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Regular Article

Rural pension, factor reallocation and agricultural productivity: Evidence from China☆

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A B S T R A C T

This study examines how pension schemes influence land reallocation and agricultural productivity. While previous research typically groups households based on the presence of elderly members, we distinguish between households where the elderly are operators and those where they are not. Our findings show that land is reallocated from elderly-operated to younger-operated households, leading to a 9.8 % increase in agricultural productivity. The rural pension scheme in China drives migration and land leasing out in elderly-operated households, while facilitating rent-in and scale expansion in younger households. These findings offer new insights into how pension schemes can enhance agricultural factor reallocation and productivity.

1. Introduction

The gap in agricultural productivity between developing and developed countries is substantial. One principal factor is the severe misallocation of land (Adamopoulos and Restuccia, 2014). This problem is further compounded by population aging, which affects both the quantity and quality of agricultural labor (Tauer, 1995). Research indicates that farm productivity tends to rise with farmers' experience and peaks in the forties (Tauer, 1995; Zhengfei and Lansink, 2006). This underlines the importance of reallocating resources among different age groups, whereby land shifts from older, low-productivity individuals to relatively younger and more productive ones. (Potter and Lobley, 1996; Calus et al., 2008; Sottomayor et al., 2011).

In the absence of pension support, elderly individuals in developing countries often continue to engage in farming activities until their physical capabilities diminish (Benjamin et al., 2003; Cai et al., 2012; Ning et al., 2016). A substantial body of research has examined the roots of misallocation—highlighting restrictions in the land market, barriers to rural-urban mobility, and insecure land tenure—as well as the impacts of reforms designed to mitigate these frictions (Ngai et al., 2019; Chari et al., 2021; Chen et al., 2022; Liu et al., 2023; Adamopoulos et al., 2024). Yet, little attention has been paid to the aging and lack of retirement mechanism in rural economies, furthermore, we still do not know whether the pension provision can facilitate retirement or alleviate the factor misallocation in agriculture sector.

Since its launch in 2009, China's New Rural Pension Scheme (NRPS) has been expanded to cover rural areas throughout the country by the end of 2012. Funded by the Chinese central government, the NRPS ensures that individuals aged 60 and above with a rural household registration (*hukou*[1]) receive a basic pension benefit at the onset of the NRPS,[2] irrespective of their previous income. Although the primary objective of pension schemes is not necessarily to facilitate factor reallocation, the rural pension scheme can play a significant role in labor behavior changes and, more importantly, factor reallocation between

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[1] *Hukou* is a household registration system used in mainland China. Under this system, each citizen must register in a single place of permanent residence. An individual's *hukou* status determines their rights and eligibility for social welfare and various services, including public education and housing, within a specific administrative unit. Generally, urban *hukou* holders receive more public services and welfare benefits compared to rural *hukou* holders.

[2] The basic pension benefit is 660 RMB per year (about 100 USD at the 2009 exchange rate).

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older and younger demographic groups. Recent studies highlight that China's NRPS has changed labor supply patterns (Huang and Zhang, 2021), affected the migration of children (Li et al., 2018), and facilitated land transfers (Wang et al., 2019; Zhu et al., 2022). Similar pension programs in other developing countries have demonstrated similar effects such as the accumulation of productive assets (Asfaw et al., 2014), changes in labor supply and intra-household allocation (Case and Deaton, 1998; Duflo, 2000, 2003; Ardington et al., 2009), and shifts in farm technical efficiency (Lovo, 2011).

Notwithstanding the emerging research on this issue, key gaps remain. First, Zhu et al. (2022) adopt a well-identified regression discontinuity design to examine the effect of the rural pension program on land transfer decisions. However, their analysis focuses only on the households that leased out land, without tracing which groups subsequently rented in and the change of production practices. Meanwhile, given the nationwide NRPS expansion in 2012—RMB 232 billion (≈4.7 % of agricultural GDP) covering 89 million rural residents—estimating the average treatment effect is essential. Second, very few studies directly examine the relationship between NRPS and farm productivity. Related evidence by Lovo (2011) suggests that pensions may improve farm technical efficiency but provides little insight into mechanisms. Zhu et al. (2022) further show that pensions induced land reallocations that may raise productivity, yet they do not analyze productivity and mechanisms due to data constraints.

Third, existing studies generally classify households by whether they contain age-eligible elderly (e.g. Ning et al., 2016; Xu et al., 2018; Shi, 2022; Zhu et al., 2022). However, household farms are typically organized around a single decision-maker—the operator (Burton, 2006), a distinction emphasized in the productivity literature (Burton, 2006; Tauer, 1995, 2019; Vigani and Kathage, 2019) and in recent development studies (Adamopoulos et al., 2024). Evidence from the China's National Fixed Point (NFP) data shows that, even before the implementation of NRPS, farms led by younger operators, no matter with or without elderly, were systematically more productive than those led by older ones (see Fig. 3 in the following section). This pattern suggests that factor reallocation under a pension shock may depend on identity of elderly, consistent with collective household models (Browning and Chiappori, 1998). In particular, whether the elderly person is the operator plausibly determines whether the pension's income effect is realized directly by the elderly or reallocated within the household, thereby shifting farm decisions.

In this study, we directly address the key gaps identified above. First, we exploit the staggered rollout of the NRPS together with the NFP crop-year panel, which provides rich input-output information with large, nationally representative sample. It supports a credible estimation of average treatment effects for a nationwide program and mitigates concerns about representativeness and selection bias. Second, using detailed input-output information, we calculate farm productivity and estimate the effect of pension on productivity. We also unpack channels by tracing land rented out and rented in, and by documenting post-transfer adjustments in labor allocation and machinery use. Third, we explicitly distinguish households by operator status, in addition to age-eligibility. This classification allows us to study how the pension shock induces factor reallocation across households and reveals heterogeneous responses across household types.

As Fig. 1 illustrates, we classify farms into three groups: households without elderly members, households where an elderly member serve as the farm operator, and households where an adult child serve as farm operator. This classification enables us to disentangle cases in which elderly members receive pensions but are not directly involved in farm management from cases where pensions affect the actual operators. In addition to this classification, the figure further outlines our main findings, showing how pension income triggers land reallocations, contributes to migration and input choices, and the improvements in agricultural total factor productivity (TFP).

