgi *et al.* (2010); Godøy and Dale-Olsen (2018); Imberman *et al.* (2012); Monstad *et al.* (2011); Nicoletti *et al.* (2018); Rege *et al.* (2012).

Table 2. Descriptive statistics

	2011 (N = 4,824)		*2013 (N = 5,968)*		*2015 (N = 6,230)*		*2018 (N = 5,103)*	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Dependent variable								
OPT	0.061	0.239	0.077	0.266	0.112	0.315	0.129	0.335
Independent variable								
OPT_C	0.066	0.126	0.083	0.137	0.117	0.147	0.130	0.169
Pension benefits								
Expected pension benefit	67.4	128.1	93.72	183.9	127.4	251.4	160.1	292.3
Statutory pension benefit	144.2	97.95	151.1	92.56	175.7	108.3	202.4	123.9
Control variables								
No depression	0.585	0.493	0.630	0.483	0.658	0.474	0.614	0.487
ORRBP enrollment	0.163	0.369	0.126	0.332	0.108	0.311	0.095	0.294
Health insurance	0.949	0.219	0.940	0.238	0.906	0.291	0.979	0.144
Age	51.66	4.179	52.14	4.168	51.91	4.076	52.93	3.588
Male	0.475	0.499	0.475	0.499	0.473	0.499	0.460	0.498
Married	0.954	0.210	0.951	0.215	0.957	0.204	0.949	0.221
Urban resident	0.249	0.432	0.246	0.431	0.264	0.441	0.273	0.445
Urban hukou	0.036	0.186	0.050	0.219	0.049	0.215	0.047	0.212
No formal education	0.230	0.421	0.203	0.402	0.163	0.369	0.118	0.323
Can read and write	0.167	0.373	0.180	0.384	0.182	0.386	0.173	0.378
Primary school	0.207	0.405	0.218	0.413	0.244	0.429	0.267	0.442
Secondary school and above	0.396	0.489	0.399	0.490	0.412	0.492	0.442	0.497
HH size	3.341	2.643	3.395	2.439	3.441	3.069	3.408	1.867
Number of children	2.267	0.947	2.344	1.013	2.265	0.936	2.196	0.929
Living with the elderly	0.148	0.355	0.106	0.307	0.095	0.293	0.111	0.314
Rely on children for old-age support	0.782	0.413	0.691	0.462	0.693	0.461	0.703	0.457
Individual annual income	14,450	58,348	15,398	65,013	17,486	34,908	21,311	48,788
House ownership	0.961	0.193	0.956	0.205	0.917	0.275	0.920	0.272

Data source: China Health and Retirement Longitudinal Study.

attitudes.[17] The health status of one's parent is an ordered categorical variable and is assigned values of 1, 2, 3, 4, and 5, corresponding to very good, good, fair, poor, and very poor health, respectively. Therefore, $\overline{Unhealthy}_{i,c,t}$ is a continuous variable indicating the average health status of peers' parents, and its value is larger if the average health status of peers' parents is worse. Specifically, we estimate the IV probit model because it fits models for binary dependent variables where some covariates are endogenous.

We are aware of the fact that 'it is difficult to be certain about the exogeneity of the instruments or the ability of structural models to remove selection problems and deliver consistent estimates of peer effects' (Sacerdote, 2001); yet, we argue that if the choice of residence is made before the implementation of the RBP, then casual effects is convincing. One may concern that our instrumental variable is potentially correlated with the average characteristics of the peer groups, which is a major source of contextual effects. Thus, following a long stream of literature (e.g., De Giorgi *et al.*, 2010, 2020), we control the contextual effects by including the average characteristics of the peer groups into the regression. We also provide empirical evidences about the validity of our instrumental variable and the validity depends on two conditions, namely, the correlation condition and the exogeneity condition. The rationale of our IV is illustrated in Figure 2.

First, we check the correlation condition of our IV. Previous studies have indicated that the severity of impairment and dementia among the disabled and elderly increases the feelings of burden and causes higher levels of psychological distress among caregivers in the family, especially the children (Kumamoto *et al.*, 2006; Andrén and Elmståhl, 2007; Bobinac *et al.*, 2010). In our case, the economic,

[17]The parents' health status can be obtained from Question CA013 in CHARLS (How is your father's health?). We use the health status of the individuals' biological father to construct the parents' health status variable, and use the health status of her/his mother or parents-in-law instead if the father's health status is missing or the father passed away.

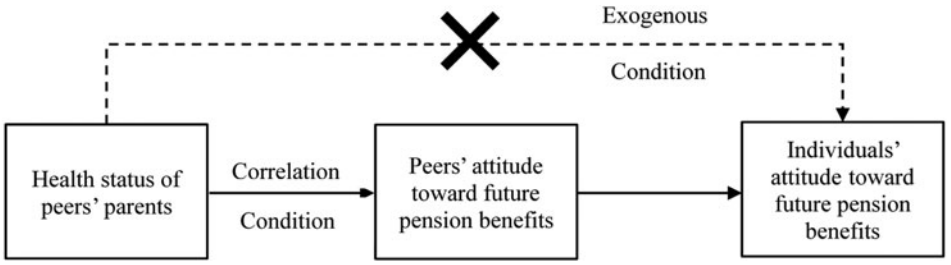

Figure 2. Validity of the instrumental variable.

psychological, and caregiving burden associated with a parent's poor health may induce pessimism among the children, which may further negatively affect peers' pension expectations.

We show evidence supporting the above correlation condition in Figure 3. We also verify the correlation condition empirically through regression, showing that $\overline{Unhealthy}_{i,c,t}$ is negatively correlated with $OPT\_C_{i,c,t}$ (see column (4) in Table 3).

