Access to Pensions, Old-Age Support, and Child Investment in China

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Abstract

This paper studies how access to a pension program affects intergenerational transfers in traditional societies. Guided by predictions from an overlapping generations model, we analyze the impact of a new pension program in rural China on old-age support and investment in children, using a difference-in-differences approach. We find that access to pensions crowds out transfers from working-age adults, especially men, to their elderly parents. Interestingly, the program reduces adults' educational investment in daughters and increases investment in sons. Gendered differences in results are consistent with women feeling greater altruism toward their parents than men.

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1 Introduction

Many people in developing countries have no access to old-age pensions. Traditional pension schemes financed by employers and employees usually do not cover rural farmers and workers in the informal sector. This has led a growing number of countries to introduce public pension programs.[1] Such pension reforms have for the first time made pensions widely available to people who traditionally rely upon children for support in old age. As the expected reliance on children for old-age support also motivates parents' investment in their children, the introduction of pensions may irrevocably alter the interdependence between parents and children.

In this paper, we examine how access to pensions affects two dimensions of intergenerational transfers – old-age support and child investment. The setting for our study is China, which introduced the New Rural Pension Scheme (NRPS) in 2009. The scheme expanded over time until it covered the entire rural population.[2] The NRPS features matched voluntary contributions as well as a social pension component. Participants aged above 60 receive government-financed pension payments right away, despite never having contributed to the program. Participants younger than age 60 need to pay an annual premium matched by a government subsidy, and receive pension payments starting at age 60.[3]

Although pensions undermine the role of children in providing old-age support, it is not obvious whether pensions crowd out private transfers between generations. First, the incentive for transfers can be multifaceted. Apart from the self-interested *exchange* motive, people can make transfers due to *altruism*.[4] Second, a pension program affects three generations in a family simultaneously but differently: elderly grandparents receive pension payments right away; working-age parents need to pay contributions

[1] For instance, Chile introduced the non-contributory solidarity pension system in 2008 to cover the poorest elderly people with no, or very little, pensions. In the same year, South Korea introduced the Basic Old-Age Pension, which provides a monthly pension payment to elderly people. In 2011, Philippine introduced a social pension for people aged 77 and above, and later expanded the benefits to the population aged 65 and above.

[2] By 2015, more than 450 million rural residents had participated in the program (Ministry of Human Resources and Social Security of China, 2016). Before the NRPS, there were some unsuccessful pilots of rural pension schemes from 1986 to 1999. Owing to inappropriate design and lack of financial support, the participation rate was very low. In 2000, only about 7% of rural residents over age 60 received pension benefits or social insurance (Salditt et al., 2007).

[3] For participants aged above 60, the level of pension payment is 55 RMB (approximately 8.5 USD) per month at minimum and varies across regions. In some provinces, it was as high as 2,000 RMB in 2018. For participants under age 60, the annual premium ranges from 100 RMB to 500 RMB – the upper bar has been raised gradually since 2009. The pension payment that they will receive after retirement positively correlate with the premiums. Refer to Appendix C for more details about the NRPS.

[4] The exchange incentive has been broadly established in the literature. For instance, elderly parents help take care of grandchildren for monetary returns from working children (Cox, 1987; Secondi, 1997). Adult children help take care of parents if they expect to receive later bequests (Horioka et al., 2016). Parents' early investment in children has also been recognized as an instrument to maximize future returns (Becker and Tomes, 1976). The altruism incentive means that people provide transfers because they care about the well-being of receivers, or they derive *warm-glow* utility from giving itself (Andreoni, 1989). The altruism incentive implies a negative correlation between the recipient's income and the probability and amount of transfers (Becker, 1974), which is empirically documented in different countries (Altonji et al., 1997; Cai et al., 2006; Park and Porter, 2014).

before retirement; the child also gets access to pensions but only receives parental investment in the short run. Third, depending on the kinship system and cultural norms, the parent-child relationship can have large gender differences. For example, in societies with patrilineal traditions, parents tend to have closer relations with and be more altruistic toward sons than daughters. Consequently, the impacts of pensions on intergenerational transfers can be gender-specific.

To capture multiple generations and incentives in a single framework and help uncover the channels through which pensions affect intergenerational transfers, we develop a simple life-cycle model with three overlapping generations: an elderly *grandparent*, a working-age *parent*, and a *child*. The parent provides upward transfers toward the grandparent, and invests in the child's human capital. We assume that upward transfers and child investment are both gender-specific. A new pension program brings windfall income for the grandparent and provides the parent with a subsidized saving tool with a higher rate of return. The model predicts a crowd-out effect of pension access on upward transfers, because the grandparent becomes wealthier. The crowd-out effect decreases in magnitude with upward altruism, meaning that a new pension program decreases upward transfers to a lesser extent if the parent feels more altruistic toward the grandparent.

The predicted impact of access to pensions on child investment is ambiguous in sign, because of two opposing effects. On the one hand, a decrease in upward transfers means that the parent has more resources to invest in the child, which we call the *income effect*. On the other hand, as the return to savings goes up with a new pension program, the parent may save more for his/her own retirement and invest less in the child – the *substitution effect*. We find that if the child's altruism toward the parent is high enough, the substitution effect dominates the income effect, and the parent will reduce child investment after getting access to pensions.[5]

With the model predictions as our guide, we then empirically examine how the new pension program in rural China simultaneously affects old-age support and child investment. Our main identification strategy employs a difference-in-differences (DID) approach, exploiting the region-time variation in the introduction of the program. Nationally representative survey data reveals that in 2011, more than 80% of people over age 45 in rural China depend on children for old-age support, while less than 10% depend

[5] The key intuition is that the parent reduces child investment because of the substitution effect – returns to savings increase. However, as the parent's wealth in old age (i.e., saving returns) increases, the child also reduces upward transfers, which counteracts the substitution effect. If the child is altruistic enough, the decrease in upward transfers is small in magnitude. Therefore, the substitution effect remains strong and crowds out child investment.

on pensions.[6] However, we find that access to the NRPS for just two years reduces the share of people who rely upon children by 7 percentage points, and increases the share relying on pensions by a similar magnitude.

Results also show that the pension program crowds out upward transfers – both the probability and the amount – from adult children to elderly parents. As a result of the NRPS, adult children are 7.5 percentage points less likely to make transfers to their parents, and the amount of transfers decreases by around 130 RMB, or 30% of the baseline level in the control group. We find that adult sons reduce upward transfers to a greater extent than daughters, consistent with adult daughters being more altruistic toward elderly parents.

Next, we study how access to pensions affects adults' educational investment in children.[7] We use two outcome variables: enrollment status and the amount of educational expenditures. Results show that the new pension program has opposite directions of influence on the investment in daughters and sons. Due to the NRPS, daughters become 5.5 percentage points less likely to attend school, while sons become 5.3 percentage points more likely to remain enrolled. For educational expenditures, we also find a positive effect of the pension program on sons and a negative effect on daughters. The gender differences are statistically significant at the 5% or 1% level. As predicted by the model, the decrease in parents' investment in daughters also suggests that in rural China, daughters are more altruistic toward parents than sons.

This paper first relates to the literature studying the impact of public transfers, especially pensions, on private transfers. Starting with Barro (1974) and Becker (1974), many researchers have explored the crowd-out hypothesis in different settings. Regarding old-age support, Cox and Jimenez (1992) find social security benefits displace upward transfers in Peru. Similarly, Jensen (2004) finds a 25 to 30 percent decrease in transfers from children as a result of an expanded pension program in South Africa. Regarding child investment, Mu and Du (2015) find that parents *increase* educational investment in children when a pension program is expanded in urban China. More recently, Bau (2019) studies the influences of pension programs on kinship practices and parental investment from a cultural perspective.

[6]Data source: the 2011 China Health and Retirement Longitudinal Study (CHALRS).

[7]In China, children start pre-school education around age three and then the primary school at age six or seven. Compulsory education, including primary school and middle school (lower secondary school), typically lasts for nine years. After that, if a student continues education, he or she usually attends three years of high school (higher secondary school) and four years of undergraduate study. Students can also attend vocational high schools and colleges. The high dropout rate in Chinese schools, especially in poor rural areas, has been a troubling issue until very recently. Based on a large-scale survey in rural China, Shi et al. (2015) find a cumulative dropout rate across middle school between 17.6 and 31 percent.

She finds that pensions *reduce* educational investment in children who traditionally live with parents. The fact that Mu and Du (2015) and Bau (2019) find opposite impact of pensions on child investment is consistent with the co-existence of a positive income effect and a negative substitution effect, as predicted by our simple model.

We contribute to the literature mainly in three ways. First, rather than looking at old-age support or investment in children separately, we study the impact of pensions on upward and downward transfers within a single framework. We take into account three generations, and examine the simultaneous decisions of old-age support and child investment. Second, we focus on gender differences in parent-child relations and show that a new pension program can have gender-specific impacts on intergenerational transfers. Finally, we develop a model featuring multiple generations, a pension shock, and gender-specific preferences. The model helps clarify the different effects of a pension program and shows how the effects depend on preference parameters.

This paper also contributes to the literature studying the socioeconomic impact of the NRPS, perhaps the largest pension program in the world, benefiting a large share of rural residents in China.[8] Existing studies have examined the influences of the NRPS on the elderly's health, labor supply, cognition, and living arrangements (Huang and Zhang, 2016; Cheng et al., 2018; Nikolov and Adelman, 2019), as well as migration and employment decisions of their children (Sun et al., 2014). This paper shows that the NRPS also affects child investment in rural China.[9]

The rest of the paper is organized as follows. Section 2 presents the conceptual framework, from which we derive predictions for the effects of pensions on intergenerational transfers. Section 3 introduces the data and empirical strategy. Section 4 presents empirical results – the impact of the NRPS on expectations of old-age support, upward transfers, and child investment. We conclude in Section 5.

2 Conceptual Framework

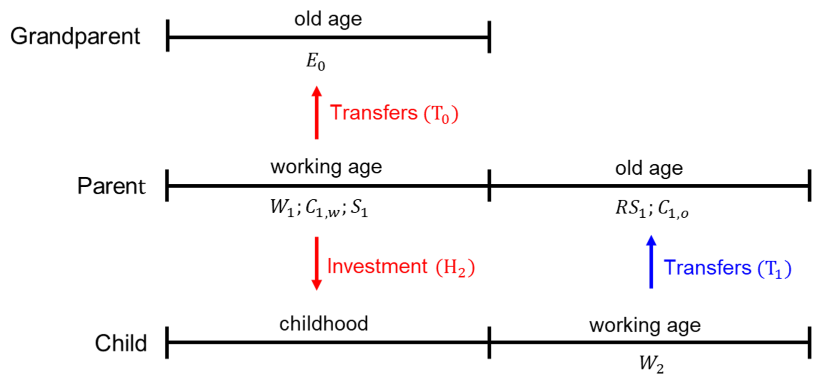
We consider a simple life-cycle model with three generations in a family: a grandparent (generation 0), a parent (generation 1), and a child (generation 2). For simplification, suppose three generations are of the

[8]Poverty among rural residents, especially elderly residents, remains a big issue in China. In 2010, around 22% of the rural elderly lived under the poverty line (*HelpAge*, 2010).

[9]More broadly, this paper adds to the literature on the effects of pension reforms. For example, Attanasio and Brugiavini (2003), Attanasio and Rohwedder (2003), and Lachowska and Myck (2018) study the impact of pension wealth on household savings. Mastrobuoni (2009), Staubli and Zweimüller (2013), and Hernæs et al. (2016) examine the effects of pension reforms on labor supply and retirement decisions.

same gender, $g \in \{f = \text{female}, m = \text{male}\}$. Intergenerational transfers can be gender-specific. As Figure 1 shows, the parent makes upward transfers (T_0^g) in working age to his/her parent – the grandparent, and makes human capital investment (H_2^g) in the child. Also, the parent in old age receives transfers (T_1^g) from the child. Suppose that upward transfers depend on the sender's gender, while child investment depends on the receiver's gender.

Figure 1: The Three-Generation Framework



The Parent's Problem At the beginning of working age, the parent maximizes the life-time utility by deciding consumption in working age ($C_{1,w}^g$) and old age ($C_{1,o}^g$), savings (S_1^g), and child investment (H_2^g), given predetermined wage income (W_1^g). As Equation (1) shows, the parent derives utility from his/her own consumption in two periods and the child's income – assumed as logarithmic functions.[10] In the utility function, β represents the discount factor which is assumed as gender-neutral, and γ^g represents the parent's altruism toward the child of gender g.

$$\max_{C_{1,w}^g, C_{1,o}^g, S_1^g, H_2^g} \quad ln(C_{1,w}^g) + \beta ln(C_{1,o}^g) + \gamma^g ln(W_2^g) \tag{1}$$

$$s.t. \quad C_{1,w}^g = W_1^g - S_1^g - H_2^g - T_0^g \tag{2}$$

$$C_{1,o}^g = RS_1^g + T_1^g \tag{3}$$

Suppose human capital or educational investment in the child costs 1 unit of income and the rate of return to education is $w > 1$. The child's wage income is a linear function of human capital, $W_2^g = wH_2^g$. Besides consumption, savings, and child investment, the parent of gender g also transfers T_0^g to the

[10]For simplification, we assume the parent only cares about the welfare of his/her direct child, but not future generations. We can also extend the model to a dynamic model with homogeneous generations, and each generation makes decisions regarding consumption, savings, and child investment in the same way as generation 1 – the parent. Because we are mainly concerned about the short-term impact of a pension program, we focus on three generations directly affected by a pension program and consider a static model.

grandparent. In the parent's old age, savings generate a total return of RS_1^g, with R denoting the rate of return to savings. Meanwhile, the parent receives T_1^g from the child. We assume that individuals do not leave any inheritance to their offspring, so they consume all of their own wealth and received transfers in old age.