Our findings indicate that the NRPS rollout has enhanced overall agricultural TFP by 9.8 %, with significant gains observed in households without elderly member and those where an adult child serve as farm operator. Conversely, the NRPS appears to have an insignificant effect on the productivity of households with an elderly farm operator. The mechanism analysis reveals that households with an elderly operator are more likely to lease out land and younger members are more likely to seek off-farm job. The land typically flows to young-operated households. Households without elderly members increase their expenditure on machinery services. Furthermore, young-operated households with elderly co-resided benefit from the pension income, which alleviates credit constraints and allows for increased land rental, investments in agricultural tools, and enhanced machinery usage.

This study contributes to the extensive literature on social pension schemes (Duflo, 2000, 2003; Lovo, 2011; Zheng and Zhong, 2016; Li et al., 2018; Huang and Zhang, 2021) by shifting the focus to rural agricultural households and explicitly accounting for heterogeneity across household types. Most pension programs focus predominantly on urban areas, examining individual consumption within households and inter-generational resource transfers (Case and Deaton, 1998; Duflo, 2003; de Carvalho Filho, 2008). We examine how a pension program affects agricultural production. In particular, we distinguish between three categories of rural households—those in which an age-eligible elderly farmer continues as the operator, those where an elderly member is present but farm operations have passed to an adult child, and those with no elderly members. This nuanced approach reveals distinct resource allocation patterns induced by pension benefits in each household type, especially the reallocation between the first two groups that was overlooked in literature, providing a broader understanding of social pensions' impact beyond the urban context.

We also contribute to the expanding study on factor misallocation and agricultural productivity (Chari et al., 2021; Chen et al., 2022; Adamopoulos et al., 2024). We show empirically that social pensions reallocate land and labor from lower- to higher-productivity operators, thereby raising aggregate productivity. Using detailed micro data and an operator-based classification, we trace land flows from elderly- to young-operated farms and the accompanying adjustments in mechanization and labor use. This offers a new lens on alleviating misallocation through social insurance and links pension policy to measurable gains in agricultural productivity.

Lastly, this study illuminates the impact of an aging agricultural population and structural change (Duesberg et al., 2017). As the agricultural population ages in both developing and developed countries, the attitudes of elderly farmers towards land transfer upon retirement play a critical role in land reallocation (Crockett, 2004; Fischer and Burton, 2014). We show that providing income security to older farmers through a pension encourages retirement or land transfer, leading to a more efficient use of agricultural resources. By facilitating the exit of senior farmers and the consolidation of farmland under more productive operators, the pension program can act as a catalyst for factor reallocation in the rural sector.

The remainder of the paper is organized as follows: Section 2 provides background information on the NRPS. Section 3 develops a conceptual framework to reveal the mechanism of productivity distribution changes based on households' demographic structure. Section 4 presents the empirical specifications and data descriptions. Section 5 discusses the empirical results and robustness checks. Section 6 explores the mechanisms, and Section 7 concludes the study.

2. NRPS in China

In the early 1990s, the Chinese government established a pension system offering extensive coverage and generous benefits for urban

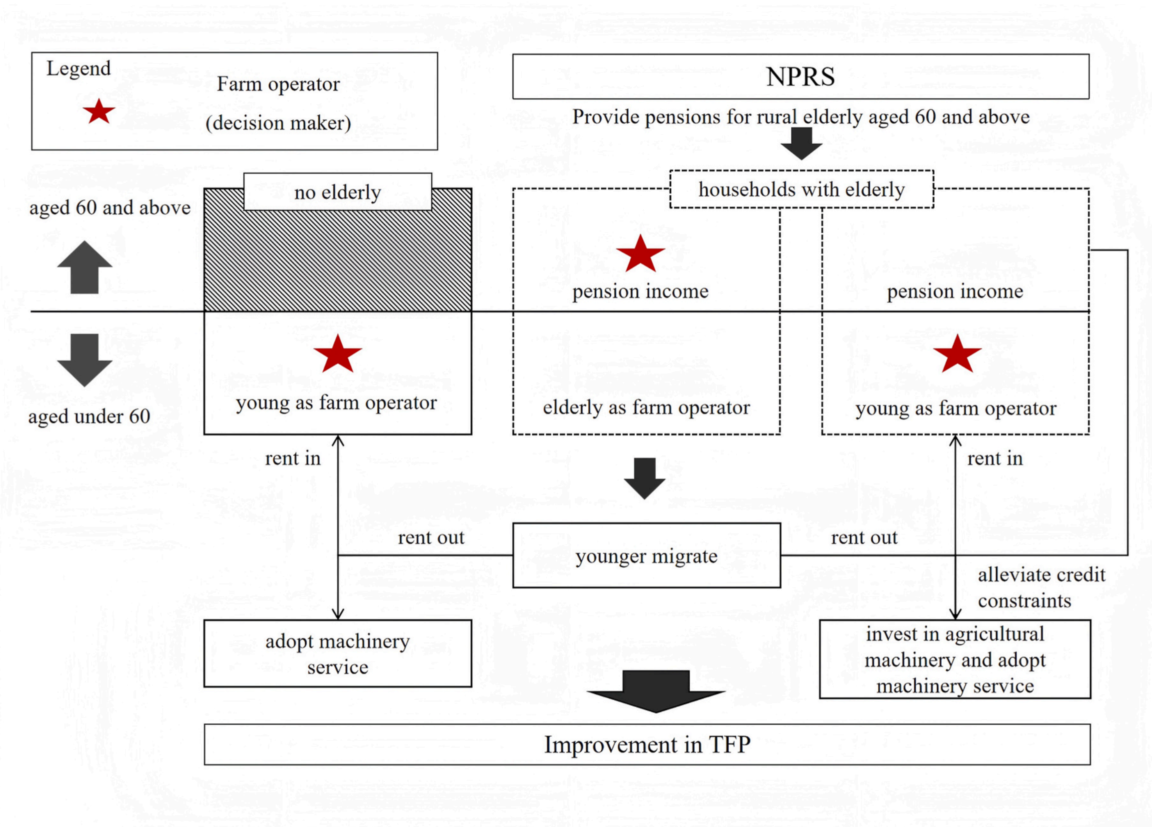

Fig. 1. Analysis Framework.
Notes: Fig. 1 illustrates the grouping methodology and outlines the analytical framework used in this study.

employees. In contrast, rural elderly in China have no public pension support for decades, compelling them to keep working in agriculture until physically unable to continue (Benjamin et al., 2003; Pang et al., 2004). Since then, these elderly individuals depend on financial support from their adult children to sustain their livelihood in their later years.