Second, we use three methods to confirm the exogeneity of our IV empirically.[18] In the first method, we regress $OPT_{i,c,t}$ on the IV $\overline{Unhealthy}_{i,c,t}$ and the endogenous variable $OPT\_C_{i,c,t}$. The p-value of the IV is 0.52, suggesting that it is not a significant determinant of $OPT_{i,c,t}$. This suggests that the IV can only affect $OPT_{i,c,t}$ via the endogenous variable $OPT\_C_{i,c,t}$. In the second method, we regress the endogenous variable $OPT_{i,c,t}$ on $OPT\_C_{i,c,t}$ and calculate the residual. Then we regress the residual on the IV $\overline{Unhealthy}_{i,c,t}$. If the IV is not significantly related to the residual, we assume the IV is not correlated with the unobserved factors. The result shows that the p-value of the IV is 0.40, verifying the assumption. In the third method, we replace the strict exogeneity assumption of typical IV probit estimates with a weaker assumption, allowing correlations between the IV and unobservable factors (Nevo and Rosen, 2012).[19] Then we calculate the lower and upper bounds of the IV probit estimation in 95% confidence interval level, which are 0.353 and 1.078, respectively. This indicates IV probit estimation is still significantly positive with 'imperfect instrumental variable' so that the violation of exogeneity condition would not bias our regression results to a certain extent.

Lastly, it is intuitive that the exogeneity condition should hold, given that peers' parents' health condition should not affect an individual's attitude toward her/his future pension benefits directly unless the individual lives in the same community with the peers' parents so that they may directly interact. To alleviate this concern, we restrict the analysis to a sample in which the peers' parents live in a different community in the robustness test in subsection 5.2.3, and our main results still hold.

5. Results on the existence of the peer effect

5.1 Baseline regression

Table 3 presents the results on the existence of the peer effect in the community. The results in column (1) indicate that an individual's probability of being optimistic about pension benefits significantly increases by 0.345 percentage point if the proportion of optimists in the community increases by 1

[18]The results are presented in Table B.1 in Appendix B.

[19]Standard solution of dealing with endogenous regressors is to use instrumental variables that are assumed to be uncorrelated with unobservable factors. Nevo and Rosen (2012) replace it with two weaker assumptions. In our case, these two assumptions are (i) the correlation between the instrumental variable, $\overline{Unhealthy}_{i,c,t}$, and the error term has the same sign as the correlation between the endogenous regressor, $OPT\_C_{i,c,t}$, and the error term, and (ii) the instrumental variable, $\overline{Unhealthy}_{i,c,t}$, is less correlated with the error term than is the endogenous regressor, $OPT\_C_{i,c,t}$. With these two weaker assumptions, we can derive lower and upper bounds for the parameters. If the lower bound of the estimated coefficient of $OPT\_C_{i,c,t}$ is still larger than zero, we may conclude that the violation of exogeneity condition would not bias our regression results to a certain extent.

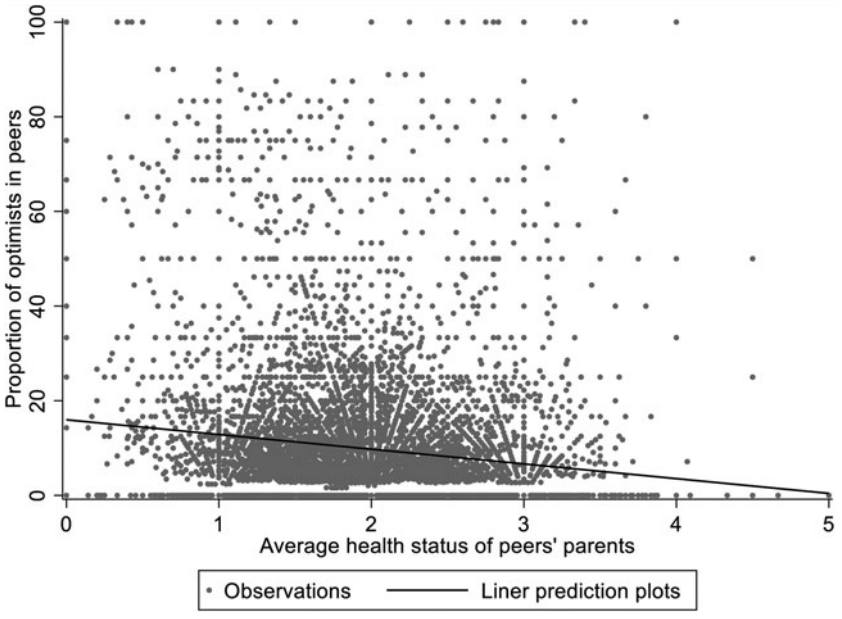

Figure 3. Correlation between the health status of peers' parents and peers' attitude toward future pension benefits (a). Leaders versus other residents (b). ORRBP experience versus no ORRBP experience.

percentage point. Taking the control variables into consideration, along with the year and province fixed effects, the results in column (3) also show a significant peer effect – the individual's probability of being an optimist significantly increases by 0.199 percentage point if the proportion of optimists in the community increases by 1 percentage point.

Columns (4) and (5) in Table 3 present the results of the correlation condition and exogeneity condition of the IV $\overline{Unhealthy}_{i,c,t}$ in the IV probit model. The results in column (4) confirm that the correlation condition of the IV is satisfied. The results in column (5) show that the IV only affects $OPT_{i,c,t}$ via the endogenous variable $OPT\_C_{i,c,t}$ since the IV is not significant. The results in column (6) show the IV probit estimation of the treatment effect. We find that the individual's probability of being an optimist increases by 0.309 percentage point if the proportion of optimists in the community increases by l percentage point.

In sum, Table 3 confirms under various specifications the significant peer effect on attitudes toward future pension benefits within a community.

5.2 Robustness tests

5.2.1 Using the lagged term of OPT_C

In the first robustness test, we use the lagged term of $OPT\_C_{i,c,t}$ as the independent variable. The individual's attitude can be affected by the peer group and vice versa, which leads to the simultaneity problem. Manski (2000) proposes that individuals' behaviors vary with lagged rather than contemporaneous values of group-mean behavior. It is reasonable that the lagged term for community attitude may affect individuals' attitudes in the current term but not vice versa. Therefore, we use the lagged term of $OPT\_C_{i,c,t}$ to solve the simultaneity problem.