Suppose that upward transfers depend on the sender's income and the receiver's pre-transfer wealth. For simplification, we model T as a linear function:

$$
\begin{aligned}
&T_0^g = \sigma^g W_1^g - \tau^g E_0^g; \\
&T_1^g = \sigma^g W_2^g - \tau^g E_1^g = \sigma^g w H_2^g - \tau^g RS_1^g. \qquad (4)
\end{aligned}
$$

$\sigma^g \in (0,1)$ is the share of the child's income offered to the parent in old age, and $\tau^g \in (0,1)$ denotes the responsiveness of transfers to the parent's wealth. Conceptually, σ^g increases with the child's reciprocity and altruism toward the parent: a child who is more altruistic and reciprocal toward his/her parent is willing to share more resources with the parent. By contrast, τ^g decreases with the child's altruism toward the parent: as the parent's wealth increases by 1 unit, the amount of transfers decreases by τ^g units, and the decrease in amount is greater if the child is less altruistic. A simple example in the footnote helps explain the motivations behind the transfer function.[11]

After plugging the budget constraints into the utility function, the parent's problem reduces to a maximizing problem with respect to S_1^g and H_2^g. The first-order conditions are:

$$
S_1^g: \quad \frac{1}{C_{1,w}^g} = \frac{\beta R(1-\tau^g)}{C_{1,o}^g}; \qquad (5)
$$

$$
H_2^g: \quad \frac{1}{C_{1,w}^g} = \frac{\beta \sigma^g w}{C_{1,o}^g} + \frac{\gamma^g}{H_2^g}. \qquad (6)
$$

The left-hand side of two equations represents the marginal cost of savings or child investment, while

[11] In a simple problem of transfers (T) motivated purely by altruism, a child maximizes a combination of his/her consumption utility, $\ln(C^c)$, and the parent's consumption utility, $\ln(C^p)$, given predetermined wealth of the child (I^c) and the parent (I^p):

$$
\begin{aligned}
\max_T \quad & \ln(C^c) + \theta \ln(C^p) \\
s.t. \quad & C^c = I^c - T \qquad C^p = I^p + T
\end{aligned}
$$

where θ denotes the degree of altruism of the child toward the parent. The optimal transfers driven by altruism is $T^* = \frac{\theta}{1+\theta} I^c - \frac{1}{1+\theta} I^p$. Suppose apart from altruism, the child also feels reciprocal and provides an extra share (π) of own income as a return to the parent's previous investment. Hence, the final amount of transfers is: $T^{**} = (\frac{\theta}{1+\theta} + \pi) I^c - \frac{1}{1+\theta} I^p$, where $\frac{\theta}{1+\theta} + \pi$ corresponds to σ and $\frac{1}{1+\theta}$ corresponds to τ.

the right-hand side represents the marginal benefit. Child investment is motivated by both altruism and self-interest: the parent derives utility from the child's income; future transfers provided by the child also increases with the investment.

Lastly, we can solve for the optimal child investment as a function of predetermined income (W_1^g and E_0^g), the rate of return to savings and human capital (R and w), the discount factor (β), and three parameters capturing the gender-specific relations between generations ($\gamma^g, \tau^g, \sigma^g$):[12]

$$H_2^{g*} = \frac{R\gamma^g(1-\tau^g)[(1-\sigma^g)W_1^g + \tau^g E_0^g]}{(1+\beta+\gamma^g)[R(1-\tau^g) - \sigma^g w]}. \tag{7}$$

Access to Pensions Suppose now a new pension scheme becomes available, and it creates two shocks: (i) a "windfall shock" for the old-age grandparent ($\Delta_E > 0$), as he/she receives pension payments right away; (ii) a "saving shock" for the parent ($\Delta_R > 0$), as the pension program serves as a new saving tool with a higher rate of return: people can save money in the pension account and receive pension payments after retirement.[13] Next, we analyze how Δ_E and Δ_R affect the parent's transfers to the grandparent and investment in the child.

Pension availability only affects upward transfers through the windfall shock (Δ_E). Consistent with the altruism theory about private transfers (Becker, 1974), an increase in the grandparent's wealth leads to lower transfers from the parent. Specifically, the impact of a new pension program on upward transfers is a decreasing function of Δ_E:

$$\Delta T_0^g = -\tau^g \Delta_E < 0. \tag{8}$$

It is straightforward to see that the crowd-out effect is stronger if τ^g is greater: $\frac{\partial \Delta T_0^g}{\partial \tau^g} < 0$. As τ^g decreases with upward altruism, the crowd-out effect is stronger if the parent is less altruistic toward the grandparent.

Access to pensions affects child investment through both Δ_E and Δ_R. As Δ_E lowers T_0^{g*}, the parent has higher income to invest in the child – the *income effect* of pension access on child investment. Meanwhile, as R goes up, the return to savings increases, so does the opportunity cost of child investment –

[12] Similarly, we can solve for the optimal savings: $S_1^{g*} = \frac{[\beta R(1-\tau^g)-(\beta+\gamma^g)\sigma^g w][(1-\sigma^g)W_1^g+\tau^g E_0^g]}{(1+\beta+\gamma^g)[R(1-\tau^g)-\sigma^g w]}$. We assume $R\beta(1-\tau^g) > (\beta+\gamma^g)\sigma^g w$, so that H_2^{g*} and S_1^{g*} are positive.

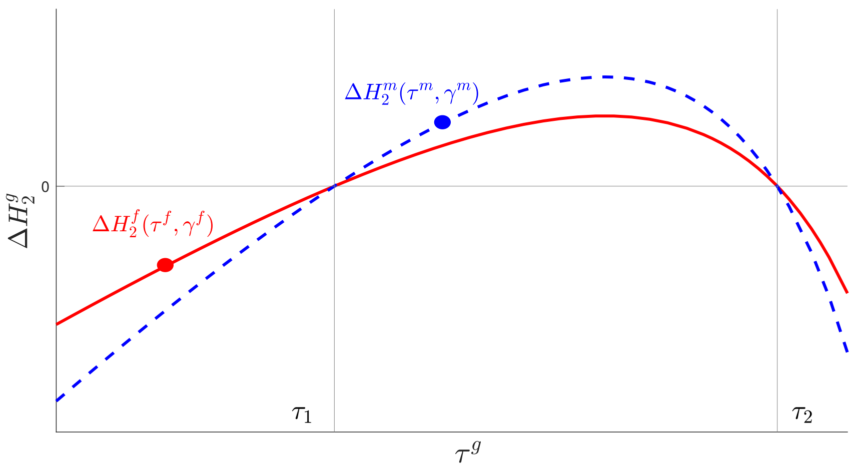
[13] We assume that both R and Δ_R are exogenously determined in a setting like rural China, where rural households' savings take a small volume compared to urban households' savings as well as enterprise and government savings. In that sense, rural residents' saving decisions should have little influence on the aggregate capital market and the government's pension policy. In Appendix C.2, we illustrate how the new pension program in rural China raises the rate of return to private savings.

the *substitution effect* of pension access on child investment. Consequently, the sign of ΔH_2^g is ambiguous and depends on the relative size of the two opposing effects:[14]

$$\Delta H_2^g = \frac{\partial H_2^{g*}}{\partial E_0^g}\Delta_E + \frac{\partial H_2^{g*}}{\partial R}\Delta_R = \underbrace{IE^g\Delta_E}_{\substack{\text{income effect}\\>0}} + \underbrace{SE^g\Delta_R}_{\substack{\text{substitution effect}\\<0}}, \tag{9}$$

where $IE^g = \frac{R\gamma^g\tau^g(1-\tau^g)}{(1+\beta+\gamma^g)[R(1-\tau^g)-\sigma^g w]} > 0$ and $SE^g = -\frac{\sigma^g w\gamma^g(1-\tau^g)[(1-\sigma^g)W_1^g+\tau^g E_0^g]}{(1+\beta+\gamma^g)[R(1-\tau^g)-\sigma^g w]^2} < 0.$

Figure 2: The Impact of Pension Access on Child Investment (ΔH_2^g) depending on τ^g and γ^g



Note: The figure shows the relationship between ΔH_2^g and τ^g, separately for $\gamma^g = \gamma^m$ (blue dashed curve) and $\gamma^g = \gamma^f$ (red solid curve). When $\tau^g < \tau_1$ or $\tau^g > \tau_2$, ΔH_2^g is negative; when $\tau_1 < \tau^g < \tau_2$, ΔH_2^g is positive. τ_1, τ_2 are two cutoffs for τ^g as specified in footnote 16. Regarding the gender difference, when $\tau^f < \tau_1 < \tau^m < \tau_2$ and $\gamma^f < \gamma^m$, we have $\Delta H_2^m > 0 > \Delta H_2^f$.

Assume that the share of income transferred from the child to the parent is small enough, $\sigma^g < \hat{\sigma} < 1/2$.[15] Under this assumption, there exist two thresholds, $\tau_1, \tau_2 \in (0,1)$, such that $\forall \tau^g \in (0,\tau_1)\cup(\tau_2,1)$, $\Delta H_2^g < 0$, and $\forall \tau^g \in (\tau_1,\tau_2)$, $\Delta H_2^g > 0$.[16] Meanwhile, the absolute value of ΔH_2^g increases with γ^g, such that when positive, ΔH_2^g increases with γ^g, and when negative, ΔH_2^g decreases with γ^g. Figure 2 shows a stylized example of ΔH_2^g as a function of τ^g and γ^g.

[14] To better understand why ΔH_2^g is ambiguous in sign, we can refer to the first-order condition *w.r.t.* H_2^g:

$$\text{MC} \equiv \frac{1}{C_{1,w}^g} = \frac{\beta\sigma^g w}{C_{1,o}^g} + \frac{\gamma^g}{H_2^g} \equiv \text{MB},$$

which pins down the optimal child investment. Moreover, $C_{1,w}^g$ increases with E_0^g but decreases with R; while $C_{1,o}^g$ increases with R. As R increases, the MC of child investment shifts up and the MB shifts down, and the optimal child investment decreases. However, as E_0^g increases, the MC shifts down, which lowers child investment.

[15] In our empirical setting, adult children only send about 1% of their income to parents as transfers (see Section 5 for details). The assumption of a small σ^g ensures that $R^2\Delta_E > w\sigma(R\Delta_E + E\Delta_R) + 2R\sqrt{\sigma w(1-\sigma)W_1\Delta_E\Delta_R}$.

[16] τ_1, τ_2 are the two solutions for the secondary-order equation with respect to τ^g:

$$R\tau^g[R(1-\tau^g) - \sigma^g w]\Delta_E - \sigma^g w[(1-\sigma^g)W_1^g + \tau^g E_0^g]\Delta_R = 0.$$

See Appendix A for detailed discussion about the sign of ΔH_2^g and how it depends on σ^g and τ^g.

Gender Differences in the Impact of Pensions We focus on the impact of pension access on transfers from the parent of gender g to the grandparent (ΔT_0^g), and the parent's human capital investment in the child of gender g (ΔH_2^g).

As shown in Equation (8), pension access crowds out transfers from the parent to the grandparent; the intensity of the crowd-out effect depends on τ^g, which is negatively correlated with the parent's altruism toward the grandparent. If a female parent (adult daughter) is more altruistic toward the grandparent than a male parent (adult son), i.e., $\tau^f < \tau^m$, then the adult son will reduce upward transfers to a greater extent than the adult daughter: $\Delta T_0^f > \Delta T_0^m$.

The impact of pensions on child investment is ambiguous in sign. Suppose that σ^g is very small and hold other factors constant, access to pensions lowers child investment if τ^g is small or large enough, and increases child investment if τ^g is in a medium range. In the case when a female child (daughter) is more altruistic toward the parent than a male child (son), and more specifically, when $\tau^f < \tau_1 < \tau^m < \tau_2$, a new pension program will reduce the parent's investment in the daughter but raise the investment in the son: $\Delta H_2^f < 0 < \Delta H_2^m$.

3 Data and Empirical Strategy

To empirically study the impact of pension access on old-age support and child investment, we exploit the region-time variation in the implementation of the New Rural Pension Scheme (NRPS) in China and use difference-in-differences (DID) as the identification strategy.

3.1 Data

We mainly use two data sets for the empirical analysis: the China Health and Retirement Longitudinal Study (CHARLS) and the China Family Panel Studies (CFPS). Both the CHARLS and CFPS are nationally representative longitudinal surveys conducted by Peking University.

The CHARLS surveys the older population (age 45 and older) of China (Zhao et al., 2012). The national baseline survey was conducted in 2011, including about 10,000 households and 17,500 individuals in 150 counties. Respondents are followed every two years. Apart from demographics, family structure, income, and consumption, the CHARLS questionnaire also covers topics like within-family transfers, retirement, and pensions. The CFPS (Institute of Social Science Survey, 2015) was launched in 2010.

The baseline survey interviewed almost 15,000 families and 30,000 individuals in these families. The respondents are then tracked bi-annually. The survey covers a wide range of topics such as demographics, employment, education, family relations, wealth, and health.