Officially implemented in 1992, the rural pension schemes was established in several economically developed provinces along the eastern coast, known as the "old rural pension". This pension worked as a savings account, requiring contributions to individual accounts that accrued interest. However, the old rural pension system faced periodic disruptions due to insufficient financial backing, mismanagement of funds, and overall poor program performance. Nevertheless, it helps to formulate the New Rural Pension System. The NRPS achieved universal coverage through four successive pilot waves from 2009 to 2012. Fig. 2 shows the initial pilot in 2009 encompassed approximately 12 % of all counties, followed by 16 % in 2010, around 38 % in 2011, and the remaining 34 % in 2012.[3] Figure A1 further reports the rollout ratio at the province level, showing that, apart from a few provinces that adopted the program province-wide, there is little evidence of selective pilot placement.

The NRPS is distinctive among developing countries as a non-contributory pension scheme. Once included in the NRPS, individuals aged 60 and above are eligible to receive a basic pension benefit of 55 yuan per month (approximately 8 USD in 2009[4]), irrespective of the beneficiaries' prior earnings or income. The pension benefit consists of two components: a fully government-funded basic pension, which is not means-tested, and a funded individual account pension based on personal and, in some cases, local government's contributions. Furthermore, all individuals possessing rural *Hukou* who are aged 16 or older (excluding students) are eligible to voluntarily join the scheme, regardless of their employment status or location. By the end of 2012, the NRPS had extended its coverage to 460 million people,[5] drawing parallels to the universal basic income model discussed by Hanna and Olken (2018). Participants can make annual contributions of 100, 200, 300, 400, or 500 yuan. To qualify for pension benefits at age 60, participants are required to contribute for a minimum of 15 years. Those who join the scheme after the age of 45 must contribute annually until reaching 60, and then make a lump-sum payment to compensate for any

[3] Documents pertaining to the NRPS pilot counties were procured from the Chinese Ministry of Human Resources and Social Security via online applications. Specifically, this information was formerly provided by the Ministry of Civil Affairs (MCA), the administrative department in charge of the NRPS. Management of the NRPS has been transferred to the Ministry of Human Resources and Social Security (MHRSS). One needs to apply to the MHRSS for this information. Disclosure Office of Government Information. 2009–2012. "County list of Pilot New Rural Pension Scheme" Ministry of Human Resources and Social Security of the People's Republic of China http://www.mohrss.gov.cn/xxgk2020/xxgksq/gksq/(accessed May 2023).

[4] The New Rural Pension Scheme (NRPS), later integrated into the unified Urban and Rural Residents Pension Scheme, initially set a national minimum basic pension standard of 55 RMB per month. This national baseline has been raised multiple times to account for economic growth and inflation. For instance, it was increased to 70 yuan in 2014, 88 yuan in 2018, 93 yuan in 2020, and reached 103 yuan in 2023. It is important to note that this is a national minimum standard; provincial and municipal governments often provide additional subsidies, meaning the actual amount received by beneficiaries in more developed regions can be significantly higher. The nationally uniform benefit level ensured the homogeneity of treatment intensity.

[5] Data source: http://lianghui.people.com.cn/2013npc/n/2013/0308/c357320-20726934.html.

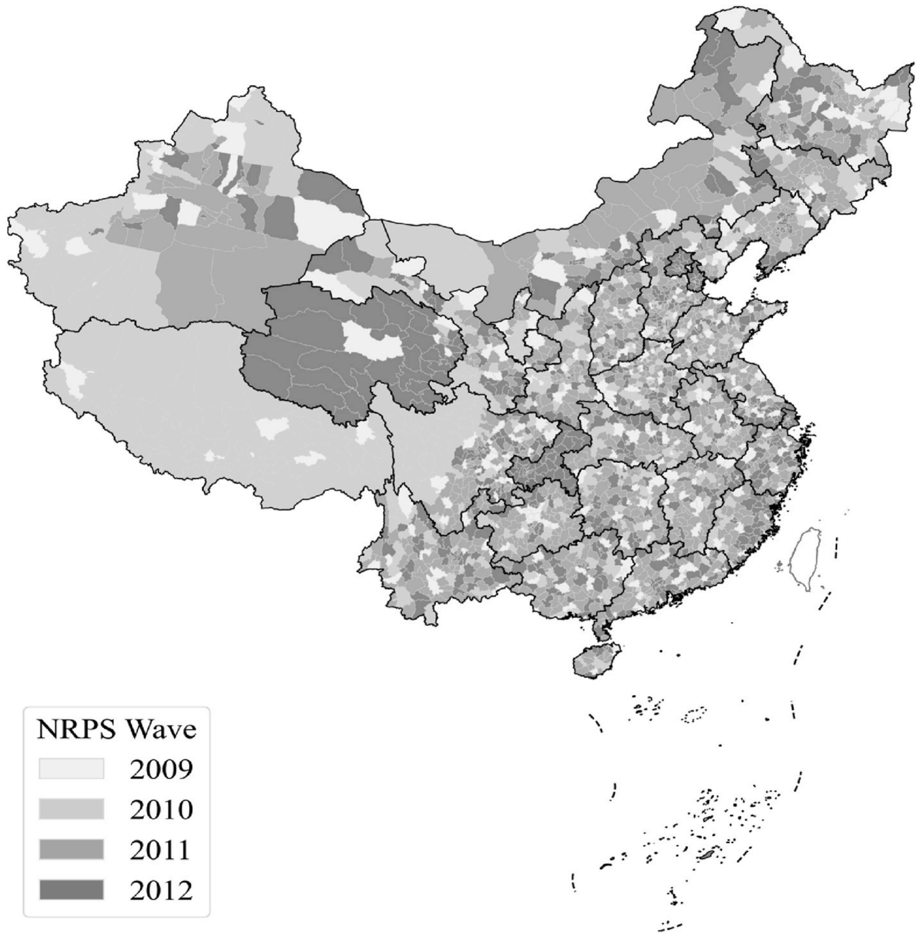

Fig. 2. County-by-county rollout of the NRPS from 2009 to 2012.
Notes: County rollout data for the NRPS were obtained from the State Council Leading Group Office of Poverty Alleviation and Development under a formal data request; these records are not publicly available. The map is schematic and should not be interpreted as exact geographic information or official boundaries.

shortfall in years of contribution.