Column (1) in Table 4 reports the results. The sample size reduces to 13,345, and the main result still holds, indicating that the individual's probability of being an optimist increases by 0.560 percentage point if the proportion of optimists in the community in the previous survey increases by 1 percentage point.

Table 3. Existence of the peer effect on the formation of pension expectations in a community

Model	Probit model estimate			IV Probit model estimate	
				First stage	Second stage
	(1)	(2)	(3)	(4)	(5)
Dependent variable	OPT	OPT	OPT	OPT_C	OPT
OPT_C	**0.345*** (0.011)**	**0.245*** (0.011)**	**0.199*** (0.012)**		**0.309* (0.169)**
Unhealthy				**−0.018*** (0.002)**	
No depression		0.008**	0.008*	0.004**	0.007*
		(0.004)	(0.004)	(0.002)	(0.004)
ORRBP enrollment		0.017***	0.018***	0.014***	0.016***
		(0.005)	(0.005)	(0.003)	(0.006)
Health insurance enrollment		0.005	0.006	−0.008*	0.007
		(0.008)	(0.008)	(0.004)	(0.008)
Age		−0.001**	−0.002***	0.000	−0.002***
		(0.001)	(0.001)	(0.000)	(0.001)
Male		0.003	0.005	0.002	0.004
		(0.004)	(0.004)	(0.002)	(0.004)
Married		−0.013	−0.015*	0.006	−0.016*
		(0.009)	(0.009)	(0.004)	(0.009)
Urban resident		0.020***	0.022***	0.063***	0.015
		(0.004)	(0.005)	(0.003)	(0.012)
Urban hukou		0.102***	0.102***	0.076***	0.092***
		(0.007)	(0.007)	(0.008)	(0.017)
No formal education		−0.029***	−0.030***	0.000	−0.029***
		(0.006)	(0.006)	(0.003)	(0.006)
Can read and write		−0.014**	−0.016***	−0.006***	−0.015***
		(0.005)	(0.005)	(0.002)	(0.006)
Primary school		−0.017***	−0.019***	0.000	−0.019***
		(0.005)	(0.005)	(0.002)	(0.005)
HH size		0.001	0.001	0.000	0.001
		(0.001)	(0.001)	(0.000)	(0.001)
Number of children		−0.003	−0.001	−0.006***	−0.000
		(0.002)	(0.002)	(0.001)	(0.002)
Rely on children for old-age support		−0.007	−0.004	−0.006**	−0.003
		(0.007)	(0.007)	(0.003)	(0.007)
Living with the elderly		−0.039***	−0.037***	−0.027***	−0.033***
		(0.004)	(0.004)	(0.002)	(0.007)
Ln(Individual annual income)		0.003***	0.002***	0.000	0.002***
		(0.001)	(0.001)	(0.000)	(0.001)
House ownership		−0.004	0.003	−0.020***	0.005
		(0.007)	(0.007)	(0.004)	(0.008)
Observations	22,125	22,125	22,125	22,125	22,125
R^2				0.266	
Wald *p*-value	0.000	0.000	0.000		0.000
F-statistics of the first stage				77.40	
Contextual effects	NO	YES	YES	YES	YES
Year fixed effects	NO	NO	YES	YES	YES
Province fixed effects	NO	NO	YES	YES	YES

Note: The sample contains middle-aged respondents in China (45–59 years old) surveyed by the CHARLS from 2011 to 2018. An individual is classified as an optimist (OPT) if she/he has optimistic pension expectations. OPT_C captures the proportion of optimists in the community where the individual lives. The instrumental variable, *Unhealthy*, is the average health status of peers' parents. 'Secondary school and above' is used to be the baseline group of education levels. We control for variables that have contextual effects, including leave-out means of age, male, married, no formal education, can read and write, primary school, and individual annual income in the community. We report the average marginal effect of the estimates in the probit model. Constants are included in the regressions but not reported. Robust standard errors are provided in parentheses. *, **, and *** indicate that the coefficients significantly differ from 0 at the 10%, 5%, and 1% levels, respectively.

5.2.2 Excluding individuals who relocated to different communities

In the second robustness test, we restrict the sample to individuals who have stayed in the same community since 2011. Individuals may move to another community in a different province to obtain

Table 4. Robustness tests (RT)

	RT1	RT2	RT3	RT4	RT5	RT6	
	(1) Lagged term	(2) No migration	(3) Excluding co-resident parents	(4) Positive future pension benefit	(5) Strict definition	(6) Less strict definition	(7) Strict peer network
Dependent variable	OPT	OPT	OPT	OPT	OPT_S	OPT_LS	OPT
OPT_C	0.560*	0.444*	0.206***	0.306*	0.089	0.143**	0.529**
	(0.295)	(0.240)	(0.017)	(0.182)	(0.064)	(0.070)	(0.251)
Observations	13,345	14,203	11,039	19,770	22,125	22,125	10,152
Wald *p*-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Contextual effects	YES	YES	YES	YES	YES	YES	YES
Control variable	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES	YES	YES	YES

Note: The sample contains middle-aged respondents in China (45–59 years old) surveyed by the CHARLS from 2011 to 2018. An individual is classified as an optimist (OPT) if she/he has optimistic pension expectations. OPT_C captures the proportion of optimists in the community where the individual lives. We report the average marginal effect of the estimates in the IV probit model in columns (1) to (4) and the average marginal effect of being optimistic in the ordered IV probit model in columns (5) and (6). Constants, contextual effects, and control variables are included in the regressions but not reported. Robust standard errors are provided in parentheses. *, **, and *** indicate that the coefficients significantly differ from 0 at the 10%, 5%, and 1% levels, respectively.

better pension coverage. The residents in a community with a well-established pension program may be more optimistic, leading to a self-selection problem and a biased estimation of the peer effect.[20]

To address the possible self-selection problem induced by re-location, we restrict our sample to those who have stayed in the same community since 2011. Column (2) in Table 4 reports the results. It indicates that the individual's probability of being an optimist increases by 0.444 percentage point if the proportion of optimists in the peer group increases by 1 percentage point.