Table 1: Descriptive Statistics of the CHARLS Sample

Panel A: Observations of Parents in 2011 & 2013 (N=5,616)					
	mean	sd	p10	p50	p90
Age	68.70	(6.23)	62	67.2	77.9
Female	0.48	(0.50)	0	0	1
Schooling Years	3.35	(3.75)	0	2	9
Spouse is Alive	0.78	(0.42)	0	1	1
Average Age of Children	39.73	(6.04)	32.3	39.7	47.3
Number of Children	3.88	(1.58)	2	4	6
Number of Male Children	2.15	(1.19)	1	2	4
Receiving Any Upward Transfers	0.72	(0.45)	0	1	1
Upward Transfers Received	1,640	(4,149)	0	550	3,800
Receiving Any Net Upward Transfers	0.70	(0.46)	0	1	1
Net Upward Transfers	1,351	(5,078)	0	500	3,600
Panel B: Observations of Adult Children in 2011 & 2013 (N=10,088)					
	mean	sd	p10	p50	p90
Female	0.47	(0.50)	0	0	1
Age	39.87	(5.70)	32	40	47
Schooling Years	6.15	(3.28)	0	6	9
Number of Siblings	3.34	(1.53)	2	3	5
Number of Children	1.84	(0.78)	1	2	3
Parents' Schooling Years	2.92	(2.77)	0	2.5	7
Parents' Age	68.46	(6.46)	61.0	67.5	77.5
Number of Parents Alive	1.70	(0.46)	1	2	2
Providing Any Upward Transfers	0.55	(0.50)	0	1	1
Upward Transfers Provided	642.6	(2,456)	0	100	1,500
Providing Any Net Upward Transfers	0.53	(0.50)	0	1	1
Net Upward Transfers Provided	495.1	(3,520)	0	100	1,400
Panel C: Gender Differences in the Provision of Upward Transfers					
	Sons (*N=5,366*)		Daughters (*N=4,722*)		Gender Diff.
	mean	sd	mean	sd	p-value
Any Upward Transfers	0.47	(0.50)	0.64	(0.48)	0.00
Upward Transfers	701.2	(2,539)	576.1	(2,358)	0.01
Any Net Upward Transfers	0.45	(0.50)	0.63	(0.48)	0.00
Net Upward Transfers	499.5	(3,676)	490.1	(3,334)	0.89

To study the impact of the NRPS on old-age support, we use the first two waves of the CHARLS, in 2011 and 2013. We examine both the expectations about future old-age support (Section 4.1) and economic transfers between generations within a family (Section 4.2). Regarding expectations, the CHARLS respondents report their expected primary source of old-age support, which can be children, savings, pensions, etc.[17] We are mainly interested in the choice between children and pensions. Regarding transfers, the survey documents detailed monetary and in-kind transfers between generations. Parents

[17]The exact wording of the question is, "Whom do you think you can rely on for old-age support?". The options include: (1) children, (2) savings, (3) pension or retirement salary, (4) commercial pension insurance and (5) other. We combine (3) and (4) as pensions, because some respondents may mistakenly perceive the NRPS as commercial pension insurance.

report how much economic support they have received from each child in the past year, and how much support they have given to each child.[18]

We present descriptive statistics for the CHARLS sample in Table 1. Panel A presents summary statistics for parents in 2011 and 2013. Our analysis includes parents satisfying the following criteria: (1) with an agricultural Hukou,[19] because only residents with the agricultural Hukou are eligible to participate in the NRPS, (2) aged 60 or above at baseline, because the windfall shock of pension payments only takes place for this group, and (3) with at least one child whose baseline age is between 25 and 50. On average, these parents are aged 69, have 3.4 years' education, and around 4 children.[20] More than 70% of them receive transfers from children, and the average amount of transfers received is about 1,600 RMB (about 230 USD) for a year.

Panel B shows summary statistics for observations of adult children in both waves. We include adult children with agricultural Hukou and between ages 25 and 50 at baseline. On average, they are 40 years old, and have 6 years' education, 3 siblings and 1.8 children; 47 percent of them are female. More than half of the children provide transfers to parents, and the average amount of transfers is about 650 RMB. Panel C shows the gender differences in adult children's provision of upward transfers. Compared to sons, adult daughters are more likely to provide transfers to parents, but the amount of transfers is lower.

To study the impact of the NRPS on educational investment, we use the first two waves of the CFPS, in 2010 and 2012. We use two proxies of educational investment: school attendance and educational expenditures. Attendance is a dummy variable indicating whether a child is formally enrolled in school. Educational expenditures are the total expenses that the family spends for a child's education in the previous year. The expenditures include the following items: tuition fees, nursery fees, costs of text-books and education software, transportation costs for schooling, boarding fees, food expenses at school, extracurricular tutoring costs, sponsorship for kindergartens or schools, and other education-related costs.[21]

[18] To be more specific, the survey includes four types of economic support from adult children: (i) regular monetary support on a monthly/quarterly/half-yearly/annually basis, (ii) regular in-kind support in monetary values, (iii) non-regular monetary support for several important festivals (e.g., Chinese Spring Festival and Mid-Autumn Festival) and other important purposes (education, medical conditions, weddings, birthday, etc.), (iv) non-regular in-kind support in monetary values. We calculate the total amount of transfers in the past year by summing the four types of support.

[19] Hukou refers to the household registration system in China. A Chinese citizen's Hukou is typically categorized as either agricultural/rural or non-agricultural/urban.

[20] For parents aged 67 in 2010 or 37 in 1980, the one-child policy (introduced in early 1980s) does not have much impact on their fertility decisions.

[21] Note that even if a child is not formally registered at school, the education expenditure can still be positive – the child can receive extracurricular education or informal training programs.

Table 2: Descriptive Statistics of the CFPS Sample

Panel A: Observations of Children in 2010 & 2012 (N=9,428)	mean	sd	p10	p50	p90
Female	0.49	(0.50)	0	0	1
Age	14.72	(5.93)	7	14	24
Number of Siblings	0.93	(0.87)	0	1	2
Parents' Average Age	41.19	(6.74)	32.5	40.5	50.0
Parents' Average Schooling Years	5.92	(3.24)	0	6	9
Enrollment	0.70	(0.46)	0	1	1
Expenditures	1,689	(3,612)	0	300	5,000

Panel B: Gender Differences in Educational Investment	Sons (N=4,810)		Daughter (N=4,618)		Gender Diff.
	mean	sd	mean	sd	p-value
Enrollment	0.70	(0.46)	0.69	(0.46)	0.083
Expenditures	1,729	(3,801)	1,647	(3,405)	0.268

We present descriptive statistics for the sample of children in Table 2. We focus on children between ages 5 and 25 at baseline, and with at least one parent holding an agricultural Hukou. Around 50 percent of children are female. On average, their parents are 40 years old and have 6 years' schooling – the typical length of primary school. Overall, 70% of children are enrolled in schools or colleges, and the annual educational expenditures are around 1,700 RMB. Panel B shows the gender differences in enrollment and expenditures. We find that compared to daughters, sons are about 1.5 percentage points more likely to attend school, and parents spend slightly more money on sons' education.[22]

3.2 Empirical Strategy

Our main identification strategy uses a difference-in-differences (DID) approach, which exploits the county-time variation in the rollout of the NRPS. The NRPS expanded in China gradually from 2009 to 2013. We use two waves of panel data from the CHARLS and CFPS, and focus on two groups of counties (see Table 3): counties covered by the NRPS only in the second wave (treatment group) and counties covered by the NRPS in both waves (control group).

Table 3: Definition of Treatment

	Access to the NRPS	
	Wave 1	Wave 2
Treatment Group	No	Yes
Control Group	Yes	Yes

[22] After controlling for county-year fixed effects and the child's age and number of siblings, and parents' age and schooling years, we find sons on average receive about 200 RMB (or 12%) more educational expenditures than daughters, and the gap is statistically significant at the 5% level.

We do not use counties without the NRPS in both waves as the control group because nearly all counties in our data have access to the program by the second wave. Based on the definition of treatment, we compare individual decisions in the treatment group and control group, and estimate the intention-to-treat effect (ITT) of the NPRS on old-age support and educational investment.

We define the availability of the NRPS in each county by using self-reported participation in the program because there is no document showing the exact timing of the NRPS implementation across regions.[23] In both the CHARLS and CFPS, respondents report their access to various pension programs, including the NRPS. Restricting attention to counties with at least 20 adult respondents with the local agricultural Hukou – the eligible group, we classify a county as covered by the NRPS if at least *five* respondents report having participated in the program; otherwise, we classify the county as not covered.[24] In Appendix Section B.1, we also present main results using alternative thresholds to define the availability of the NRPS. The results are overall similar qualitatively and quantitatively.

More specifically, the DID specification is as follows:

$$Y_{ict} = \alpha + \beta Treat_c \times Post_t + \gamma X_{ict} + \delta_c + \theta_{pt} + \varepsilon_{ict}. \tag{10}$$

Y_{ict} is the outcome of individual i in county c and year t. We are mainly interested in three outcomes: expectations of old-age support, transfers from adult children to elderly parents, and working-age parents' educational investment in children. On the right-hand side, $Treat_c = 1$ if county c is in the treatment group. $Post_t = 1$ if t represents the second wave. In X_{ict}, we control for individual-level and household-level characteristics like age, gender, schooling years, and family structure. To rule out aggregate-level shocks and cross-county differences, we also control for county fixed effects (δ_c) and province-year fixed effects (θ_{pt}). Finally, ε_{ict} is the residual term. The coefficient of interest is β, which estimates the relative change in the outcome from wave 1 to wave 2 in the treatment group, compared to the change in the outcome in the control group. We cluster standard errors at the county level.

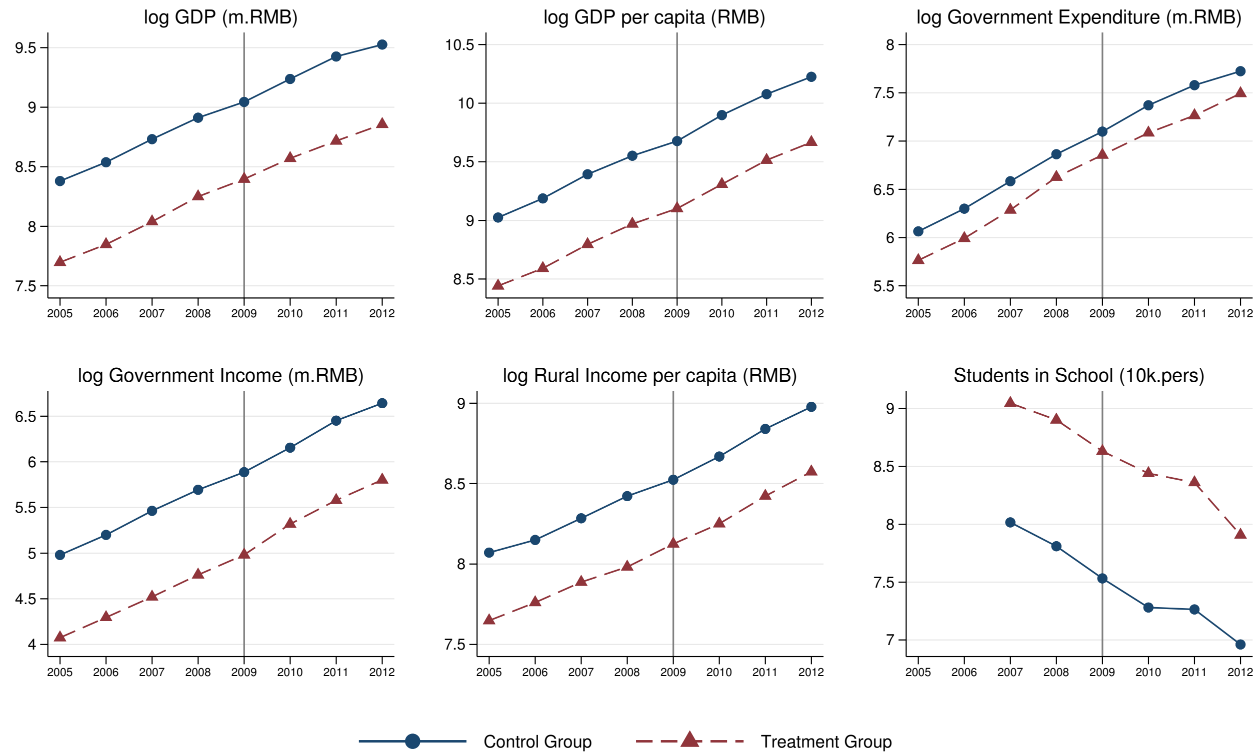
An important assumption of the DID strategy is that no omitted confounding factors influence the treatment group and control group differently from the first wave to the second wave, so that the difference

[23] Officially, the central government does announce pilot counties from 2009 to 2012, without detailed information on the month. The actual implementation can precede or lag behind the timing of the announcement. The NRPS is financed by the central government and local governments, and local governments have the authority to decide their subsidy level. Some local officials may strive to start as early as possible, as encouraged by the central government. Some counties may postpone the piloting to bargain for more financial support from the central government.

[24] By requiring at least 20 eligible subjects, we reduce the chance of mistakenly classifying a county as *not-covered*; by requiring at least five eligible participants, we reduce the chance of mistakenly classifying a county as *covered*.

in trends between the treatment and control group is only due to the NRPS. However, due to the lack of household data in the pretrend period, we are unable to directly test whether outcomes in the treatment group and control group have parallel pretrends. We do the following things to mitigate this concern.

Figure 3: Trends of Aggregate Socioeconomic Variables by Treatment

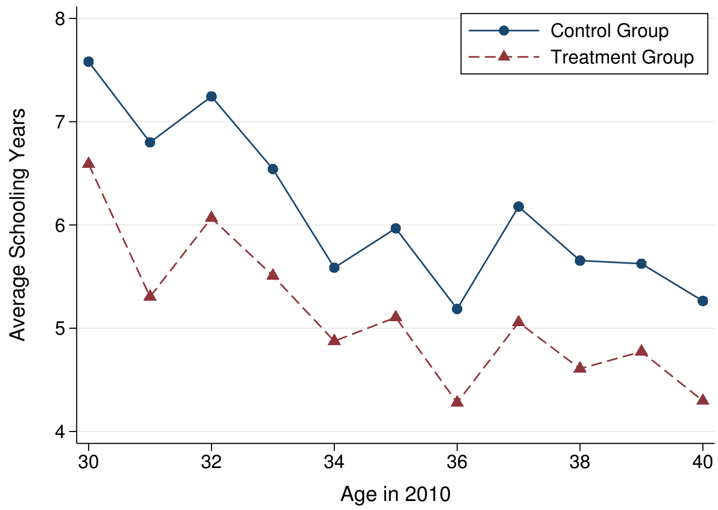


Note: The graph plots the trends of county-level characteristics for the treatment and control group, in the period from 2005 to 2012. Due to missing data, we only plot the trends for students in school from 2007 to 2012.

First, for the CFPS data, we link the counties in our sample to county-level data from other sources, and compare the pretrends of aggregate socioeconomic characteristics. We collect the following county-level variables from the *CEIC Global Database* and *China County (City) Socioeconomic Statistical Yearbooks*: GDP, GDP per capita, government revenues and expenditures, income per capita for rural residents, and the number of students in compulsory education (primary school and lower secondary school). Figure 3 plots the trends of these variables by the treatment status. The raw trends in the pre-NRPS period seem very similar in the treatment group and control group. More broadly, Huang and Zhang (2016) show that counties announced as pilot counties for the NRPS in different years also have similar pretrends of aggregate economic variables.[25]

[25]Based on documents from the State Council of China, the authors find that 320 counties (12 percent) were announced as pilot counties for the NRPS in 2009, followed by 450 counties in 2010, 1,075 counties in 2011, and all the rest in 2012.