At the inception of the NRPS, there were no funds in the individual accounts for enrollees aged 60 and above, which meant that these individuals only received the basic pension benefit provided by the government. Given the limited variation in pension payments across regions during our study period, we identify the NRPS effects by exclusively relying on the timing variation of its implementation. This approach provides an exogenous source of income for eligible elderly individuals, offering an excellent opportunity to estimate the impact of pension on resource allocation across households and overall agricultural productivity. Concerns may arise that the impact of the NRPS might be limited as the pension benefit is only 55 yuan per month. However, it is important to notice that this amount is almost at the median monthly income level for rural elderly residence in China (Huang and Zhang, 2021). Consistent with this, Figure A2 shows the mean pension share by income decile: the 55-yuan accounts for a large fraction of income for those at the median and low-income level. Thus, the NRPS transfer is economically important and can plausibly induce farm practice changes and reallocation.

Considering the unique role of the NRPS and previous studies on labor supply, land transfer, and related farm outcomes (Ardington et al., 2009; Lovo, 2011; Ning et al., 2016; Shi, 2022), the incentive of leasing out land for households with older members suggests that the pension program not only enhances the welfare of elderly by reducing labor input in agriculture but also potentially increase overall productivity (Zhu et al., 2022). Thus, China's NRPS provides a compelling context for studying the reallocation of agricultural resources from across generations and its contribution to agricultural productivity.

3. Conceptual framework

In this section, we develop a simple framework to study how the NRPS affects agricultural TFP depending on farm demographic structure and operator identity of the elderly. Prior work typically identifies effects by age eligibility (Ning et al., 2016; Zheng and Zhong, 2016; Li et al., 2018; Huang and Zhang, 2021; Zhu et al., 2022). We instead classify households with elderly members by operator identity—distinguishing those with an elderly operator from those with a young operator—because production decisions are concentrated in the farm operator (Burton, 2006), a point emphasized in the productivity literature (Tauer, 1995, 2019; Vigani and Kathage, 2019) and recent development studies (Adamopoulos et al., 2024).

In the context of China, agricultural production is typically organized at the household level with the farm operator making most of the decisions (e.g., plot allocation, machinery services purchases, and land rental). Two facts motivate this distinction. First, as shown in Fig. 3, the left panels (A, C) show operator-based classification and plot pre-NRPS mean productivity using NFP data. The right panels (B, D) replicate the comparison under the age-based grouping used in previous pension literature (e.g., Huang and Zhang, 2021; Zhu et al., 2022), pooling G21 and G22 into the "households with elderly" category. These descriptive patterns indicate that, for productivity, the key margin is the age of the farm operator, not simply the presence of an elderly member. As a result, when analyzing agricultural production, using conventional

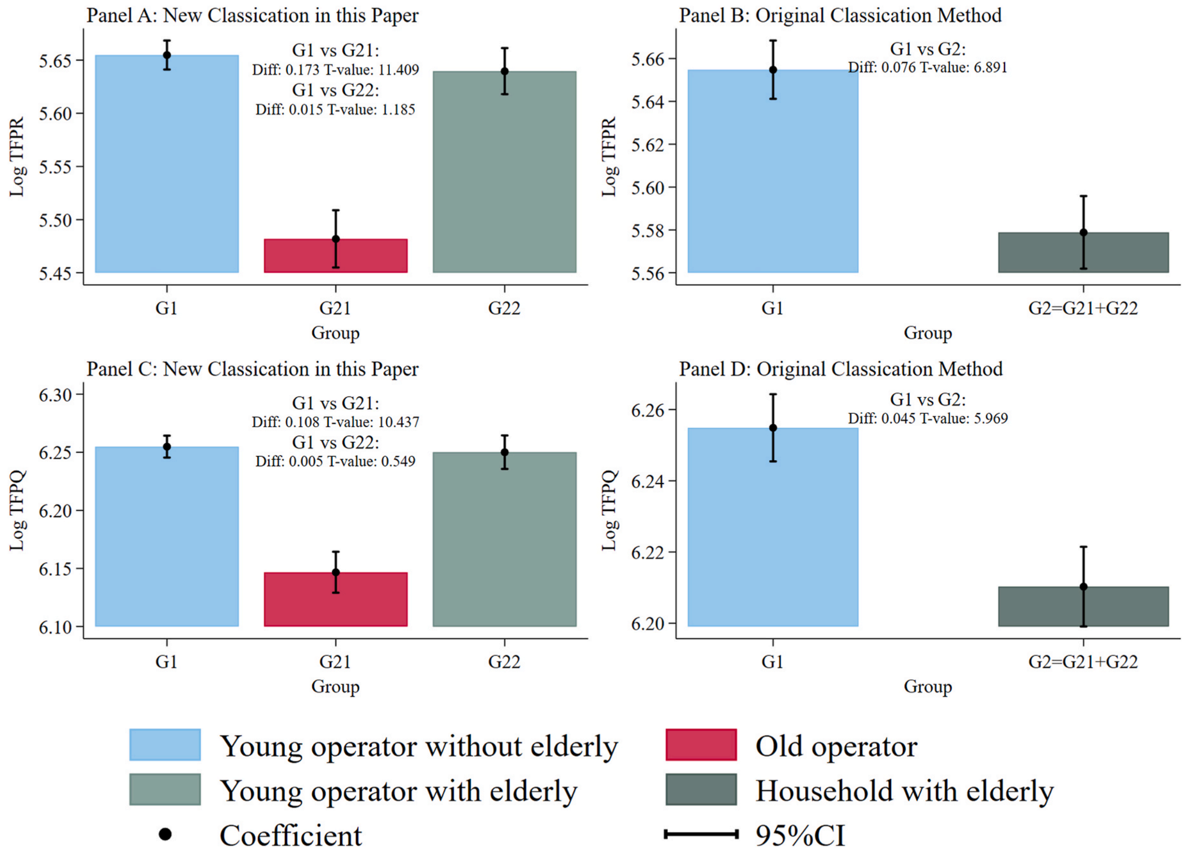

Fig. 3. Pre-NRPS productivity by operator (2006–2008).
Notes: G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. Bars show group means in log TFPR (revenue-based TFP, top) and log TFPQ (quantity-based TFP, bottom); whiskers are 95 % CIs. Differences and t-values are annotated on the panels. Data come from the National Fixed-Point (NFP) rural individual panel for 2006–2013.

classifications will mix G22 and G21. Classifying households by who operates the farm therefore isolates the heterogeneity generated by operator identity and yields a clearer interpretation of pension effects, including distinct behavioral responses and outcomes within the "households with elderly" group. Second, operators supply the bulk of on-farm labor and treat farming as their primary occupation: in the NFP data (Table 1), operators supply on average 219.61 days of agricultural labor versus 77.64 for non-operators, and fewer non-agricultural days (83.25 vs. 112.94). This indicates that operators not only bear the main share of farm work but are also more likely to make production decisions.