5.2.3 Excluding co-resident parents

In the third robustness test, we only consider the sample of individuals whose parents live in another community. Individuals may directly interact with peers' parents if they live in the same community, which may negate the validity of our instrumental variable. To avoid the estimation bias caused by this problem, we retest the peer effect on pension expectations using the sample whose parents live in a different community. This restriction reduces the sample size from 22,125 to 11,039, and the results remain robust. The results in column (3) in Table 4 indicate that the individual's probability of being an optimist increases by 0.206 percentage point if the proportion of optimists in the peer group increases by 1 percentage point.

5.2.4 Excluding those without positive expected pension benefits

In the fourth robustness test, we consider only the sample whose expected pension benefits are positive. In the baseline sample, 2,355 of 22,125 observations have zero expected pension benefits. However, these 2,355 observations reported positive contributions to the public pension system. The case in which the expected pension benefit is zero may be because the individuals have misunderstood the question. Therefore, we retain only the sample with a positive expected pension benefit in this robustness test. This test reduces the sample size from 22,125 to 19,770, and the results remain robust. The results in column (4) in Table 4 indicate that the individual's probability of being an optimist increases by 0.306 percentage point if the proportion of optimists in the peer group increases by 1 percentage point.

[20]Of the original 22,125 observations, only 15,203 reported whether she/he change the community she/he lives. Of those, 94% (14,203 individuals) did not move, and only 6% changed to a different location during the sampling period.

5.2.5 Alternative definitions of an optimist

In the main analysis, we define an optimist pension participant if her/his expected benefits are greater than the statutory benefits. In this robustness test, we redefine an optimist pension participant using two alternative criteria, allowing for a reasonable degree of overestimating the benefits. Specifically, the strict version redefines an individual to be an optimist only if she/he overestimates the benefits by more than 25% ($OPT\_S = 2$ if $P_{i,t}^{bias} > 25\%$), while the accurate predictors are those whose percentage of bias is no more than 25% ($OPT\_S = 1$ if $-25\% \leq P_{i,t}^{bias} \leq 25\%$), and the pessimists are those who underestimate the benefit by more than 25% ($OPT\_S = 0$ if $P_{i,t}^{bias} < -25\%$). The less strict version (OPT_LS) applies a 10% bias percentage as the threshold; that is, an individual is categorized as an optimist if $P_{i,t}^{bias} > 10\%$, and a pessimist if $P_{i,t}^{bias} \leq 10\%$.

Columns (5) and (6) in Table 4 present the peer effect results using the two alternative definitions, respectively. We conduct an ordered IV probit model and report the marginal effects of being optimistic in the results. The results indicate that the individual's probability of being an optimist increases by 0.089 percentage point (the strict definition) and 0.143 percentage point (the less strict definition), respectively, if the proportion of optimists in the peer group increases by 1 percentage point. This is reasonable because fewer participants are classified as optimists by these two definitions; thus, the peer effect gets smaller. These peer effect coefficients remain significant and are comparable to the result (0.309 percentage point) in our baseline analysis in Table 3.

5.2.6 An alternative definition of a peer group

In the main analysis, we use a broad definition to treat the individuals living in the same community as a peer group. Guo and Qu (2022) investigated the peer effect on households' educational investment for students and argued that the peer group should be students with a similar academic performance instead of all students in a class, because the top-ranked students in the classroom are less likely to interact with the bottom-ranked ones. Similarly, we use an alternative definition to restrict the peer group to those who engaged in community-related activities in the same community in this section as a robust check. Intuitively, individuals interact directly when they participate in community-related activities and share information. Specifically, we define individuals living in the same community who engaged in community club activities or community-related organizations in the last month as a peer group.[21] Column (7) in Table 4 presents the peer effect results using this stricter alternative group definition. The sample size is reduced from 22,125 to 10,152 because we drop those observations without engaging in community-related activities. As expected, the results remain consistent with our main results.

5.2.7 Changing assumptions when calculating the statutory pension benefits

In this robustness test, we change the assumptions related to interest rate and BPB growth rate when calculating the statutory pension benefit. The baseline calculation assumes that the one-year fixed deposit rate is 1.5% after 2023. In the robustness test, we assume that the one-year fixed deposit rate after 2023 is 1% and 2% instead of 1.5%. Moreover, we assume that pension benefits after 2021 increase at the same average growth rate over 2018–2021 (3-year average growth rate) instead of the average growth rate over 2016–2021 (5-year average growth rate). We then calculate the statutory pension benefit under different assumptions and construct the optimist dummy variable based on the updated statutory pension benefit and the expected pension benefit. Lastly, we repeat the regression to estimate the peer effect, and our main findings still hold that the peer effect on pension expectations is significant.[22]

[21]The information of these activities can be obtained in Question DA056 in CHARLS.

[22]The result is presented in Table B.2 in Appendix B.

6. Additional discussions

6.1 Mechanisms of the peer effect

The results above show the existence of the peer effect on individuals' attitudes toward future pension benefits in a community. There are two plausible channels, social learning and social norms, through which the peer effect operates (Manski, 2000; Mas and Moretti, 2009; Liu *et al.*, 2014).

Social learning occurs when an individual shares information with others in the community, leading to convergence in behaviors or attitudes. In our context, an RBP participant who knows the updated benefit amount from the information kiosk may spread the information or knowledge to others in the community. Thus, they change their expectations with their peers based on the same information or knowledge. The other channel of the peer effect is social norms, which indicate that an individual tends to follow the behaviors of the majority of her/his peers.