Figure 4: Average Years of Schooling by Treatment and Cohort



Note: The graph plots the average years of schooling for different cohorts by the treatment status. We use adult sample from CFPS 2010 with different ages. Suppose people do not continue further education after age 30. The schooling years for different cohorts serve as a proxy for the education level of people reaching age 30 in different years.

Second, to further check if human capital investment has similar pretrends in the control and treatment group, we calculate the average years of schooling for different cohorts observed in the CFPS 2010. Assuming that educational investment typically does not continue after age 30, we focus on people reaching age 30 in different years. Figure 4 shows the average years of schooling for people with the agricultural Hukou, living in rural areas, and between ages 30 and 40 in 2010, separately for the treatment group and control group. We find the trends are overall parallel, suggesting that child investment in the treatment group and control group potentially follow similar trends before 2010.

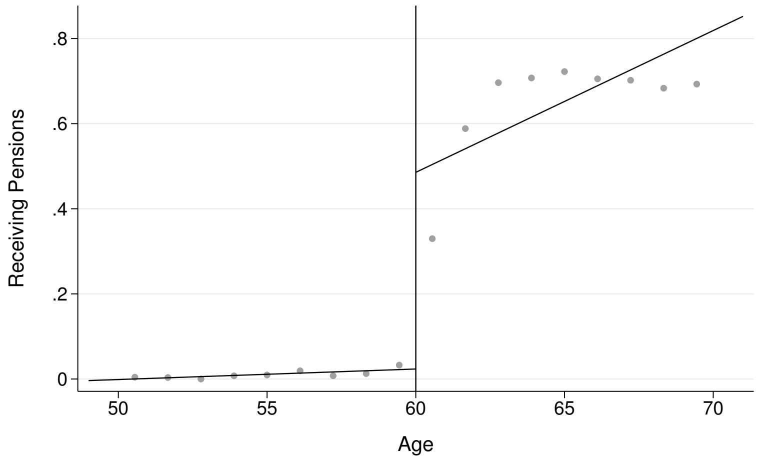
Additionally, we control for county-level contemporary trends and pretrends in the DID regression, when estimating the impact of the NRPS on child investment. As Equation (11) shows, we first control for time-varying characteristics of counties in 2010 and 2012 (Z_{ct}): the contemporary trends. Then we allow the 2010-2012 difference to vary flexibly with pretrends by including the interaction of county-level controls lagged for l years ($W_{c,t-l}$) and the $Post_t$ dummy. Both Z_{ct} and $W_{c,t-l}$ include log(GDP), log(population), log(government revenue), and log(government expenditure).[26] We find the results are generally robust to the inclusion of county-level controls as well as the selection of pretrend periods (l).

$$Y_{ict} = \alpha + \beta Treat_c \times Post_t + \gamma X_{ict} + \delta_c + \theta_{pt} + \eta Z_{ct} + \kappa W_{c,t-l} \times Post_t + \varepsilon_{ict} \tag{11}$$

[26] We have not included other variables like GDP per capita and rural income per capita in the regressions, because some counties do not report those statistics. The missing values shrink the sample size greatly.

Finally, for the CHARLS data, we can not link the sample of counties to other data due to the lack of county identifiers. For robustness, we estimate the causal effects of pension payments on old-age support, using another identification strategy – the regression discontinuity (RD) design. According to the NRPS policy, access to pension payments is discontinuous at age 60. Participants aged above 60 receive the payments, while those below 60 must make contributions to the program. As Figure 5 shows, we do find that only people older than age 60 receive pension payments. Given that the participation rate is lower than 100%, we use the fuzzy RD design. The *windfall shock* of pension payments, as predicted by the model, induces an increase in elderly parents' income, which may crowd out transfers from adult children. Therefore, we expect to see a discontinuous drop of transfers at the cutoff age.

Figure 5: Pensions-Receiving Status around Age 60



Note: The graph plots the status of receiving pension payments against age, using the CHARLS sample of parents in 2013.

Note that the RD design is different from the DID approach in a few ways. DID estimates the overall impact of the NRPS availability on parents aged above 60, while the RD design compares parents above 60 to those below 60. Therefore, if the pension program affects transfers through both the windfall shock (Δ_E) and the savings shock (Δ_R), then DID captures the aggregate effect of the two shocks, while RD only identifies the effect of the windfall shock. Lastly, RD relies on the assumption that people are budget constrained – they can not borrow from the future.[27]

[27]We can only apply the RD design when using the CHARLS data, because the CFPS does not provide detailed information on elderly parents – or better called *grandparents* when studying child investment.

4 Empirical Results

4.1 Cultural Change: Expectations of Old-Age Support

A key conjecture of this paper is that the availability of pension programs undermines the importance of children for old-age support, causing a transition from relying on children to relying on pensions. This cultural crowd-out effect is implicitly assumed by Bau (2019) when she studies the impact of pensions on cultural practices in Ghana and Indonesia. Using data from the CHARLS, we are able to directly test whether the implementation of pensions triggers a cultural change regarding old-age support.

Table 4: The Impact of the NRPS on Expectations of Old-Age Support

	(1)	(2)	(3)	(4)	(5)	(6)
	All parents		Parents aged < 60		Parents aged ≥ 60	
Rely on ... for old-age support	children	pensions	children	pensions	children	pensions
Treat $\times$ Post	-0.073**	0.075***	-0.070**	0.051**	-0.075**	0.091***
	(0.030)	(0.022)	(0.033)	(0.023)	(0.037)	(0.030)
Female	0.035***	-0.015**	0.026**	-0.003	0.037***	-0.021***
	(0.008)	(0.006)	(0.013)	(0.009)	(0.012)	(0.008)
Observations	10,844	10,844	5,228	5,228	5,616	5,616
R-squared	0.079	0.088	0.097	0.112	0.097	0.113
Control T0 Mean	0.812	0.0928	0.818	0.0820	0.806	0.104

Note: All columns use OLS regressions with parent-year observations from the CHARLS 2011 and 2013. In odd columns, the dependent variable (DV) is an indicator for relying on children for old-age support. In even columns, the DV is an indicator for relying on pensions. Controls include age, schooling years, if the spouse is alive, the number of all children and male children, and the average age of children. We also control for county fixed effects and province-year fixed effects. *Control T0 Mean* refers to the average baseline level of outcomes in the control group. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

We use the DID estimation strategy as outlined in Equation (10). The outcome variable is an indicator of relying on pensions or children for old-age support. The coefficient of the interaction term, Treat×Post, estimates the intention-to-treat effect of pension availability on the probability of relying on children or pensions. We use simple OLS regressions and control for county fixed effects, province-year fixed effects, as well as individual age, schooling years, indicator for whether spouse is alive, the number of children and male children, and the average age of children.

Table 4 presents the estimation results. Columns (1)–(2) show the results for all respondents. Overall, access to the NRPS lowers the likelihood of relying on children for old-age support by 7.3 percentage points, and increases the likelihood of relying on pensions by 7.5 percentage points. The similar magnitude of change suggests that pensions primarily replace the roles of children for old-age support. Columns (3)–(4) present the results for respondents younger than 60 and columns (5)–(6) for people older than age 60. This comparison suggests that pensions especially change the perceptions of people already in their old age. They become 7.5 percentage points less likely to depend on children and 9 percentage points more likely to depend on pensions.

4.2 Upward Transfers

In this section, we examine the impact of the NRPS on actual old-age support – upward transfers from adult children to elderly parents. We employ DID to estimate the intention-to-treat effect. Given that a parent can have multiple children, we first look at transfers provided by each child, then look at the total transfers received by a parent.

Transfers Provided by Adult Children We first look at transfers provided by adult children, using observations of adult children from the CHARLS. We use the same DID estimation as specified in Equation (10). The outcome variable, Y_{ict}, is an indicator for any transfers or the amount of transfers provided by child i in county c and year t. We winsorize the amount of transfers at the top 1 percentile to avoid extreme values driving the results.[28]

We present results in Table 5. In columns (1)–(4), we examine only upward transfers from children to parents, and in columns (5)–(8), we examine net upward transfers – transfers provided by children minus transfers from parents. The dependent variables are respectively an indicator for any upward transfers, the amount of upward transfers, an indicator for any net upward transfers, and the amount of net upward transfers. In odd columns, we only include county and province-year fixed effects. In even columns, we further control for individual characteristics. On the child side (the provider), we control for the gender, age, schooling years, number of siblings and children. On the parent side (the receiver), we control for their average schooling years, age, and whether both parents are alive.

Focusing on results presented in even columns, we find that access to pensions reduces the likelihood of children providing any transfers by 7.8 percentage points – 18% of the control-group baseline level, and the amount of transfers by around 100 RMB – 28% of the control-group baseline level. The results are very similar when we look at net upward transfers.

[28]Note that we do not exclude children living together with parents for two reasons. First, the living arrangement can change over time. Second, we also observe some transfers between parents and non-co-resident children, although very few. When we exclude children who live with parents in both waves, we find similar results (see Appendix Table B8).

Table 5: The Impact of the NRPS on Transfers from Adult Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any Transfer		Transfer		Any Net Transfer		Net Transfer	
Treat × Post	-0.073**	-0.078**	-91.5*	-103.6*	-0.075**	-0.081**	-93.3*	-107.9*
	(0.036)	(0.037)	(54.7)	(55.8)	(0.037)	(0.038)	(54.7)	(55.7)
Female		0.177***		-16.9		0.177***		-1.8
		(0.016)		(38.5)		(0.015)		(37.3)
Age		0.006***		-5.6**		0.006***		-6.0**
		(0.001)		(2.7)		(0.001)		(2.6)
Schooling Years		0.009***		34.7***		0.009***		32.5***
		(0.002)		(5.1)		(0.002)		(4.9)
Number of Siblings		0.014**		-35.7***		0.010		-37.6***
		(0.006)		(10.9)		(0.006)		(10.4)
Number of Children		0.003		9.2*		0.001		6.7
		(0.003)		(5.3)		(0.003)		(5.4)
Parents' Schooling Yrs		0.001		-1.5		0.002		0.4
		(0.002)		(3.3)		(0.002)		(3.2)
Parents' Age		0.001		76.1**		-0.001		68.3**
		(0.016)		(34.6)		(0.016)		(32.9)
Both Parents Alive		-0.004		6.4		-0.001		4.6
		(0.008)		(22.0)		(0.009)		(21.8)
Control T0 Mean	0.418	0.425	369.6	372.9	0.415	0.421	352.7	355.5
Observations	10,088	9,766	10,088	9,766	10,088	9,766	10,088	9,766
R-squared	0.139	0.178	0.089	0.109	0.129	0.166	0.081	0.099

All columns use OLS regressions with child-year observations from the CHARLS 2011 and 2013. Columns (1)–(4) examine upward transfers from adult children, and columns (5)–(8) examine *net* upward transfers (upward minus downward transfers). The dependent variables (DVs) in columns (1)–(2) and (5)–(6) are an indicator for any (net) transfers: whether a child provides positive amount of (net) transfers. The DVs in remaining columns are the amount of (net) transfers. All regressions control for county fixed effects and province-year fixed effects. *Control T0 Mean* refers to the mean of the DV in the control group at baseline. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Table 6: Impact of the NRPS Availability on Transfers from Male/Female Children

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Transfer		Transfer Wins. 1%		Transfer Wins. 5%	
Transfer from ...	daughter	son	daughter	son	daughter	son
$\hat{\beta}$ (Treat×Post)	-0.052	-0.101***	-20.3	-185.2**	-14.5	-140.4***
	(0.054)	(0.032)	(75.9)	(74.4)	(44.9)	(46.2)
Observations	4,690	5,076	4,690	5,076	4,690	5,076
R-squared	0.205	0.166	0.155	0.128	0.203	0.164
Control T0 Mean	0.489	0.365	347.6	397.0	314.5	312.6
Wald Test: $\hat{\beta}^{daughter} = \hat{\beta}^{son}$						
χ^2	1.173		2.829		4.976	
p-value	0.279		0.093		0.026	

Note: All columns use simple OLS regressions. The dependent variables are an indicator for positive transfers, the amount of transfers winsorized at the top 1 percentile and 5 percentiles. Control variables include county and province-year fixed effects, and all individual characteristics as listed in even columns of Table 5. *Control T0 Mean* refers to the mean of the DV in the control group at baseline. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Next, in Table 6, we present the estimated effect of the NRPS on transfers provided by adult daughters and sons separately. For robustness, we look at three outcome variables: an indicator for any upward transfers, the amount of transfers winsorized at the top 1 percentile, and transfers winsorized at the top 5 percentiles. We find all coefficients are negative in sign, but only statistically significant for sons.

The magnitude of the crowd-out effect is also stronger for sons than for daughters. When using the 1-percentile winsorized transfers, we find that adult sons reduce transfers by about 190 RMB, while adult daughters reduce transfers by only 20 RMB. Wald tests suggest the gender difference in the impact of pension access on the amount of transfers is significant at the 10% level.

According to the model prediction that $\Delta T^g = -\tau^g \Delta_E$, the gender difference in the impact of pension access on upward transfers ($\Delta T^m < \Delta T^f$) is consistent with adult daughters in rural China being more altruistic toward elderly parents, i.e., $\tau^f < \tau^m$. Based on the NRPS policy, we can further derive an approximate estimation for τ^g: $\tau^f = 0.02$ and $\tau^m = 0.16$.[29] Using the transfer data, we can also estimate σ^g, the share of a child's income transferred to the parent. As Appendix Table B10 shows, both adult daughters and sons in rural China transfer about 1% of their annual income to parents. More specifically, we have $\sigma^f = \sigma^m = 0.011$.

Transfers Received by Elderly Parents Considering that a parent can have multiple children and transfers from different children may respond differently to pensions, we also study how the NRPS influences the total transfers received by a parent. If both parents are alive, we only observe transfers received by the couple together. In this case, we divide transfers by two and take each parent as an observation. Similarly, we look at the following proxies for old-age support: an indicator for receiving any (net) transfers and the amount of (net) transfers received. Each proxy corresponds to a column in Table 7. Results show that the NRPS reduces both the probability and the amount of (net) transfers that parents receive, but the impact on the probability of receiving any transfers is not statistically significant. On average, with access to the pension program, the amount of net transfers received by elderly parents decreases by more than 300 RMB.