The framework yields potential distinct channels across three types of households. When the recipient is operator, the income effect may encourage retirement (Coile and Gruber, 2007). Meanwhile, by reducing older parents' reliance on eldercare, it also lowers migration barriers for their adult children (Gai et al., 2025), raising younger members' employment and, in turn, increasing the likelihood of leasing out land. When the recipient is a co-resident non-operator, within-household transfers may relax liquidity constraints and shift intra-household allocation in ways predicted by collective models (Lundberg and Pollak, 1993; Browning and Chiappori, 1998; Duflo, 2000, 2003). Because these households typically have a younger operator, the relaxation of constraints may allow production scale to expand. For younger-operated households without elderly, the increases land supplies to the land market by older households can generate general equilibrium effects. Given that younger operators are usually more productive, so they rent in more land to get closer to the optimal farm scale.

In light of these considerations, we address the biases that arise from solely relying on the presence of elderly members in the household to assess changes in farming engagement due to the NRPS. Our analysis primarily focuses on the issue of land reallocation and the consequent improvement in agricultural productivity, measured by TFP. To establish a clear link between land reallocation and TFP, we base our analysis on the land holdings of different groups. Using the average TFP per unit of land of each household type, we demonstrate changes in TFP under the impact of the NRPS. We consider three groups in agricultural production within a closed village community: G1, G21, and G22. The amounts of households in these three groups are m, n, and r respectively, and the land areas are represented by $l_{i,G1}$, $l_{i,G21}$, and $l_{i,G22}$, respectively. L denotes the total land in the village.

We assume that the TFP of $l_{i,G1}$ owned by households i in G1 is $\phi_{i,G1}$, and that of G21 and G22 are $\phi_{i,G21}$ and $\phi_{i,G22}$, respectively. To simpilfy the analysis, we assume that land is equally distributed. Given that G1 and G22 are operated by younger operators, it is reasonable that $\phi_{i,G21} <$

Table 1
Agricultural and non-agricultural labor supply by operator status.

Operator Status	Observations	Agricultural Labor Supply (Days)	Non-agricultural Labor Supply (Days)
Non-operators	142,891	77.64(58.19)	112.94(126.03)
Operators	138,583	219.61(103.45)	83.25(131.09)

Notes: Labor supply is measured as total labor days contributed annually; standard deviations are in parentheses. Data come from the National Fixed-Point (NFP) rural individual panel for 2006–2013. For comparability, we exclude individuals younger than 18, and drop samples with zero agricultural labor supply.

$\phi_{i,G22} = \phi_{i,G1}$, and the TFP is similar within group, which is supported by Fig. 3. The land-weighted aggregate TFP shares for each group are Φ_{G1}, Φ_{G2}, Φ_{G3}, which can be expressed as: $\frac{\sum_{i=1}^{m}(\phi_{i,G1}\times l_{i,G1})}{L}$, $\frac{\sum_{i=1}^{n}(\phi_{i,G21}\times l_{i,G21})}{L}$, and $\frac{\sum_{i=1}^{r}(\phi_{i,G22}\times l_{i,G22})}{L}$, respectively.

We further evaluate the impact of the NRPS. For simplicity, based on existing research (Shi, 2022; Zhu et al., 2023; Hu et al., 2023), we presume that adult children in households classified as G21 will migrate, prompting these households to rent out their land. Conversely, as G22 is managed by younger individuals, these households do not engage in renting out. We focus exclusively on households engaged in agricultural operations and neglect exit probabilities for each group. For supply side, assuming the proportion of land rented out by household i in G21 is denoted by ρ_i $(0 \le \rho_i \le 1)$. For the demand side, given that G1 and G22 are managed by younger members, we assume the proportion of land rented in by household i is q_i for G22 and $1-q_i$ for G1. Moreover, we exclude the possibility that households in G22 may both rent out and rent in land.

The land-weighted aggregate TFP shares of G1, G21, and G22 are represented as follows:

$$\Phi_{G1} = \frac{\sum_{i=1}^{m}\left\{\phi_{i,G1}\left(l_{i,G1} + \frac{(1-q_i)\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{m}\right)\right\}}{L}$$
$$\Phi_{G21} = \frac{\sum_{i=1}^{n}\{\phi_{i,G21}(1-\rho_i)l_{i,G21}\}}{L} \tag{1}$$
$$\Phi_{G22} = \frac{\sum_{i=1}^{r}\left\{\phi_{i,G22}\left(l_{i,G22} + \frac{q_i\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{r}\right)\right\}}{L}$$

By assuming that these three kinds of households are equally distributed within the village, we can compute the TFP disparities among these groups based on different classifications. Using the operator-based classification, when aggregating G21 and G22 into G2, the land-weighted TFP share of G2 is as given below:

$$\Phi_{G2} = \frac{\phi_{i,G21}}{2L}(1-\rho_i)l_{i,G21} + \frac{\phi_{i,G22}}{2L}\left(l_{i,G22} + \frac{q_i\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{r}\right) \tag{2}$$

Equation (2) indicates that the combined TFP share of G21 and G22. Our framework has documented productivity improvements from land transferred to G1 and G22. Consequently, we can compute the aggregate TFP share disparities among these three groups.