If the social learning channel dominates the social norms channel, that is, the peer effect exists mainly due to information sharing, we anticipate that the peer effect should decrease over time (Dahl *et al.*, 2014; Liu *et al.*, 2014). In our context, information sharing about the pension program among individuals is at a peak when the program is provided for the first time. Then, as the participants become familiar with the program and access their individual account information online, social learning should play a less critical role in forming the peer effect. On the contrary, if social norms dominate, the peer effect on individuals' pension expectations should be a stable, long-term effect.

We present two pieces of evidence to identify which channel dominates in the peer effect. First, we estimate whether the peer effect varies over time, adding the interaction term '*OPT_C* × *New participants*' into the regression. *New participants* is a dummy variable and assigned the value 1 if the individual participated in the RBP program for the first time in the survey year and assigned the value 0 if the individual participated in the RBP program for more than 1 year (i.e., contribution years are more than 1 year).

The idea is straightforward: if the social learning channel is the dominant channel for transmitting information about pension expectations, the peer effect should be larger for new participants. Therefore, the coefficient of the interaction term '*OPT_C* × *New participants*' should be significantly positive. This hypothesis is confirmed, as shown in Table 5. Column (1) indicates that the coefficient of '*OPT_C* × *New participants*' is significantly positive, which indicates that the peer effect is larger for new participants. This is our first piece of evidence supporting that the social learning channel dominates the social norms channel.

To support our finding that the dominating mechanism is social learning, we also test three conjectures that are based on the social learning channel.[23] First, individuals would be influenced less by their peers if they had more convenient access to modern communication systems and alternative informational channels. Therefore, in an IV probit estimation design shown in Equation (4), we control the interaction term '*OPT_C* × *Internet access*' in the regression. *Internet access* refers to whether the individual has internet access. The interaction term in column (4) in Table 5 is negative, as expected, but not significant. Second, their peers would influence individuals more if they trust their peers more. This is most likely true if the pension participant grew up in a close-knit (harmonious) neighborhood.[24] Therefore, we include the interaction between community attitude (*OPT_C*) and '*Close-knit neighborhood*.' As shown in column (3), the interaction term is significantly positive, as expected. Third, individuals would be influenced more by their peers if the individuals were engaged in more social activities. Therefore, we include the interaction between community attitude (*OPT_C*) and '*Social activities*,' representing whether the individual has been involved in certain social activities[25] in the past month. As shown in column (4), the interaction term is significantly positive, as

[23]It is noteworthy that the verification of these three conjectures is not a sufficient condition for confirmation of the social learning channel, but rather a necessary condition.

[24]The variable 'Close-knit neighbors' is a dummy variable and assigned the value 1 if the respondent says she/he lived in a very close-knit or harmonious neighborhood as a child.

[25]The social activities include meeting friends, playing Ma-jong, chess, cards, and going to the community club.

Table 5. Mechanisms of the peer effect

	(1)	(2)	(3)	(4)
Model	IV Probit	IV Probit	IV Probit	IV Probit
Dependent variable	OPT	OPT	OPT	OPT
OPT_C	0.264	0.428*	0.313*	0.272
	(0.176)	(0.230)	(0.174)	(0.177)
OPT_C × New participants	0.538*			
	(0.335)			
OPT_C × Internet access		−0.321		
		(0.232)		
OPT_C × Close-knit neighbors			0.307*	
			(0.180)	
OPT_C × Social activities				0.322*
				(0.199)
New participants	−0.048			
	(0.029)			
Internet access		0.021***		
		(0.005)		
Close-knit neighbors			−0.001	
			(0.004)	
Social activities				0.002
				(0.004)
Observations	22,125	22,125	22,125	22,125
Wald *p*-value	0.000	0.000	0.000	0.000
Contextual effects	YES	YES	YES	YES
Control variable	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES

Note: The sample contains middle-aged respondents in China (45–59 years old) surveyed by the CHARLS from 2011 to 2018. An individual is classified as an optimist (OPT) if she/he has optimistic pension expectations. OPT_C captures the proportion of optimists in the community where the individual lives. We report the average marginal effects of the estimates in the probit model. Constants, contextual effects, and control variables are included in the regressions but not reported. Robust standard errors are provided in parentheses. *, **, and *** indicate that the coefficients significantly differ from 0 at the 10%, 5%, and 1% levels, respectively.
The variable 'New participants' is a dummy variable assigned the value 1 if the respondent participated in the pension program in the first year.
The variable 'Internet access' is a dummy variable assigned the value 1 if the individual has access to an internet connection (Question I024: Does your residence have a broad-band internet connection?).
The variable 'Close-knit neighbors' is a dummy variable assigned the value 1 if the respondent says she/he lived in a very close-knit or harmonious neighborhood as a child. (Question D4: Were the neighbors of the place where you lived as a child very close-knit? Is it very close-knit, somewhat close-knit, not very close-knit, or not close-knit at all?).
The variable 'Social activities' is a dummy variable and assigned the value 1 if the individual engaged in social activities in the past month (Question DA056: Have you done any of these activities such as meeting friends, playing Ma-jong, chess, cards, and going to the community club in the last month?).

expected. Our results are consistent with the literature, indicating that social learning is the dominating channel in the peer effect in the context of program participation (Dahl *et al.*, 2014; Liu *et al.*, 2014; Cai *et al.*, 2015).[26]

It is straightforward to ask which type of information is diffused among peers and served as the foundation of pension expectations in RBP. As Van Duijn *et al.* (2013) revealed, two essential components explain the mismatch between expected and estimated replacement rates, namely lack of knowledge of pension institutions and uncertainty about the future, and they conclude that the mismatch is mostly related to poor institutional knowledge. We then discuss under this framework.