As a placebo test, we also show the DID results for transfers received by parents aged below 60. Because access to the NRPS does not bring an instant increase in wealth for the below-60 age group (suppose they can not borrow from the future), we should not observe a negative effect of the NRPS on transfers received by them. Indeed, results in Appendix Table B9 show that the NRPS does not have a significant impact on transfers received by these parents.

[29] The windfall shock (Δ_E) brought by the NRPS is at least and most likely equal to 660 RMB per year for one parent. In our sample, adult children on average have 1.7 parents alive. Hence, we assume that the total windfall shock is 1,122 RMB for the parents of an adult child, and we approximate τ^g for female/male children as $\tau^f = 20/1,122 \approx 0.02$ and $\tau^m = 185/1,122 \approx 0.16$.

Table 7: The Impact of the NRPS on Transfers Received by Parents

	(1) Any Transfer	(2) Any Net Transfer	(3) Transfer	(4) Net Transfer
Treat × Post	-0.036	-0.074*	-214.3*	-335.0***
	(0.041)	(0.043)	(118.3)	(124.3)
Observations	5,616	5,616	5,616	5,616
R-squared	0.246	0.231	0.153	0.126
Control T0 Mean	0.325	0.309	942.4	803.9

Note: All columns use simple OLS regressions. The dependent variables in columns (1)–(4) are respectively, an indicator for receiving any transfers, an indicator for any net transfers, the amount of transfers and the amount of net transfers. Control variables include county and province-year fixed effects, individual age, schooling years, gender, whether the spouse is alive, the number of children and male children, and the average age of children. *Control T0 Mean* refers to the mean of the DV in the control group at baseline. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Because we can not directly test the pretrends of old-age support for the DID strategy, for robustness, we further employ the regression discontinuity design to test the causal impact of the NRPS on old-age support. As mentioned, participants in the pension program older than 60 receive pensions right away, while those younger than 60 still must pay premiums until they reach age 60. This policy creates a discontinuous access to pension payments around the threshold age, and we exploit the discontinuity to estimate the effect of pension payments on transfers. As results in Appendix Section B.2 show, transfers received by parents (especially the amount of transfers) display a significant drop at the cutoff age, suggesting that pension payments do decrease upward transfers.

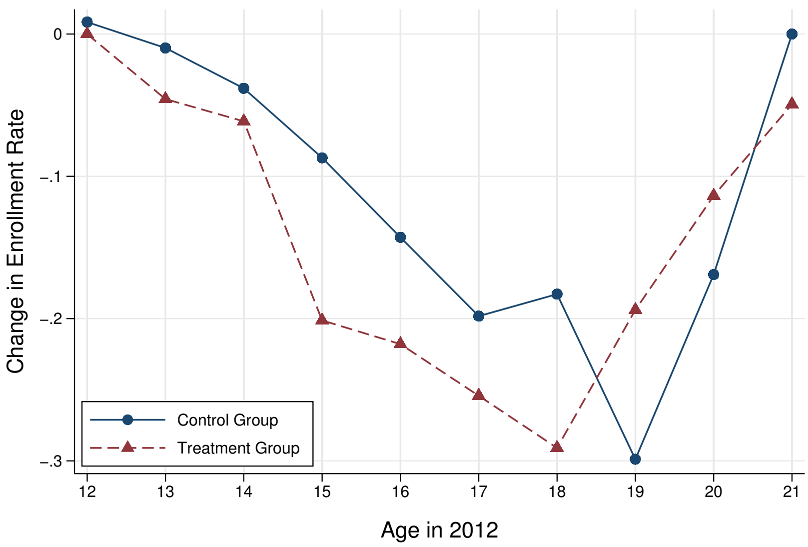
4.3 Child Investment

A pension program affects two decisions of working-age parents simultaneously: transfers to their parents in old age and investment in their children. Next, we examine the impact of the NRPS on child investment, using a DID approach and the CFPS data.

Graphical Patterns As the DID strategy compares the treatment-control difference in changes between the two waves, we plot the changes in the average enrollment rate by the treatment status in Figure 6. For each age cohort, we calculate the change in the enrollment rate from 2010 to 2012, separately for the treatment group and control group. A zero change means that the enrollment rate stays the same in the two waves. A negative change implies that there have been dropouts: some children who attend school in 2010 have dropped out by 2012.

We find that for children aged 15 to 18 in 2012, the drop-out rate is higher in the treatment group than in the control group. Typically, students complete 9-year compulsory education at around age 15 and graduate from high schools at around age 18. Therefore, the pattern suggests that access to pensions induces more children to drop out after completing compulsory or high-school education. For the control group, the drop-out rate reaches the peak at age 19. For the treatment group, the peak arrives at age 18, suggesting that children in treated counties stop education earlier. After the peak, the drop-out rate shrinks, because the baseline enrollment rate is already low – many students have dropped out in 2010.

Figure 6: Enrollment Rate by Cohort and Treatment



Note: The figure shows the change in enrollment rate from 2010 to 2012 for each age cohort, in either the control group or treatment group. A negative change in enrollment rate means a positive dropout rate, i.e., some children previously enrolled in schools/colleges drop out by 2012. Figure B4 plots the change in enrollment rate by gender.

Main Results We use the DID specification in Equation (11) to estimate the intention-to-treat effects of pension availability on child investment. Note that the CFPS data allows us to control for county-level characteristics in 2010, 2012, and earlier years.

We first examine the impact of the NRPS on enrollment status of children, separately for daughters and sons. Table 8 presents the results, with an indicator for enrollment as the dependent variable. In columns (1)–(2), we include only county and province-year fixed effects. In columns (3)–(4), we include basic individual controls (age, parents' age and education). In columns (5)–(6), we also control for contemporary trends and the pretrends of county-level characteristics from 2005 to 2009: log(GDP), log(population), log(government revenue) and log(government expenditure). Appendix Figure B5 shows that the main results are similar qualitatively and quantitatively when we only control for pretrends or contemporary trends, or use different periods of pretrends.

Table 8: The Impact of the NRPS on Enrollment by Child Gender

	(1)	(2)	(3)	(4)	(5)	(6)
Enrollment of ...	daughter	son	daughter	son	daughter	son
$\hat{\beta}$ (Treat × Post)	-0.047**	0.026	-0.049**	0.026	-0.055***	0.053**
	(0.021)	(0.018)	(0.021)	(0.018)	(0.019)	(0.024)
Observations	4,618	4,810	4,614	4,802	4,491	4,684
R-squared	0.069	0.078	0.466	0.440	0.464	0.442
County & Province-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	No	Yes	Yes	Yes	Yes
County Trends	No	No	No	No	Yes	Yes
Control T0 Mean	0.678	0.720	0.679	0.720	0.679	0.720
Wald Test: $\hat{\beta}^{daughter} = \hat{\beta}^{son}$						
χ^2	5.18		4.97		12.79	
p-value	0.023		0.026		0.000	

Note: All columns use OLS regression. The dependent variable is an indicator for school/university attendance. Individual controls include the age, parents' average age and average schooling years. County-level controls include log(GDP), log(population), log(government revenue), and log(government expenditure) in 2012, 2010, and five lagged years (2009-2005). *Control T0 Mean* means the mean of the DV in the control group at baseline (in 2010). Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

We find that parents' access to the NRPS significantly lowers the enrollment rate of their daughters and increases the enrollment rate of their sons. According to results with full controls in columns (5)–(6), the NRPS reduces daughters' enrollment by 5.5 percentage points – 8% of the baseline enrollment rate in the control group. The NRPS, nevertheless, increases sons' enrollment rate by 5.3 percentage points – 7% of the control-group baseline level. We also find that the gender differences in the effects of pension access on enrollment (null hypothesis: $\hat{\beta}^{daughter} = \hat{\beta}^{son}$) are statistically significant at the 5% or 1% level.

Table 9: The Impact of the NRPS on Educational Expenditures by Child Gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw Expenditures		Expenditures Wins. 1%		Expenditures Wins. 5%	
Expenditures for ...	daughter	son	daughter	son	daughter	son
$\hat{\beta}$ (Treat × Post)	-287.9*	616.5**	-187.6	597.4***	-130.1	456.8***
	(159.0)	(260.0)	(159.9)	(214.3)	(117.5)	(164.3)
Observations	4,491	4,684	4,491	4,684	4,491	4,684
R-squared	0.143	0.123	0.150	0.142	0.160	0.156
Control T0 Mean	1140	1231	1138	1165	1044	1078
Wald Test: $\hat{\beta}^{daughter} = \hat{\beta}^{son}$						
χ^2	12.95		14.35		13.27	
p-value	0.000		0.000		0.000	

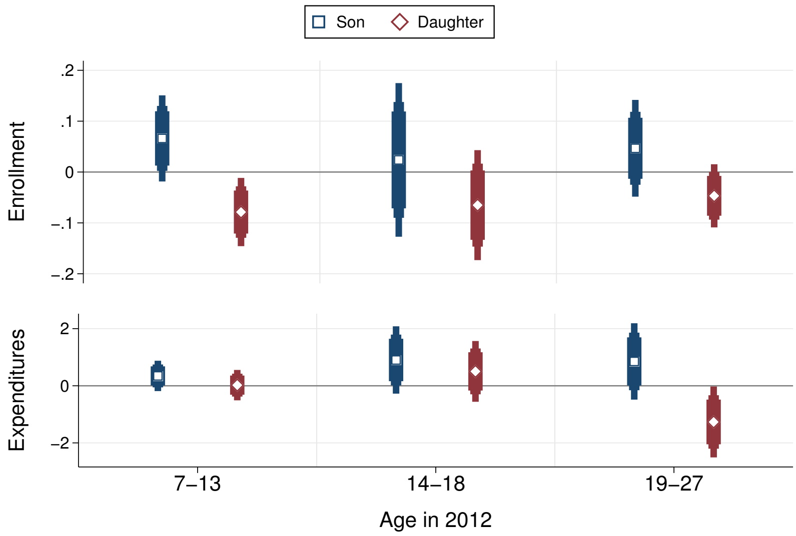
Note: All columns use OLS regression. We use three dependent variables (DV): the raw amount of expenditures in columns (1)–(2), the expenditures winsorized at the top 1 percentile in columns (3)–(4), and expenditures winsorized at the top 5 percentiles in columns (5)–(6). All columns control for county and province-year fixed effects, individual-level and county-level controls as specified in Table 8. *Control T0 Mean* means the mean of the DV in the control group at baseline (in 2010). Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Next, we analyze the impact of the NRPS on educational expenditures in Table 9. For robustness, we use three outcome variables: the raw amount of expenditures, expenditures winsorized at the top 1 percentile and 5 percentiles. We control for all fixed effects, and county-level and individual-level controls as specified above. We find a similar pattern for expenditures as for enrollment: access to the pension program raises parents' educational investment in sons, but lowers their investment in daughters. Using the 1%-winsorized expenditures, we find that the NRPS increases the expenditures for sons by about 600 RMB – around 50% of the control group baseline level, but decreases the expenditures for daughters by around 185 RMB – 16% of the control-group baseline level. Wald tests suggest that the effects are significantly different for daughters and sons.

As predicted by the theoretical model, the impact of pension availability on child investment (ΔH_2^g) is ambiguous in sign, because of two opposing effects. In the circumstance when σ^g is small enough, the sign depends on the degree of upward altruism or the responsiveness of transfers to parents' wealth (τ^g). If τ^g is small or large enough ($\tau^g < \tau_1$ or $\tau^g > \tau_2$), ΔH_2^g is negative; otherwise, ΔH_2^g is positive. Given that the gender difference in the impact of the NRPS on upward transfers is consistent with $\tau^f < \tau^m$, the gender difference in the impact of the NRPS on child investment is consistent with $\tau^f < \tau_1 < \tau^m < \tau_2$. Overall, gender differences in the simultaneous effects of the NRPS on old-age support and child investment in rural China are consistent with the daughters being more altruistic toward parents than sons.

Results by Cohort As Figure 6 implies, the impact of pension access on educational investment can vary with age. To formally analyze this dimension of heterogeneity, we divide children into three age groups: (i) age 7 to 13 in 2012 (or 5–11 in 2010), approximately corresponding to the period of compulsory education, (ii) age 14 to 18 in 2012, typically when students transit from compulsory education to high school, (iii) age 19 to 27 in 2012, the period of higher education. We then estimate the impact of the NRPS on educational investment separately for each age group by gender.

Figure 7: The Impact of the NRPS on Educational Investment by Age Group



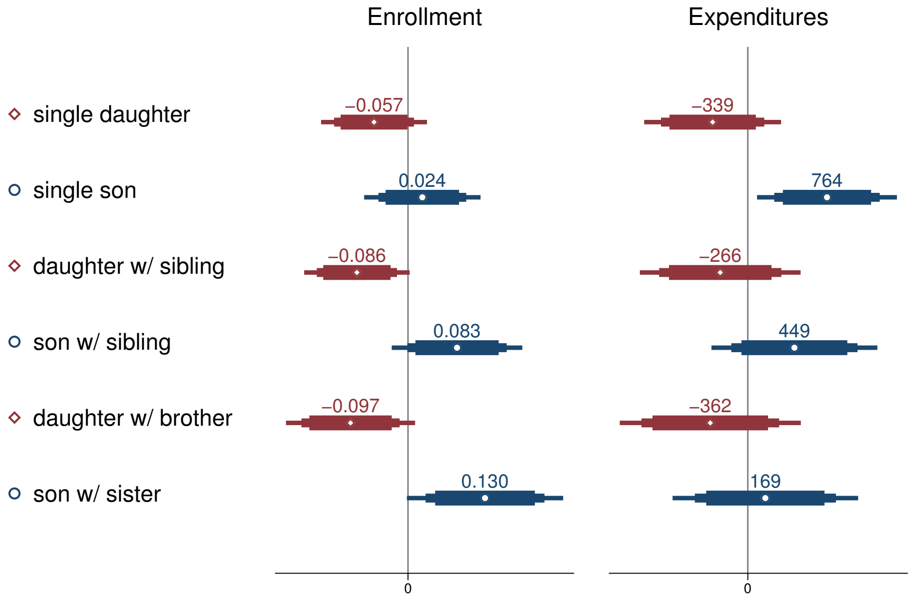
Note: Each point in the graph corresponds to the estimated coefficient of the interaction term Treat×Post with 99%, 95% and 90% confidence intervals, for a certain cohort and gender. The dependent variables are an indicator of enrollment and expenditures in thousand RMB (winsorized at the top 1 percentile). The regression specification is the same as in Table 9.