The aggregate TFP share gap between G21 and the combined groups of G1 and G22 is specified as follows:

$$\Phi^1_{dif} = \frac{\phi_{i,G1}}{2L}\left(l_{i,G1} + \frac{(1-q_i)\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{m}\right) + \frac{\phi_{i,G22}}{2L}\left(l_{i,G22} + \frac{q_i\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{r}\right) - \frac{\phi_{i,G21}}{L}(1-\rho_i)l_{i,G21} \tag{3}$$

When G21 and G22 are combined into G2, the difference in aggregate TFP share between G1 and G2 is articulated as:

$$\Phi^2_{dif} = \frac{\phi_{i,G1}}{L}\left(l_{i,G1} + \frac{(1-q_i)\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{m}\right) - \frac{\phi_{i,G21}}{2L}(1-\rho_i)l_{i,G21} - \frac{\phi_{i,G22}}{2L}\left(l_{i,G22} + \frac{q_i\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)}{r}\right) \tag{4}$$

Given that G1 and G21 have the same productivity and that initial land endowments are equal across the three groups, the difference in aggregate TFP share gaps between the operator-based classification and the age-based classification can be simplified to:

$$\Phi^1_{dif} - \Phi^2_{dif} = \frac{1}{2L}\left[\phi_{i,G22}\left(l_{i,G22} + \frac{2q_i}{r}\sum_{i=1}^{n}(l_{i,G21}\times\rho_i) - \frac{(1-q_i)}{m}\sum_{i=1}^{n}(l_{i,G21}\times\rho_i)\right) - \phi_{i,G21}(1-\rho_i)l_{i,G21}\right] \tag{5}$$

Since G22 is more productive than G21, we can apply this ordering to obtain the following inequality:

$$\Phi^1_{dif} - \Phi^2_{dif} \ge \frac{\phi_{i,G21}}{2L}\left[l_{i,G21}\times\rho_i + \sum_{i=1}^{n}(l_{i,G21}\times\rho_i)\left(\frac{q_i}{r} - \frac{(1-q_i)}{m}\right)\right] \tag{6}$$

Under our assumptions, the magnitude of Equation (6) depends only on the shares of land rented in by G1 and G22. Whenever a strictly positive share flows to G22, we can obtain:

$$\Phi^1_{dif} > \Phi^2_{dif} \tag{7}$$

The simple analysis above shows that overlooking the individual roles of farm operators can lead to a misinterpretation of the calculated differences in aggregate-level TFP between the two household classification methods.

In conclusion, it is crucial to differentiate whether the elderly are farm operators. Merely categorizing them as elderly or young households ignores significant variations within these groups, particularly in terms of the NRPS's impact on the elderly within households managed by younger individuals. Without a more detailed classification of households affected by the NRPS, a comprehensive understanding of the mechanisms by which it influences farmers' production decisions and the broader implications of social security programs on family dynamics remains elusive. Additionally, exploring the heterogeneous effects of the NRPS can yield valuable insights for the development and enhancement of social security programs in other developing nations.

4. Identification strategies and data

4.1. Identification strategies

We investigate the impact of the NRPS on agricultural productivity using a staggered DID model. We split the sample based on the demographic structure and the identity of operator into G1, G21, and G22 as shown in Section 3. This classification enables a thorough examination of the heterogeneous effects on households with and without elderly members, and the varying impacts stemming from the identity of elderly in farm management decisions within these households. The model specification is as follows:

$$Y_{ict} = \beta_0 + \beta_1 NRPS_{ct} + \boldsymbol{X}_{ict}\boldsymbol{\beta} + \gamma_i + \delta_t + \varepsilon_{ict} \tag{8}$$

Where Y_{ict} represents the outcome variables for household or individual i in county c at year t. In the regression, it denotes agricultural TFP along with other variables related to agricultural inputs such as labor, land, and capital. $NRPS_{ct}$ is a binary variable, assigned a value of 1 if county c was designated as a pilot for NRPS in year t, and 0 otherwise. Once a county is selected as a pilot, it is considered part of the treatment group for the subsequent periods. The control group is the counties that had not yet implemented the NRPS. $\boldsymbol{X}_{ict}$ includes a series of control variables, such as age, education years, temperature and precipitation. Individual characteristics were obtained from the farm operator. γ_i is the household-fixed effect, absorbing all time-invariant characteristics at the household level. δ_t is the year-fixed effect, controlling for common characteristics within the same period. ε_{ict} is the error term. For the details of relevant variables used above, see Table 2.

Our identification relies on the assumption that in the absence of NRPS, the trajectories of county-level fundamentals would have been parallel between treated and control counties. To examine this, we plot six county-year indicators by rollout wave including gross value of agricultural output, total power of agricultural machinery, irrigated area, rural electricity consumption, government income, and government expenditure, as shown in Figure A3. The pre-trends are highly similar across waves, with no systematic divergence before NRPS implementation. F-statistic and corresponding p-values are reported in each figure, which suggests no significant nonparallel trends.

In addition, a growing literature shows that in staggered difference-in-differences settings, the conventional TWFE estimator can be biased when treatment effects vary across cohorts or over time (De Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Because the NRPS's impact on agricultural productivity may plausibly differ across counties and calendar years, we re-estimate the baseline specification using three methods from the above literature that consistently estimate a staggered DID model allowing heterogeneous treatment effects across villages and over time, the results are consistent with the baseline specification (Table B1).

4.2. Measurement of productivity

Productivity is measured by Total Factor Productivity, estimated using the Cobb-Douglas production function (Chari et al., 2021). We estimate factor elasticity using Equation (9) and subsequently calculate household-level TFP with Equation (10).

$$ln\, y_{hvt} = \alpha \log L_{hvt} + \beta \log T_{hvt} + \gamma \log K_{hvt} + \delta \log M_{hvt} + \{FE_s\} + \varepsilon_{hvt} \qquad (9)$$

Table 2
Household-level data descriptive statistics.[a]