First, individuals may exchange knowledge of pension institutions with peers. We propose that at least two types of pension knowledge are highly relevant in our context: pension policy knowledge and financial literacy. Pension policy knowledge refers to original information released by the government

[26]We notice that peer effect is insignificant in columns (1) and (4), indicating the peer effect may not be significant when the individuals are not new participants and are not involved in social activities. However, the *p*-value of OPT_C in column (1) is 0.136 and is 0.134 in column (4), nearly significant.

that is crucial to calculate the pension benefits, e.g., receiving eligibility criteria. For example, Giles *et al.* (2021) found that a poor understanding of social insurance, both the enrollment process and costs and benefits, drives the relatively low participation rates in urban health insurance and pension programs among China's rural-urban migrants. Financial literacy refers to the necessary ability to process and understand pension policy knowledge, e.g., calculating compound interest. For example, Alessie *et al.* (2011) proposed that enhancing financial literacy can help individuals to improve their retirement planning.

Second, individuals may exchange with peers about their subjective opinions on uncertainties related to future pension benefits, such as rate-of-return uncertainty and longevity uncertainty. Regarding the rate-of-return uncertainty, individuals may doubt the financial sustainability and fiscal risks in the long run (Fang and Feng, 2018) and thus make a pessimistic pension expectation. Such belief is greatly subjected to the subjective credibility of the pension program in the long run. If individuals exchange their subjective beliefs among the peer group, pessimism will spread among peers. Regarding longevity uncertainty, according to China's policy arrangements, the RBP program does not cease to pay pension benefits until the participant dies, regardless of the amount of the individual pension account balance. In other words, the government bears the longevity risk for RBP participants[27]. In this case, the information on health expectations, e.g., life expectancy, seems less relevant than the three mentioned types of information. Meanwhile, it is unlikely that an individual would expect to have a longer life expectancy just because her/his peers are healthier.[28]

In conclusion, different types of information are diffused among peers and serve as the foundation of pension expectations in RBP. However, due to data limitations, we cannot distinguish which type of information is diffused among peers. In the next two sections, given that information sharing plays an essential role in forming the peer effect in pension expectations, we further check the direction and quality of the information the influential peers spread in the network.

6.2 Identification of influential peers

In the baseline model, we assume that the peer effect in pension expectations is symmetric, that is, peers have the same influence on each other. However, evidence shows that there exist 'herding groups' and 'opinion leaders' among peers, especially when decision making requires more information, such as the stock market and physicians' prescription choices (Chiang and Zheng, 2010; Nair *et al.*, 2010). It has been illustrated that individuals with specific characteristics related to their social status and experience with particular programs have a larger peer effect on others (Mas and Moretti, 2009; Banerjee *et al.*, 2013; Liu *et al.*, 2014; Cai *et al.*, 2015).

It is reasonable to assume that specific individuals in the community with more information or experience play a major role in influencing others' pension expectations, and we try to identify the influential peers. Following the literature (Banerjee *et al.*, 2013; Cai *et al.*, 2015), we focus on two types of possible opinion leaders, leaders in village or township[29] and those with ORRBP enrollment experience.

Specifically, we use leaders as an example to illustrate our method to identify the disparity in the peer effect between leaders and other residents in the community. The same method applies to the

[27]Thus, a rational agent should be more interested in the expected per-month benefits rather than the expected actual value of the RBP program.

[28]However, it is noteworthy that the longevity uncertainty could be relevant in the context of pension participation and contribution decisions. For example, only those who expect to live longer than the pension actuarial age (the age at which the actuarial value of total pension benefits an individual receives equals the actuarial value of total pension contributions an individual pays) would choose to participate in the pension program; and those with longer life expectancy would have a higher incentive to contribute more to the pension program. In these cases, diffusion of health information among peers may serve as an essential foundation of pension participation and contribution decisions.

[29]Leaders in village or township refer to the cadre or party officer in local government of the village or township. The information can be found in Question FD013 in CHARLS.

ORRBP participants versus those without ORRBP experience.

$$Probit(OPT_{i,c,t}) = \alpha + \beta_o OPT\_C_{i,c,t}^{leader} + \beta_v OPT\_C_{i,c,t}^{other} + \gamma X_{i,c,t} + \lambda Z_{c,t} + \varphi Province_c + \phi Year_t + \varepsilon_{i,c,t}. \quad (5)$$

As shown in Equation (5), the independent variable of interest is the proportion of optimists in the specific subsample (leaders or other residents) in the community (OPT_C^{leader} *and* OPT_C^{other}). The variables OPT_C^{leader} and OPT_C^{other} capture the influence of the leaders and other residents on the pension expectations of other residents in the community, respectively, using the following two equations:

$$OPT\_C_{i,c,t}^{leader} = \frac{\sum_{j\in\{h_i,leader\}} OPT_{j,c,t}}{N_{c,t} - N_{h_i,t}},\ OPT\_C_{i,c,t}^{other} = \frac{\sum_{j\in\{h_i,other\}} OPT_{j,c,t}}{N_{c,t} - N_{h_i,t}}. \quad (6)$$

We compare the coefficients β_o and β_v in Equation (5). Specifically, if β_o is greater than β_v, it suggests that leaders are more influential than the other residents, and vice versa. Considering that the peer effect may vary among different subpopulations, we run regressions as in Equation (5) repeatedly for the full sample and subsamples (leaders and other residents, respectively). Column (1) in Table 6 reports the peer effects of the different groups in the full sample. Columns (2) and (3) additionally consider the peer effect within the subgroups to investigate the influential group in those with specific observable characteristics.

As shown in column (1) in panel A in Table 6, in the full sample, the individual's probability of being an optimist significantly increases by 0.299 percentage point if the proportion of leaders' optimists in the peer group increases by 1 percentage point. However, the proportion of other residents' optimists in the peer group has no effect, indicating that the leaders are more influential overall. Column (3) in panel A presents the results for the other residents subsample. It also confirms that the leaders have a larger and significant peer effect on the other residents.[30]

Using the same method as above, we investigate the disparities in ORRBP experience, and the results are summarized in panel B in Table 6. We find that those with ORRBP experience are more influential than the others in a consistent way.

In sum, we find that leaders and those with experience with old pension programs are more influential in affecting others' pension expectations. The remaining question becomes whether these influential opinion leader groups spread more accurate information about future pension benefits in the network.