Figure 7 plots the estimated coefficients of Treat × Post with 99%, 95%, and 90% confidence intervals. Regarding enrollment, we find that coefficients are overall positive for sons and negative for daughters, irrespective of the age group. The positive impact on sons is only significant for the 7-13 group, while the negative impact on daughters is generally significant. Regarding expenditures, we find sons of all age groups receive significantly more expenditures due to the NRPS. For daughters, only the 19-27 age group receives significantly lower expenditures from parents, suggesting a crowd-out effect of the pension program on daughters' higher education.

Results by Sibling Structure We next examine how the impact of pension access on education investment varies with the sibling structure of children. We distinguish three types of children: (i) without siblings, i.e., single daughters and sons, (ii) with any sibling(s), and (iii) with opposite-gender siblings, i.e., daughters with brothers and sons with sisters.[30] The sibling structure implies potential differences in parental altruism toward the child and the budget constraint that parents face.

[30]In the period from early 1980s to 2015, most families in China are enforced to have only one child. However, in most rural districts, the *one-and-half* policy was always been in place, which allowed parents with a single daughter to have a second child. Given that, families with a female firstborn may decide to have a second child, which is more likely if they have a son preference.

Figure 8: The Impact of on the NRPS on Educational Investment by Sibling Structure



Note: The figure plots the coefficients of Treat × Post for different types of children with 90%, 95% and 99% confidence intervals. The left panel presents the impact on enrollment, while the right panel presents the impact on expenditures (winsorized at the top 1 percentile). For single daughters and sons, we use the same specification as above. For children with siblings, we control for family fixed effects and cluster the standard errors at the family level.

Figure 8 plots the estimated coefficients of Treat×Post by the child's gender and sibling structure, with 99%, 95%, and 90% confidence intervals. In terms of enrollment, we find that the gender-specific impact of pension access is relatively weak for single daughters/sons. However, for children with opposite-gender siblings, the gender-specific impact is strong and significant. As the NRPS becomes available, daughters with brother(s) are about 10 percentage points more likely to drop out of school, while the enrollment rate of sons with sister(s) increases by 13 percentage points. The finding suggests potential resource reallocation from daughters to sons within a family, probably because parents with both daughters and sons are more altruistic toward sons.

For educational expenditures, we find a significant gender difference in the impact of the NRPS even for single daughters and sons, suggesting that the gender difference is not only driven by resource reallocation within families. For parents with one child, the gender of the child matters for the direction of change in child investment. As implied by the model, the potential reason is that daughters feel more altruistic toward parents. For children with siblings, the coefficients are not significant and the magnitude also shrinks for sons, possibly because the average amount of investment per child is lower for families with multiple children.

5 Conclusion

The intergenerational support system – parents invest in children and children support elderly parents – plays a crucial role in human capital accumulation and old-age well-being in traditional societies. Due to kinship traditions and social norms, the support system can exhibit salient gender differences. In such traditional societies, the introduction of public pension programs helps provide better insurance for the elderly population, but may unexpectedly hamper the private support system between generations.

This paper examines the simultaneous effects of new pension programs on old-age support and child investment in families, with a special focus on the gender differences in such effects. We first present a conceptual framework to help clarify the roles of different generations and multiple incentives for transfers, and disclose the channels through which pensions can influence intergenerational transfers. The model predicts that a new pension program crowds out upward transfers from adult children to elderly parents, and the magnitude of the crowd-out effect decreases with children's altruism toward parents. However, the impact of pension availability on child investment is ambiguous in sign, because of two opposing effects. Parents become wealthier as their transfers to grandparents decrease, but meanwhile, parents have a lower incentive to invest in the child as they have access to old-age pensions now.

Empirically, we utilize the recent introduction of a large-scale pension program in rural China to estimate the impact of pension access on old-age support and human capital investment in children. We find evidence suggesting that the pension program alters cultural norms about old-age support. Parents become more likely to rely on pensions rather than children for economic support in old age. Pensions also crowd out transfers received by elderly parents from adult children, especially adult sons.

At the same time, access to pensions affects parents' educational investment in children, but differently for sons and daughters. Before pensions are introduced, parents tend to spend more money for the education of sons than daughters, consistent with the widely-documented son preference in rural China. When pensions become available, sons receive even more investment from parents, while daughters' enrollment rate and received expenditures decrease – suggesting a even greater gender gap in human capital accumulation.

Taken together, our results suggest that public pension programs can fundamentally alter the traditional support system between generations. The positive effect of pension payments on the old-age generation can be partly offset by the decrease in transfers from adult children, as implied by the crowd-out theory (Barro, 1974; Becker, 1974). Moreover, as pensions replace the role of children in providing old-age support, parents may also reduce investment in the child, especially if the investment is driven by the prospect of future support from the child. In view of such unintended effects, when introducing public pensions, governments may need to implement policies to reduce school drop-outs and provide financial support for students with limited parental investment.

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A Details of the Model

To simplify notations, we drop the gender indicator in this section. As derived in Section 2, the impact of pension access on child investment is:

$$\Delta H_2 = \frac{\gamma(1-\tau)}{(1+\beta+\gamma)[R(1-\tau)-\sigma w]^2}\left\{\underbrace{R\tau[R(1-\tau)-\sigma w]\Delta_E - \sigma w[(1-\sigma)W_1+\tau E_0]\Delta_R}_{\equiv f(\tau)}\right\}$$

Since $\tau \in (0,1)$, the sign of ΔH_2 depends on the sign of $f(\tau)$. We can rewrite $f(\tau)$ as follows:

$$f(\tau) = \underbrace{-R^2\Delta_E}_{\equiv a}\tau^2 + \underbrace{[R^2\Delta_E - \sigma w(R\Delta_E + E_0\Delta_R)]}_{\equiv b}\tau \underbrace{-\sigma(1-\sigma)wW_1\Delta_R}_{\equiv c}$$

As a secondary-order function of τ, and with $f_{\tau=0} < 0, f_{\tau=1} < 0$, the sign of $f(\tau)$ has the following scenarios:

- If $b^2 - 4ac \leq 0$, we have $\forall\tau, f(\tau) \leq 0$
- If $b^2 - 4ac > 0$, $f(\tau) = 0$ has two solutions: τ_1, τ_2
  - If $b < 0$, $f(\tau)$ monotonically decreases with $\tau \in (0,1)$, and $\forall\tau \in (0,1)$, we have $f(\tau) < 0$
  - If $b > 0$, we have $0 < \tau_1 < \tau_2 < 1$, and
    * $\forall\tau \in (0,\tau_1) \cup (\tau_2, 1)$, we have $f(\tau) < 0$
    * $\forall\tau \in (\tau_1,\tau_2)$, we have $f(\tau) > 0$

In summary, the sign of $f(\tau)$ can be both positive and negative in the domain of $(0,1)$ only if $b^2 - 4ac > 0$ and $b > 0$; in other words, only if $b > 2\sqrt{ac}$:

$$b > 2\sqrt{ac} \iff R^2\Delta_E > \underbrace{\sigma w(R\Delta_E + E_0\Delta_R) + 2R\sqrt{\sigma(1-\sigma)wW_1\Delta_R\Delta_E}}_{\equiv l(\sigma)}$$

Otherwise, if $R^2\Delta_E < l(\sigma)$, $f(\tau)$ is negative for any $\tau \in (0,1)$.
Assume that $\sigma < 1/2$, i.e., the child does not transfer above half of the income to the parent. Under the assumption, it is obvious to see that $l(\sigma)$ increases with σ. Note that $l_{\sigma=0} = 0$, and $l_{\sigma=.5} = \frac{w(R\Delta_E + E\Delta_R)}{2} + R\sqrt{wW_1\Delta_R\Delta_E}$.

- If $l_{\sigma=.5} < R^2\Delta_E$, we have $\forall\sigma \in (0,1/2), R^2\Delta_E > l(\sigma)$
- If $l_{\sigma=.5} > R^2\Delta_E$, then $\exists\hat{\sigma} \in (0,1/2)$, such that $\forall\sigma \in (0,\hat{\sigma}), R^2\Delta_E > l(\sigma)$

By assuming that σ is small enough and close to zero – estimation using the empirical sample shows that σ is only about 0.01, we can ensure that $b > 2\sqrt{ac}$. That means there exist $\tau_1, \tau_2 \in (0,1)$ as specified below

$$\tau_1 = \frac{-b - \sqrt{b^2-4ac}}{2a} \qquad \tau_2 = \frac{-b + \sqrt{b^2-4ac}}{2a}$$

such that $\forall\tau \in (0,\tau_1) \cup (\tau_2,1)$, $f(\tau) < 0$, and $\forall\tau \in (\tau_1,\tau_2)$, $f(\tau) > 0$.
Moreover, as noted in Section 2, the optimal child investment and savings are as follows:

$$H_2^* = \frac{R\gamma(1-\tau)[(1-\sigma)W_1 + \tau E_0]}{(1+\beta+\gamma)[R(1-\tau)-\sigma w]} \qquad S_1^* = \frac{[\beta R(1-\tau) - (\beta+\gamma)\sigma w][(1-\sigma)W_1 + \tau E_0]}{(1+\beta+\gamma)[R(1-\tau)-\sigma w]}$$

To ensure that H_2^* and S_1^* are both positive, we impose an additional assumption: $R\beta(1-\tau) > (\beta+\gamma)\sigma w$, i.e., $\tau < 1 - \frac{(\beta+\gamma)\sigma w}{R\beta}$. Suppose that $\tau_1 = 1 - \frac{R^2\Delta_E + \sigma w(R\Delta_E + E\Delta_R) + \sqrt{b^2-4ac}}{2R^2\Delta_E} < 1 - \frac{(\beta+\gamma)\sigma w}{R\beta} < 1$. Then we have that

- When $0 < \tau < \tau_1,\ f(\tau) < 0$ and $\Delta H_2 < 0$
- When $\tau_1 < \tau < \min\{\tau_2, 1 - \frac{(\beta+\gamma)\sigma w}{R\beta}\},\ f(\tau) > 0$ and $\Delta H_2 > 0$
- When $\tau_2 < \tau < \max\{\tau_2, 1 - \frac{(\beta+\gamma)\sigma w}{R\beta}\},\ f(\tau) < 0$ and $\Delta H_2 < 0$

B Additional Results

B.1 Main Results Using Alternative Definitions of Treatment

In this section, we present main empirical results using two alternative definitions of the NRPS availability. First, we lower the threshold from five participants to three participants, i.e., the NRPS is defined as available if *at least three* subjects report to have enrolled in the program. Using this relatively loose definition, more counties will be categorized as covered by the NRPS in both waves, and accordingly, the sample size of treatment group and control group are different. We refer to the treatment status using this definition as "Treatment-Loose". Second, we use a more strict definition. Besides requiring at least five participants, we impose an extra condition – *at least 5 percent* of subjects report to have enrolled in the program. Similarly, it also changes the relative sample size of the treatment group. We call the treatment status defined in this way as "Treatment-Strict".

Table B1: The Impact of the NRPS on the Expected Source of Old-age Support

	(1)	(2)	(3)	(4)	(5)	(6)
	All parents		Parents aged < 60		Parents aged ≥ 60	
Rely on ... for old-age support	Children	Pensions	Children	Pensions	Children	Pensions
Panel A: Using "Treatmen-Loose"						
Treat × Post	-0.079**	0.073***	-0.063*	0.041	-0.089**	0.094***
	(0.031)	(0.024)	(0.036)	(0.026)	(0.038)	(0.032)
Observations	10,844	10,844	5,228	5,228	5,616	5,616
R-squared	0.079	0.087	0.097	0.111	0.098	0.113
Panel B: Using "Treatment-Strict"						
Treat × Post	-0.074**	0.076***	-0.067**	0.051**	-0.079**	0.094***
	(0.030)	(0.022)	(0.033)	(0.023)	(0.037)	(0.030)
Observations	10,844	10,844	5,228	5,228	5,616	5,616
R-squared	0.079	0.088	0.097	0.112	0.098	0.113

Note: All regressions control for county FEs, province-year FEs, individual age, schooling years, if the spouse is alive, number of children and male children, and average age of children. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Table B2: The Impact of the NRPS on Transfers from Adult Children

	(1) Any Transfer	(2) Transfer	(3) Any Net Transfer	(4) Net Transfer
Panel A: Using "Treatment-Loose"				
Treat × Post	-0.081*	-96.3*	-0.086**	-103.0*
	(0.041)	(50.3)	(0.043)	(52.6)
Observations	9,766	9,766	9,766	9,766
R-squared	0.178	0.109	0.166	0.099
Panel B: Using "Treatment-Strict"				
Treat × Post	-0.075*	-106.7*	-0.078**	-110.9*
	(0.038)	(56.0)	(0.039)	(56.0)
Observations	9,766	9,766	9,766	9,766
R-squared	0.178	0.109	0.166	0.099

Note: All regressions control for county FEs, province-year FEs, child characteristics (gender, age, schooling years and number of siblings), and parents' characteristics (age, schooling years & if both alive). Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Table B3: The Impact of the NRPS on Educational Investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Enrollment				Expenditure			
	Treatmen-Loose		Treatmen-Strict		Treatmen-Loose		Treatmen-Strict	
	daughter	son	daughter	son	daughter	son	daughter	son
Treat × Post	-0.047***	0.049**	-0.067***	0.032	-94.5	472.3*	-363.1**	665.2**
	(0.016)	(0.024)	(0.021)	(0.021)	(195.3)	(246.1)	(168.2)	(281.5)
Observations	4,513	4,702	4,039	4,202	4,513	4,702	4,039	4,202
R-squared	0.464	0.443	0.463	0.446	0.144	0.123	0.141	0.122

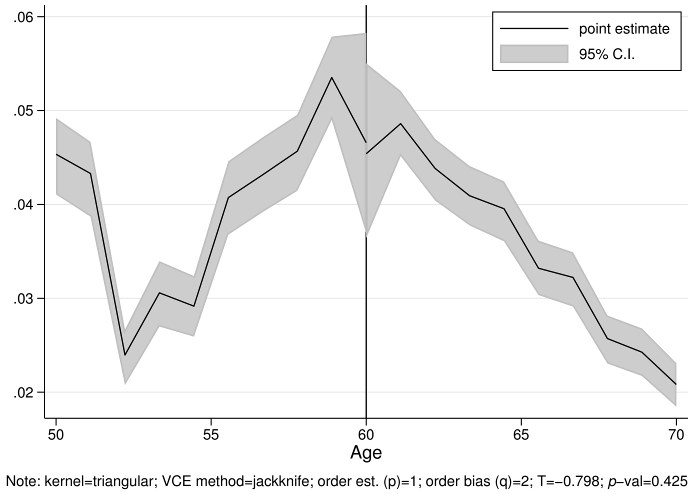
Note: All regressions control for county FEs, province-year FEs, child's age, parents' average age and schooling years, as well as county-level (pre-)trends (including log GDP, population, government revenues and expenditures). Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

B.2 The Impact of the NRPS on Transfers: Regression Discontinuity Design

As mentioned, the NRPS creates a discontinuous access to pension payments: only participants aged above 60 receive pensions. This *windfall shock* of pension payments, as predicted by the model, may crowd out transfers from adult children to elderly parents. Therefore, we expect to see a discontinuous drop of transfers at the cutoff age. In Figure 5, we have already shown that age 60 is the *de facto* threshold for pension payments, but the participation rate in the program is lower than 100%. We therefore use the fuzzy regression discontinuity (FRD) design to estimate the treatment effect of pension payments on transfers.