VARIABLES	Mean	Std. dev.	Min	Max
Panel A: Variables in Calculation of TFP				
Gross output value (Thousand RMB)	18.93	53.77	0.1	12,001.66
Gross output (Thousand RMB)	15.55	218.91	0.1	1768.87
Labor (days)	0.37	6.33	0.1	1008.68
Land(mu)	12.33	41.20	1.00	8164.20
Intermediate input (Thousand RMB)	0.96	4.67	0.1	763.91
Capital (Thousand RMB)	12.75	17.82	0.1	122.08
Panel B: Variables in baseline Regression				
Log (TFPR)	5.92	1.00	0.61	13.24
Log (TFPQ)	6.27	0.72	1.17	11.02
NRPS (0/1)	0.34	0.47	0.00	1.00
Age	49.10	11.39	14.50	80.00
Education (years)	6.62	2.52	0.00	15.00
Village cadre (0/1)	0.07	0.26	0.00	1.00
Township cadres (0/1)	0.04	0.20	0.00	1.00
Party member (0/1)	0.15	0.35	0.00	1.00
Agriculture is main business of family (0/1)	0.85	0.36	0.00	1.00
Rainfall variation (SD/mean)	0.02	0.15	−0.36	0.79
Temperature variation (SD/mean)	0.07	0.17	−0.12	1.74
Land certification policy (0/1)	0.84	0.37	0.00	1.00

Notes: $N = 70{,}103$. We include county-year controls to reduce confounding of the estimated NRPS effects. Rainfall variation is the coefficient of variation (SD/mean) of total rainfall and captures intra-annual precipitation shocks that affect productivity. Temperature variation is the standard deviation of average temperature during the growing season and captures thermal stress that can alter crop performance and measured TFP. Land certification (0/1) flags whether the rural land certification program is in effect in the province; this contemporaneous policy can affect tenure security, investment incentives, and land rental activity and thus directly influence productivity. Including these controls helps isolate the NRPS impact from climatic shocks and other policy changes.

[a] Our input and output data align with existing research. For instance, the average land area at household level approximates 12.3 mu, basically consistent with the 12.7 mu reported by Wang et al. (2020), and the 12 mu found in studies by Chari et al. (2021) and Huang et al. (2024).

$$lnTFP_{hvt} = y_{hvt} - \hat{\alpha} \log L_{hvt} - \hat{\beta} \log T_{hvt} - \hat{\gamma} \log K_{hvt} - \hat{\delta} \log M_{hvt} \qquad (10)$$

Where y_{hvt} is the logarithm of farm output for household h in county v in year t. We use revenue-based TFP (TFPR) in our baseline specification. We use household revenues from crop sales as the output value and inputs value by their costs rather than physical quantities, thus capturing returns relative to input expenditures. Meanwhile, we also use TFPQ (quantity-based TFP) as robustness check, with physical quantities of crops produced as the output to calculate TFPQ. L_{hvt} represents labor input, T_{hvt} stands for land input, K_{hvt} indicates capital, including and M_{hvt} is the cost of intermediate input, indicating the total expenditure on fertilizer, seeds, diesel fuel, and pesticides. $\{FE_s\}$ absorbs year and household fixed effects. The logarithm of TFP $lnTFP_{hvt}$ is calculated. $\hat{\alpha}$, $\hat{\beta}$, $\hat{\gamma}$, $\hat{\delta}$ are estimated by Equation (2). For the details of measurement, refer to Appendix C.

4.3. Data

NFP Data. Our primary source is the National Fixed Points data (NFP), conducted by the China Ministry of Agriculture Research Center of Rural Economy (RCRE). The NFP has been extensively utilized in related academic studies (Kinnan et al., 2018; Chari et al., 2021), with its high quality affirmed by Benjamin et al. (2005). This dataset provides comprehensive household-level data on farm inputs and outputs, both in physical quantities and prices. The sample villages of NFP were based on criteria such as region, income, cropping patterns, population size, and non-farm activities, as described by Adamopoulos et al. (2024). A significant advantage of the NFP data is that it provides detailed information on agricultural input and output at the household crop-year level,[6] as well as information on land transfers and employment. Our analysis covers an eight-year sample period between 2006 and 2013, which provides adequate pre-treatment and post-treatment observations for our estimation.

Since our purpose is to analyze the effects of NRPS on agricultural productivity and the allocation of agricultural factors, we construct a sample of farming households from rural China through the following steps. First, we match the household survey with the individual survey, obtaining 179,710 household-year observations from 399 villages. Second, we drop households for which the farm operator cannot be identified, leaving 131,857 household-year observations from 394 villages. Third, we match the sample to the NRPS rollout schedule. Due to missing county codes for some villages, this reduces the sample to 127,657 household-year observations from 361 villages. Finally, we exclude households that lack complete agricultural input-output information required to compute TFP, yielding a final analytical sample of 70,103 household-year observations from 348 villages.

Regarding the definition of the farm's primary operator, the NFP survey prior to 2009 asked household members *"Are you a participant in farm operation?"* After 2009, the question is *"Are you the main decision-maker in your family?"* Therefore, the survey conducted before 2009 is hard to directly identify which household member served as the operator. Following Adamopoulos et al. (2024), we identify the household's farm operator subject to the additional requirement that operators must supply at least 60 days of agricultural labor annually. The individual is identified as the operator if he/she is the only one meeting the criteria within their households. Otherwise, the operator is assigned to the household member with the largest agricultural labor input; in the event of a tie, we choose the individual who devotes the least time to non-agricultural activities. This process targets the household's full-time farm operator—the person primarily responsible for agricultural

[6] Including five types of cereal crops (wheat, rice, corn, soybeans, potatoes) and ten types of cash crops (cotton, oil crops, sugar crops, hemp, tobacco, fruits, tea, sericulture, medicinal herbs, and vegetables).

production decisions and for maintaining production needed to retain the household's allocated land.

5. Results

5.1. Baseline result

Table 3 illustrates the impact of the NRPS on agricultural TFP at the household level. Column (1) displays results for the entire sample, while Column (2) presents outcomes for G1. Columns (3), (4), and (5) show the results for G2, G21, and G22, respectively. These groups represent households with elderly members, households with an elderly member as the farm operator, and households where the farm operator is an adult child of elderly members. This arrangement allows for an investigation of the NRPS's impact on TFP from a traditional perspective based on the presence of elderly members by comparing Columns (2) and (3). Columns (4) and (5) further delineate the internal differences within G2.

Compared to households in untreated counties, the implementation of NRPS has facilitated an additional 9.8 % growth in TFP among households in treated counties. Our analysis across different groups reveals that the NRPS primarily influences TFP in two subgroups: households without elderly members and households where adult children serve as farm operators. However, the impact on households where an elderly member serves as farm operator is negligible and tends to be negative. Moreover, there is a significant disparity in the impact between these groups. For households without elderly members, NRPS implementation leads to an additional 14.58 % growth in TFP, whereas this effect increases to 11.89 % for households with an adult child as farm operator. In addition, we also re-estimate TFP using gross output quantities as the dependent variable (see Table B2). The results are virtually consistent with the baseline.