6.3 Do influential peers spread more accurate information?

After identifying the influential groups, we naturally want to investigate the quality of the information they spread in the network. Specifically, we want to verify whether they are spreading more accurate information on pension expectations so that the peer effect helps to improve the group's ability to estimate the benefits. We first classify the participants into two groups: accurate and inaccurate predictors. The accurate predictors are those whose absolute value of pension expectation bias, $P_{i.t}^{bias}$, is less than 25%, and the others with larger bias are defined as inaccurate predictors.

Figure 4 reports the proportion of accurate predictors in different groups using the two characteristics we identified above. We also calculate the *p*-value for testing the difference in this proportion of accurate predictors between the different groups.[31] The results show that leaders and those with

[30]The result in column (2) in panel A indicates that the proportion of other residents' optimists has a significantly negative effect on the leaders' probability of being an optimist. This may be due to the small subsample size.

[31]The *p*-value for testing whether the proportion of accurate predictors among leaders is significantly larger than that among other residents is 0.0024, and the corresponding *p*-value for the differences between those with ORRBP experience and those with no experience is 0.0000.

Table 6. Asymmetric peer effect: Identifying opinion leader groups

IV probit model	(1)	(2)	(3)
Dependent variable	OPT	OPT	OPT
Panel A: Leaders versus other residents	Full sample	Leaders	Other residents
OPT_C (Leaders)	0.299*	1.577	0.343**
	(0.171)	(135.345)	(0.166)
OPT_C (Other residents)	−0.045	−0.131	0.011
	(0.328)	(105.900)	(0.326)
Observations	22,125	334	21,791
Wald *p*-value	0.000	0.000	0.000
Panel B: With versus w/o ORRBP experience	Full sample	ORRBP	No ORRBP
OPT_C (ORRBP experience)	0.362**	0.486*	0.303
	(0.165)	(0.254)	(0.239)
OPT_C (No ORRBP experience)	0.301*	0.485	0.308
	(0.179)	(0.446)	(0.192)
Observations	22,125	2,696	19,429
Wald *p*-value	0.000	0.000	0.000
Contextual effects	YES	YES	YES
Control variables	YES	YES	YES
Year fixed effects	YES	YES	YES
Province fixed effects	YES	YES	YES

Note: The sample contains middle-aged respondents in China (45–59 years old) surveyed by the CHARLS from 2011 to 2018. An individual is classified as an optimist (OPT) if she/he has optimistic pension expectations. OPT_C captures the proportion of optimists in the community where the individual lives. We report the average marginal effects of the estimates in the probit model. Constants, contextual effects, and control variables are included in the regressions but not reported. Robust standard errors are provided in parentheses. *, **, and *** indicate that the coefficients significantly differ from 0 at the 10%, 5%, and 1% levels, respectively.

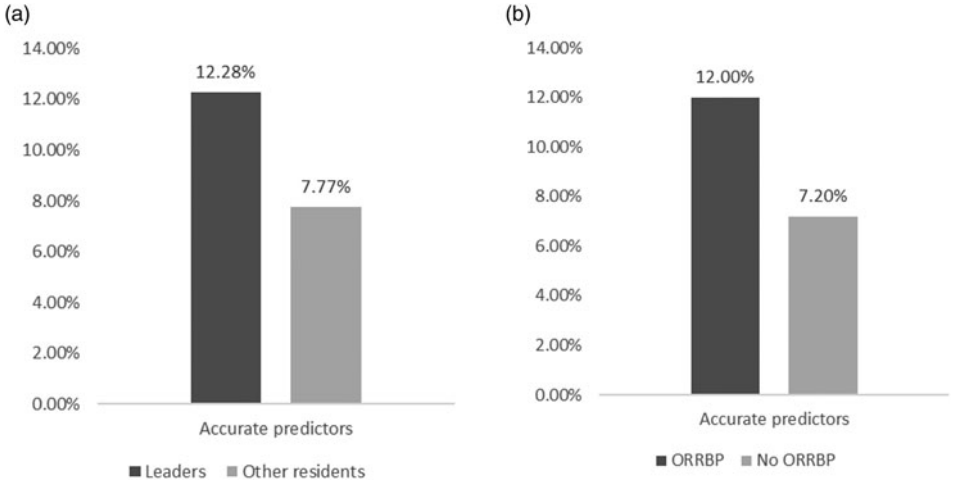

Figure 4. Proportions of accurate predictors in different groups.
Note: The *p*-value for testing whether the proportion of accurate predictors among leaders is significantly greater than that of other residents is 0.002, and the corresponding *p*-value for the differences between ORRBP participants and those with no experience is 0.000.

ORRBP experience predict future pension benefits more accurately than their counterparties. For example, the proportion of accurate predictors among the leaders is 12.28%, which is significantly higher than the proportion (7.77%) among the other residents (p-value = 0.002). The proportion of accurate predictors among the ORRBP participants is 12.00%, which is significantly higher than the proportion (7.20%) among the non-ORRBP participants (p-value = 0.000).

In sum, we find that leaders and those with ORRBP experience are more influential in the community and spread more accurate information on the pension benefit.

6.4 Other peer effects in pension decisions

Our main analysis focuses on the peer effect on the optimism about pension benefits. In this section, we instead investigate two different but related peer effects in pension decisions, including the pension participation decision and the pension contribution level decision.[32]

First, we examine the peer effect in pension participation decisions, i.e., the probability of an individual participating in the RBP program increases with the proportion of RBP participants in the community. We first calculate the RBP participation rate in the community (Participation_C) and regress individual participation status (Participation) on Participation_C. IV probit model is applied.[33] Column (1) in Table 7 presents the peer effect in the RBP participation decision: RBP participation rate increases by 0.693 percentage points if the RBP participation rate in the community increases by 1 percentage point. To further address the endogeneity issue, we also use the lagged term of Participation_C as the independent variable to repeat the analysis, and the result in column (2) in Table 7 remains consistent that there is a peer effect on RBP participation decision.