To estimate the impact of pension incomes on old-age support, we focus on the sample of parents in 2013, when the NRPS is available in all counties. We first check if age, the running variable, is continuous around the cutoff age. Using the manipulation test proposed by Cattaneo et al. (2018), we find no evidence of a discontinuity in density around age 60 (see Figure B1).

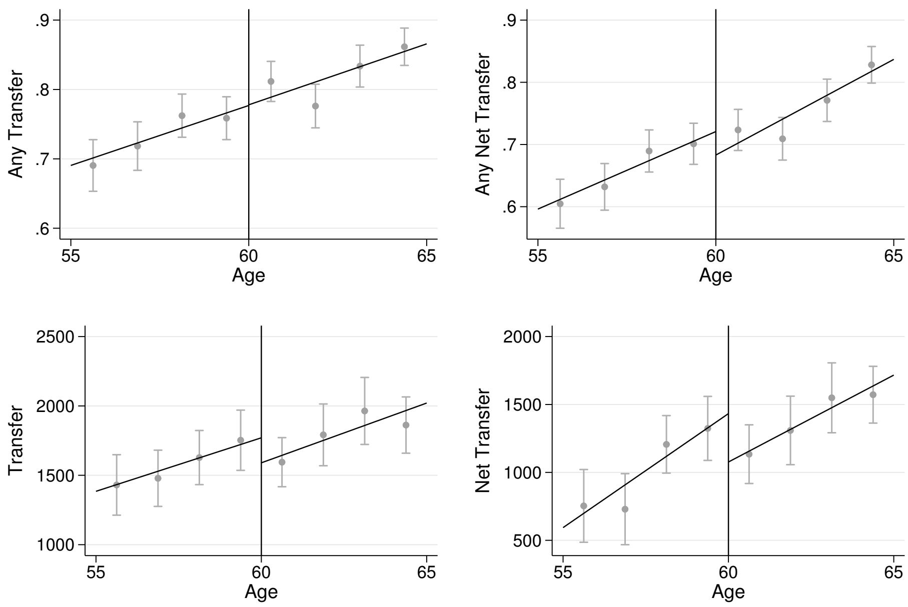
Figure B1: Manipulation Test of the Running Variable (Age)



Note: Use the manipulation test of Cattaneo et al. (2018). The testing results are robust to the choice of kernel functions, order of local-polynomial for estimation (p), and order of local-polynomial for bias correction (q).

Next, we examine whether the outcome variables exhibit a discontinuous change around the cutoff – the reduced form. Figure B2 plots the likelihood and amount of (net) transfers around the age 60, with 90% confidence intervals. We find that the likelihood of transfers seems continuous at age 60, while the amount of (net) transfers shows a downward jump at the cutoff.

Figure B2: Likelihood and Amount of Transfers around the Cutoff Age (Reduced Form)



Note: RD plot with 90% confidence intervals. Dependent variables in four graphs are respectively the indicator of receiving any transfers, any net transfers, the amount of transfers and net transfers.

Table B4: The Impact of Pension Payments on Upward Transfers: Robust FRD Estimates

	Any Transfer	Any Net Transfer	Transfer	Net Transfer
Kernel Function: Triangular				
Bandwidth (h)	3.3	3.1	5.2	4.9
Eff. Observations (left)	1297	1236	1947	1851
Eff. Observations (right)	1263	1212	1894	1799
First-stage Estimate	0.115	0.103	0.234	0.216
Robust p-Value	0.006***	0.014**	0.000***	0.000***
Treatment Effect Estimate	**0.198**	**-0.192**	**-1252.3**	**-1884.6**
Conventional S.E.	0.302	0.384	750	1001
Robust p-Value	0.413	0.543	0.027**	0.014**
Robust 95% CI	[-0.369, 0.898]	[-1.038 , 0.546]	[-3666, -226]	[-5180, -570]
Kernel Function: Epanechnikov				
Bandwidth (h)	3.1	3.1	4.3	4.2
Eff. Observations (left)	1198	1198	1696	1630
Eff. Observations (right)	1182	1182	1652	1605
First-stage Estimate	0.123	0.124	0.215	0.205
Robust p-Value	0.003***	0.002***	0.000***	0.000***
Treatment Effect Estimate	**0.242**	**-0.093**	**-1433.8**	**-2017.6**
Conventional S.E.	0.288	0.306	872	1101
Robust p-Value	0.312	0.697	0.030**	0.023**
Robust 95% CI	[-0.292, 0.915]	[-0.756 , 0.505]	[-4228, -221]	[-5473, -399]
Kernel Function: Uniform				
Bandwidth (h)	2.3	2.3	2.8	3.8
Eff. Observations (left)	941	941	1114	1483
Eff. Observations (right)	922	922	1098	1426
First-stage Estimate	0.109	0.032	0.154	0.234
Robust p-Value	0.016**	0.014**	0.001***	0.000***
Treatment Effect Estimate	**0.289**	**-0.060**	**-1380.6**	**-1882.4**
Conventional S.E.	0.357	0.376	1471	918
Robust p-Value	0.325	0.861	0.173	0.010***
Robust 95% CI	[-0.368 , 1.110]	[-0.835, 0.698]	[-5443, 978]	[-4787, -661]

Note: The bandwidth is chosen by a common MSE-optimal bandwidth selector, based on the *rdrobust* command in STATA. We present results respectively using the triangular, Epanechnikov and uniform kernel functions. In each panel, we show the chosen bandwidth, the effective number of observations on the left/right of the threshold, the first-stage point estimates (including the conventional standard errors and robust p-values), and the treatment effect estimates (including the conventional standard errors, robust p-values and 95% confidence intervals). We control for individual characteristics like gender, education level, whether the spouse is alive, the number of (male) children, children's average age, as well as county fixed effects. Standard errors are clustered at the county level. Significance level is based on the robust p-value. $*p < .1, **p < .05, ***p < .01$.

Robust Non-Parametric Estimation We present the non-parametric data-driven estimations of treatment effects in Table B4 based on the approach of Calonico et al. (2014) and Calonico et al. (2019). As mentioned, we use the FRD design, where age is the running variable and the pension-receiving dummy indicates the treatment status. We use local linear regression ($p = 1$), second-order local polynomial for bias correction, and the default MSE-optimal common bandwidth selector. For robustness, we present results using three different kernel functions: the triangular function, the Epanechnikov function and the uniform function. We control for gender, education level, whether the spouse is alive, the number of children and male children, and children's average age, as well as county fixed effects. We cluster standard errors at the county level.

In terms of the first stage, all specifications indicate that being older than age 60 increases the likelihood of receiving pensions (significant at the 5% or 1% level). For the likelihood of receiving any (net) transfers from children, the estimated results are not statistically significant. However, we find that pension payments reduce the amount of transfers – mostly significant at the 5% level. Compared to the DID results presented in Table 7, the FRD estimations show a similar pattern: access to pensions lowers the amount of transfers that elderly parents receive, but does not significantly change the likelihood of them receiving any positive amount of transfers. In Table B5, we manually set the bandwidth as 4, 6, 8, or 10, we find the FRD estimates generally decrease in magnitude as the bandwidth increases.

Table B5: Impact of Pension Payments on Transfers: FRD Estimates with Manually Set Bandwidths

	Any Transfer	Any Net Transfer	Transfer	Net Transfer
BW=10 (First-Stage Estimate: 0.382)				
Treatment Effect Estimate	**-0.039**	**-0.094**	**-319.4**	**-520.2**
Conventional S.E.	0.053	0.059	349.1	406.4
Robust p-Value	0.631	0.038**	0.036**	0.008***
BW=8 (First-Stage Estimate: 0.333)				
Treatment Effect Estimate	**-0.045**	**-0.131**	**-555.0**	**-905.2**
Conventional S.E.	0.068	0.076	438.3	515.4
Robust p-Value	0.920	0.085*	0.024**	0.008***
BW=6 (First-Stage Estimate: 0.265)				
Treatment Effect Estimate	**-0.042**	**-0.166**	**-1033.7**	**-1446.7**
Conventional S.E.	0.095	0.107	621.0	733.3
Robust p-Value	0.571	0.221	0.032**	0.018**
BW=4 (First-Stage Estimate: 0.162)				
Treatment Effect Estimate	**0.077**	**-0.164**	**-1939.0**	**-2521.8**
Conventional S.E.	0.190	0.210	1259.8	1508.8
Robust p-Value	0.357	0.272	0.052*	0.041**

Note: The table presents the FRD estimates of the impact of receiving pensions on upward transfers, for different choices of bandwidths. We present results using triangular kernel function; other kernel functions give similar results. For each panel of results, we show the first-stage estimates, treatment effect estimates, the conventional standard errors and robust p-values. We control for county fixed effects and individual characteristics like gender, schooling years and whether the spouse is alive. Standard errors are clustered at county level. Significance level is based on the robust p-value. $*p < .1, **p < .05, ***p < .01$.

Robustness and Placebo Test In Table B6, we test if individual control variables are continuous around age 60. For all the covariates – gender, schooling years, schooling years, indicator of alive spouse, number of children, number of male children, and the average age of children, we do not find a significant jump at the cutoff. In Table B7, we conduct a placebo test for counties without the NRPS in 2011. We find no evidence for discontinuous changes in the likelihood or amount of transfers around age 60.

Table B7: Placebo: Upward Transfers in Counties without the NRPS

	Any Transfer	Net Transfer	Transfer	Net Transfer
Kernel Function: Triangular				
Bandwidth (h)	4.93	6.03	6.33	5.76
Treatment Effect Estimate	-0.031	-0.009	42.55	53.20
Robust P-Value	0.461	0.754	0.762	0.731
Kernel Function: Epanechnikov				
Bandwidth (h)	4.33	5.14	6.07	5.37
Treatment Effect Estimate	-0.038	-0.015	37.99	49.98
Robust P-Value	0.386	0.697	0.788	0.718
Kernel Function: Uniform				
Bandwidth (h)	3.82	4.07	5.00	5.04
Treatment Effect Estimate	-0.048	-0.010	3.51	81.24
Robust P-Value	0.347	0.792	0.997	0.621

Note: the table presents the RD estimates of the impact of being aged above 60 on upward transfers, for counties not covered by the NRPS in 2011. We present results using triangular, Epanechnikov and uniform kernel functions. Bandwidth is chosen by the MSE-optimal bandwidth selector. For each estimation, we show the selected bandwidth, treatment effect estimate and the robust p-value.

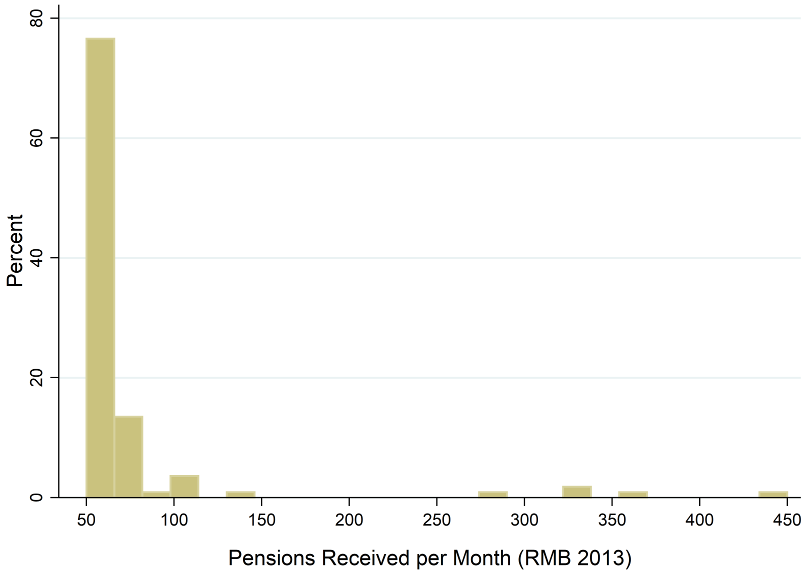
Table B6: Continuity of Covariates around the Cutoff Age

	Male	Schooling Years	Spouse Alive	N.Children	N.MaleChildren	Avg.Child Age
Kernel Function: Triangular						
Bandwidth (h)	4.217	4.920	5.814	4.091	4.151	4.791
RD Estimates	**0.012**	**-0.299**	**-0.007**	**0.069**	**0.019**	**0.193**
Robust P-Value	0.811	0.574	0.535	0.679	0.972	0.917
Kernel Function: Epanechnikov						
Bandwidth (h)	3.781	4.994	5.700	3.906	4.216	4.434
RD Estimates	**0.003**	**-0.322**	**-0.005**	**0.075**	**0.024**	**0.198**
Robust P-Value	0.977	0.483	0.615	0.619	0.946	0.902
Kernel Function: Uniform						
Bandwidth (h)	3.327	3.319	3.528	3.241	3.725	4.057
RD Estimates	**0.002**	**-0.137**	**-0.013**	**0.079**	**0.022**	**0.238**
Robust P-Value	0.917	0.952	0.499	0.592	0.993	0.773

Note: The table presents the robust RD estimates of the impact of being aged above 60 on different covariates, in order to test if the covariates are continuous around the cutoff age. The covariates include gender, schooling years, indicator for alive spouse, number of children, number of male children, and the average age of children. We present results using triangular, Epanechnikov and uniform kernel functions. We control for county fixed effects and cluster standard errors at the county level.

B.3 Additional Figures and Tables

Figure B3: Distribution of Monthly Pension Payment



Note: We use reported amount of pension payment in the CHARLS 2013. We look at counties with at least 10 non-missing reported values (in total 111 counties). Then we derive the mode of all reported amounts at the county level, and plot the distribution of county-level pension payment.

Table B8: The Impact of the NRPS on Upward Transfers (Excluding Co-resident Children)

	(1) Transfer > 0	(2) Transfer	(3) NetTransfer > 0	(4) NetTransfer
Treat × Post	-0.079**	-104.7*	-0.082**	-111.5*
	(0.038)	(57.4)	(0.039)	(58.6)
Observations	9,498	9,498	9,498	9,498
R-squared	0.174	0.112	0.161	0.099

Note: All results are from simple OLS regressions, controlling for county fixed effects and province-year fixed effects. The dependent variable (DV) in columns (1) and (3) is the dummy variable, which is equal to 1 if a child provides positive (net) upward transfers, and 0 otherwise. The DV in columns (2) and (4) is the amount of (net) upward transfers. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Table B9: The Impact of the NRPS on Transfers Received by Parents Aged below 60

	(1) Any Transfer	(2) Any Net Transfer	(3) Transfer	(4) Net Transfer
Treat × Post	-0.027	0.009	-294.471	-58.919
	(0.052)	(0.041)	(180.459)	(207.551)
Observations	4,026	4,026	4,026	4,026
R-squared	0.296	0.257	0.186	0.122
Control T0 Mean	0.326	0.305	550.8	314.5

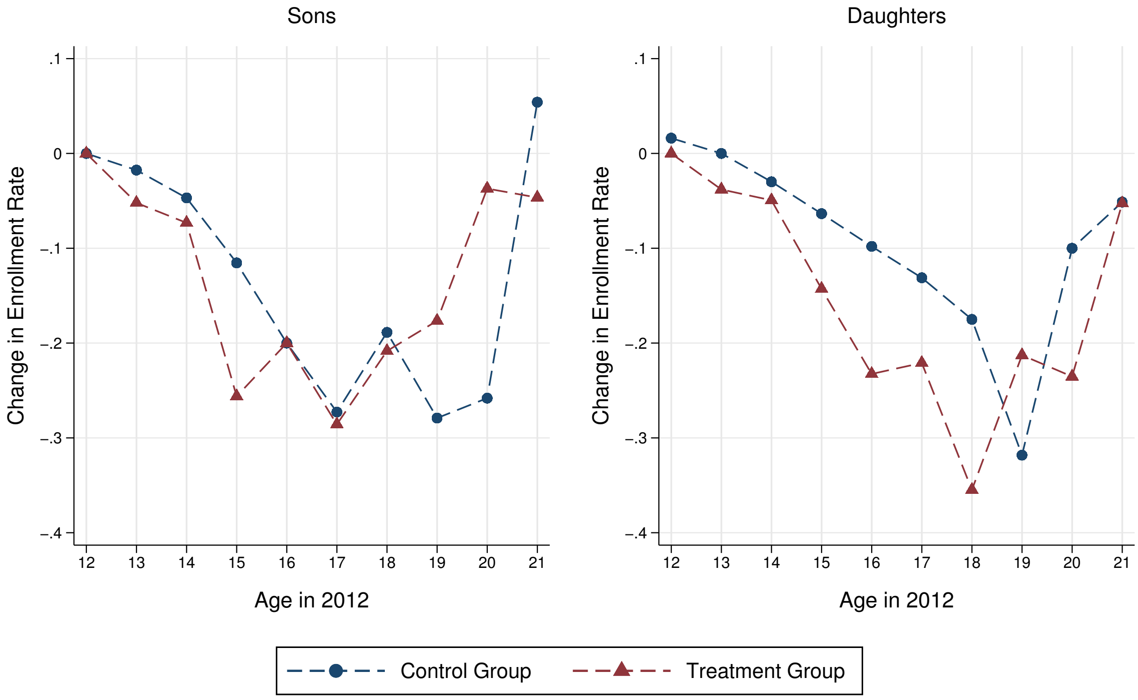
Note: All columns use simple OLS regressions. The dependent variables in columns (1)–(4) are respectively, the indicator of receiving any transfers, the indicator of any net transfers, the amount of transfers and the amount of net transfers. Control variables include county and province-year fixed effects, individual age, schooling years, gender, whether the spouse is alive, the number of children and male children, and the average age of children. *Control T0 Mean* refers to the mean of the DV in the control group at baseline. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Table B10: The Share of the Child's Income Provided to Elderly Parents

	(1) Female	(2) Male	(3) Female	(4) Male
Child Income	0.012***	0.012***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls	No	No	Yes	Yes
Observations	2,153	1,893	2,149	1,847
R-squared	0.250	0.193	0.287	0.229

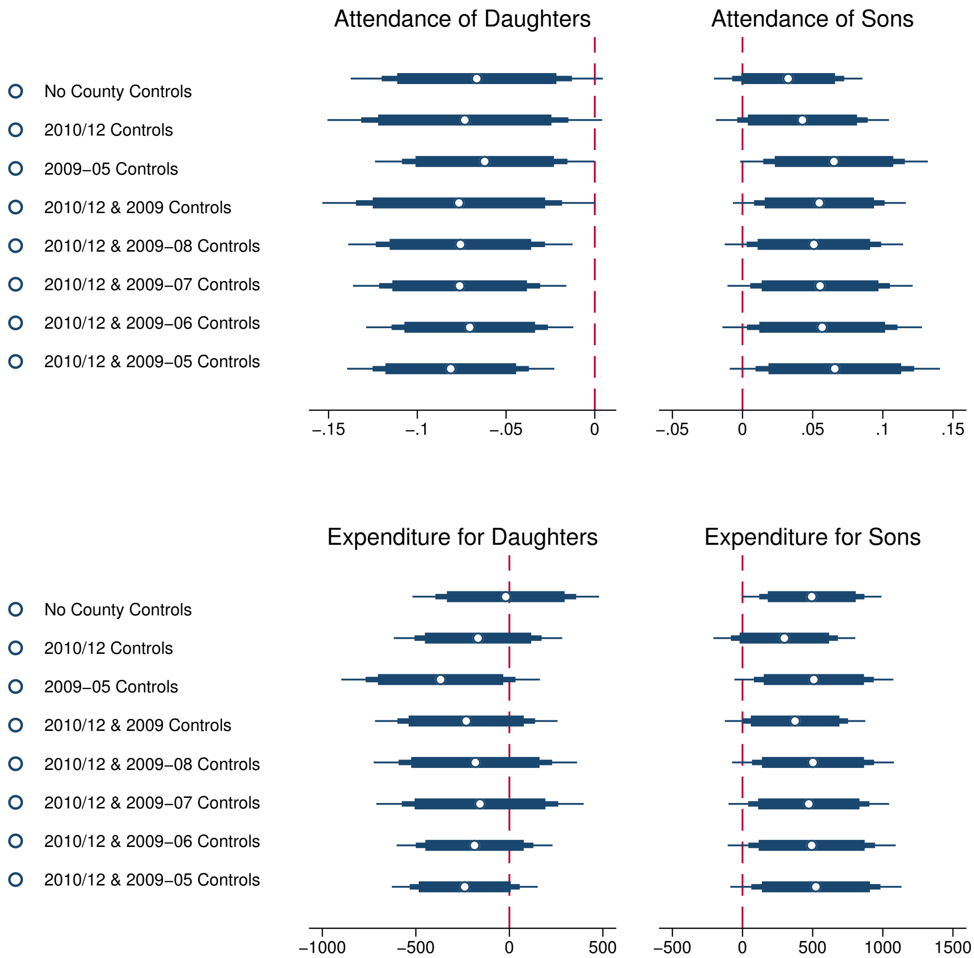
Note: The estimation uses observations of adult children from the CHARLS, and include only those providing positive amount of transfers to elderly parents. CHARLS records the child's income in categories (no income, less than 2000, 2000–5000, 5000–10,000, etc.). We approximate child income by taking the average amount of each bin. The dependent variable is the amount of upward transfers winsorized at the top 1 percentile. All columns use simple OLS regressions and control for county fixed effects and province-year fixed effects. Columns (3)–(4) also control for the child's age, schooling years, number of children and siblings, as well as parents' average age and education years, and whether both parents are alive. Standard errors are in parentheses and clustered at the county level. $*p < .1, **p < .05, ***p < .01$.

Figure B4: School Enrollment by Cohort and Treatment Status



Note: The graph plots the change of school enrollment from 2010 to 2012 for each age cohort, in either the control group (navy dots) or treatment group (maroon crosses). The left graph shows the change of enrollment for male children and the right graph shows the change of enrollment for female children.

Figure B5: Robustness Check: County Trends



Note: For both school attendance and education expenditure, we plot the estimated coefficient of the interaction term Treat×Post for female children and male children, i.e., $\hat{\beta}^F$ and $\hat{\beta}^M$. The estimation model is the same as in Table 8 and 9. Educational expenditure is measured by log(Expenditure + 1). For each estimated coefficient, the hollow circle represents the value of $\hat{\beta}$, and the lines represent the 99%, 95% and 90% confidence intervals.

C The New Rural Pension Scheme (NRPS)

C.1 Details of the NRPS

The New Rural Pension Scheme of China was initiated in 2009, and different counties were gradually included in the program in several waves. Each year, a batch of counties in difference provinces were included into the program. By 2013, universal coverage was achieved. As already mentioned, the NRPS creates two shocks: (i) a wealth windfall for the current old generation, and (ii) a better saving tool for working-age generations to prepare for their retirement.

When the NRPS is implemented, participants older than age 60 immediately become eligible to claim a pension payment on a monthly basis. The payment is composed of two parts, funded by the central government and the local government. The central government provides a subsidy of 55 RMB ($\approx$ 8.5 USD) per month, and the local government also provides a subsidy at different levels. In Figure B3, we show the distribution of county-level pension payment that elderly participants receive. The payment can go as high as 450 RMB per month, but in most counties, participants receive the basic level (55 RMB/month).

Participants younger than age 60 must pay a fixed amount of premium every year, which is saved in the pension account. The premium ranges from 100 RMB ($\approx$ 15 USD) up to 500 RMB. Besides individual premiums, the local government also provides a subsidy for participants. Both individual premiums and local government subsidies are saved in the pension account on a yearly basis, and receive accumulative interests until age 60. After turning 60, participants can withdraw 1/139 of the accumulated savings in their pension account each month, plus the basic pension payment (55 RMB) funded by central government.

For a low-income residents in rural China with a normal expected longevity, without access to high-return investment tools, the NRPS is beneficial. First, the premiums they save in the pension account is returned with interests. Second, they receive local government's subsidy, which is also saved in the pension account. Third, the central government will pay a basic pension unconditionally after age 60. In next Section, we present a simple example which calculates the rate of return in the scenario without pensions and the scenario with pensions. It is clear to see that the NRPS does raise the rate of return to savings.

C.2 The Rate of Return to Private Savings

In this section, we present a simplified example to calculate the rate of return to private savings before and after the NRPS. The main purpose is to convince the readership that the NRPS does increase the rate of return to savings, for low-income residents in rural China.

Consider a 45-year-old farmer named Bo, living in a village of China. Bo grows some rice and vegetables, and raises some pigs and chicken. In a typical year, Bo has some small amount of cash left. Before the government launches the pension program, he usually goes to the bank in the nearest town and saves the cash there. His plan is to save $X = 100$ RMB every year until age 60. Then from 60 to 75 (his expected longevity), he will withdraw $X(1+r)^{15}$ per year. Suppose the annual interest rate that the bank offers is $r = 2\%$. Then the total amount of returns to savings that Bo receives in his old age will be $W^S = 15X(1+r)^{15} = 2019$ RMB. And the aggregate annual rate of return from working age to old age is simply: $R^S = (W^S/15X)^{\frac{1}{15}} = 1 + r = 1.02$.

Now, suppose the government introduces the pension program. Bo decides to save X in the pension account, rather than putting it in the bank, because he heard that money in the pension account also returns interests in the same rate as the bank. More specifically, his total savings in the pension account will be returned to him by $X\sum_{m=1}^{15}(1+r)^m/139$ per month, from age 60 to 75. Additionally, the government will provide a basic pension of $T = 55$ RMB per month when he gets old. That means, Bo can receive a total income of $W^P = (T + X\sum_{m=1}^{15}(1+r)^m/139) * 12 * 15 = 12,184$ RMB, which is about 5 times higher than W^S! And in this case, the aggregate annual rate of return from working age to old age is $R^P = (W^P/15X)^{\frac{1}{15}} = 1.14$.

Consider another farmer, Wei. He is very similar to Bo, except that he lives in another county. In Wei's county, if he participates in the pension program, the local government also provides a subsidy to him ($U = 50$ RMB per year). That subsidy also accumulates in the pension account until age 60, and returns to the participant by $U\sum_{m=1}^{15}(1+r)^m/139$ per month. That means Wei will receive a total income of $W^{PU} = [T + (X+U)\sum_{m=1}^{15}(1+r)^m/139] * 12 * 15 = 13,326$ RMB in his old age, and the aggregate annual rate of return is equal to $R^{PU} = 1.16$.

Suppose Bo and Wei are wealthier and have more cash left each year. They can save $X = 1000$ every year either in the bank or in the pension account. If they use the traditional bank saving, the aggregate rate of return doesn't change, still equal to $R^S = 1 + r = 1.02$. If they participate in the NRPS, they will receive more in their old age, respectively $W^{P'} = 32,742$ and $W^{PU'} = 33,884$. The aggregate rate of return of rich Bo and Wei is respectively $R^{P'} = 1.05$ and $R^{PU'} = 1.06$, lower than that of poor Bo and Wei, but still higher than the rate of return of savings in the bank.