Second, we show that the peer effect also works in choosing the pension contribution level, i.e., an individual would prefer to choose a higher pension contribution level if her/his peers in the community do. We first calculate the average annual contribution to the RBP program in the community (Contribution_C) and regress annual individual contributions on Contribution_C. The 2SLS (Two Stage Least Squares) model is applied.[34] Column (3) in Table 7 presents the peer effect in the pension contribution level: individual annual contribution increases by 2.125 Yuan if the average annual contribution in the community increases by 1 Yuan. We also use the lagged term of Contribution_C as the independent variable, and the result in column (4) in Table 7 remains consistent.

Moreover, we want to verify whether low contribution level results from a pessimistic attitude so that improving the proportion of optimists in the community helps enhance the individual contribution level. Figure 1 shows that annual individual contributions may be positively related to the proportion of community optimists. We further analyze to regress annual individual contribution on the proportion of the optimists in the community (OPT_C) by applying the IV Probit model. The result indicates that increasing the proportion of optimists in the community can increase individual annual contributions in RBP:[35] annual individual contribution increased by 4.02 Yuan if the proportion of optimists in the community increased by 1 percentage point. We also use the lagged term of OPT_C as the independent variable to repeat the analysis, and the result remains consistent that an optimistic attitude promotes individual contribution in RBP.

7. Conclusion

In China, the RBP already covers 548 million residents, accounting for most of its target population; however, participants generally have a low willingness to contribute to the RBP, resulting in an inadequate old-age protection level. The pessimism toward future pension benefits among participants is one of the key drivers. Underestimating future pension benefits leads to underinvestment in the voluntary pension program. To break this pattern, the government should provide participants more updated and accurate information about the pension program. We show that while the official information distribution channel is being constructed, private information sources

[32]We also investigate the peer effect in the pension expectation bias, i.e., an individual would have a higher probability to form an accurate pension expectation if his/her peers in the community do. The result is in Table B.3 in Appendix B. The pension expectation bias is defined in Equation (3). We first calculate average pension expectation bias in the community (Pension expectation bias_C) and regress individual pension expectation bias on average pension expectation bias in the community. We apply the 2SLS model to estimate the peer effect on pension expectation bias. The result indicates that there is peer effect on pension expectation bias: individual pension expectation bias increased by 0.616 percentage points if the average pension expectation bias in the community increased by 1 percentage points.

[33]The IV is still the average health status of peers' parents.

[34]The IV is still the average health status of peers' parents, the same as that in IV probit model.

[35]The result is presented in Table B.4 in Appendix B.

Table 7. The peer effect on other pension decisions

Model	(1) IV Probit	(2) Probit	(3) 2SLS	(4) OLS
Dependent variable	Participation	Participation	Contribution	Contribution
Participation _C	0.693***			
	(0.023)			
Participation_C_lag		0.223***		
		(0.009)		
Contribution_C			2.125*	
			(1.248)	
Contribution_C_lag				0.961***
				(0.022)
Observations	57,064	39,963	22,125	13,345
Wald *p*-value	0.000	0.000		
R^2			0.235	0.218
Contextual effects	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES

Note: The sample contains middle-aged respondents in China (45–59 years old) surveyed by the CHARLS from 2011 to 2018. We report the average marginal effects of the estimates in the probit model. Constants, contextual effects, and control variables are included in the regressions but not reported. Robust standard errors are provided in parentheses. *, **, and *** indicate that the coefficients significantly differ from 0 at the 10%, 5%, and 1% levels, respectively.
'Participation' is a dummy variable assigned the value 1 if the individual participated in RBP.
'Participation_C' refers to the community-level participation rate in RBP.
'Participation_C_lag' is the lagged term of 'Participation_C.'.
'Contribution' refers to annual individual contributions in RBP.
'Contribution_C' refers to the community-level average annual individual contribution in RBP.
'Contribution_C_lag' is the lagged term of 'Contribution_C.'.
The sample size in columns (1)–(2) changes because we use a larger sample, including those not involved in RBP.

via peer groups could act as a supplement to boost the proportion of optimistic pension participants among the group.

Our results show that the probability of being an optimistic pension participant increases by 0.309 percentage point if the proportion of optimists in the community increases by l percentage point. This result confirms the existence of the peer effect in forming pension expectations among the middle-aged. Moreover, we find that the social learning channel dominates the social norms channel, meaning that the peer effect occurs via transmitting information about the pension program. These results underscore the importance of private information sources, or peer groups, in shaping individuals' attitudes toward the pension system. Then, we show that leaders and residents with old pension program experience are opinion leaders in the peer group, and they spread more accurate information about future pension benefits. Lastly, we find that there are peer effects in other pension decisions such as pension participation as well as contribution size and the contribution size increases by the proportion of optimists in the community.

Our findings have several important policy implications. First, in constructing the public pension system, the government should build an accessible and efficient information distribution channel. It is vital to design a pension system thoughtfully, and it is equally important to deliver updated information to the participants, so that they will not have pessimistic expectations toward the pension benefits in a biased manner, which would impair the effects of the pension program.

Second, the government should pay attention to the role of private information sources in distributing information on the public pension system. Private information sources act as an important supplement to the public information channels. Thus, combining the two sources could bridge the gap between the government and participants in an efficient way.

Third, the government should exploit the role that opinion leaders play in the private information sources to facilitate efficient dissemination of information. The opinion leaders are the key persons to

drive the expectations and behaviors among the peers. We find that the opinion leaders – leaders and individuals with ORRBP experience – are not only more influential than other individuals, but they also estimate the future benefits more accurately. If the government could make use of these opinion leaders by providing pension training sessions for them, especially after a reform or change in pension design, it could help the general public to foster more accurate pension expectations in an efficient manner. Considering our findings, we consider that the peer effect on pension expectations through social media is a promising area for future research.

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