However, Column (3) shows that when G21 and G22 are combined, the estimated impact of NRPS on TFP becomes insignificant. This reflects that pooling these two groups masks the internal heterogeneity of land reallocation and productivity effects within G2, thereby obscuring the distinct roles of elderly-versus young-operated households. These results corroborate our theoretical analysis and estimations discussed in previous sections, highlighting the need for subgroup differentiation among households with elderly members.

5.2. Testing for the parallel pre-trends assumption

We implement TWFE event-study specifications, the group-time ATT event study (Callaway and Sant'Anna, 2021), and the interaction-weighted event study (Sun and Abraham, 2021) specifications for TFPR and TFPQ. As shown in Figure A4, the results indicate that there were no significant differences between the treatment groups and control groups before the implementation of NRPS. However, post-implementation, a notable improvement in TFP was observed among the households covered by NRPS except for G21. All results support the parallel-trends assumption.

5.3. Robustness checks

Our main findings withstand a variety of robustness tests as detailed in Appendix D. We implement five specific robustness checks. The first aims to eliminate the effects on productivity that might arise from operator changes. The second restricts the sample to households observed in multiple periods to control the effects caused by households' entry and exit. The third excludes the top 20 % of counties with the highest rates of outward migration. The fourth robustness check is to rule out the influence on estimation of geographic anticipation effect. The fifth addresses the concern that other dynamics in province with concentrated adoption within a single year might drive our results.

6. Mechanisms

6.1. Land reallocation

In Table 4, Panels A, B, and C present the effects of the NRPS on land-related factors across three distinct groups. Columns (1) to (3) respectively analyze the impacts on households' decision on rental and farm size. The findings suggest that the NRPS encourages land rental outflows particularly from households where the elderly are the operators, leading to a slight reduction in their operated land area. Meanwhile, the land rented out by these households predominantly flows to the young-

Table 3
The impact of NRPS on TFP by age group.

VARIABLES	Log TFP				
	All sample	Sub-sample			
		Household without elderly	Household with elderly		
		Young operator	Young & Old	Old operator	Young operator
		G1	G2 = G21+G22	G21	G22
	(1)	(2)	(3)	(4)	(5)
$NRPS_{ct}$	0.0980***	0.1458***	0.0601	−0.0273	0.1189**
	(0.0328)	(0.0443)	(0.0381)	(0.0378)	(0.0492)
HH FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
N	70,103	31,783	38,320	13,002	25,318
R^2	0.6875	0.7589	0.7275	0.7448	0.7581

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly members, G2 represents households with elderly members, G21 represents households with an elderly farm operator, and G22 represents households with an adult child as farm operator. All dependent variables are expressed in logarithmic values. Model specifications include household fixed effects and year fixed effects. Standard errors listed in parentheses are clustered at county level.

Table 4
Impact of NRPS on household land transfer and total area.

VARIABLES	Rent out (yes = 1)	Rent in (yes = 1)	Log (land area)
	(1)	(2)	(3)
Panel A: G1 (Households without elderly - young operator)			
$NRPS_{ct}$	−0.0056	0.0266*	0.0533**
	(0.0115)	(0.0145)	(0.0237)
N	31,828	31,828	31,464
R^2	0.4381	0.4898	0.9020
Panel B: G21 (Households with elderly - old operator)			
$NRPS_{ct}$	0.0374**	−0.0128	−0.0500**
	(0.0151)	(0.0105)	(0.0235)
N	13,099	13,099	13,002
R^2	0.4772	0.4670	0.8687
Panel C: G22 (Households with elderly - young operator)			
$NRPS_{ct}$	0.0001	0.0422**	0.0314†
	(0.0123)	(0.0209)	(0.0250)
N	25,510	25,510	25,177
R^2	0.5656	0.5786	0.8913
HH FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

Notes: ***, **, *, and † denote statistical significance at the 1%, 5%, 10%, and 15% levels, respectively. G1 represents households without elderly members, G21 represents households with an elderly farm operator, and G22 represents households with an adult child as farm operator. Model specifications include household fixed effects and year fixed effects. Standard errors listed in parentheses are clustered at county level.

operated households, with significant farm size expansion.

6.2. Labor and capital factors inputs

We further examine the changes in labor and capital inputs under the rearrangement of land. Columns (1) to (2) of Table 5 illustrate the impact of the NRPS on the agricultural labor inputs, while Columns (3) to (4) explore the effects of NRPS on agricultural fixed asset investment and machinery service fees. Our analysis continues to focus on groups G1, G21, and G22, corresponding to Panels A, B, and C, respectively.

The results indicate that NRPS had no significant impact on labor input across all three household types. However, agricultural machinery service expenses increased for these groups. Notably, in households with an elderly farm operator, NRPS appears to cause a reduction in labor inputs, though this effect was not statistically significant. This observation is consistent with facts that elderly individuals often reduce their labor supply intensity with age. Moreover, with NRPS providing pensions, these individuals have incentives to decrease their labor supply by purchasing agricultural machinery services. In households with adult children serving as the operator, the changes in input factors significantly increase in agricultural tools investments and machinery service costs.

Further analysis explores why households in G22 rent more land in and invest more in agricultural tools and machinery service. The main distinction between G22 and G1 is that the elderly in G22 receive pensions from NRPS. As a permanent income source, pension can alleviate credit constraints for households, thereby mitigating risks associated with farm operations (Catherine et al., 2020; Shi, 2022). Consequently, we investigate the heterogeneity of credit constraints within G22, with results summarized in Table 6. We categorize this group into two sub-samples based on credit constraints: those with low constraints (above median income) and those with high constraints (below median income). This section focuses on changes in land, capital, and machinery service inputs. The findings show that households facing high credit constraints rent more land in and spend more on machinery service following an additional increase in rented land. Meanwhile, the impact of NRPS is insignificant for the low credit constraint group. These results suggest that NRPS has a more substantial marginal impact on the household with high credit constraints.

Table 5
Impact of NRPS on labor and capital factors.

VARIABLES	Log (family labor)	Log (hired labor)	Log (capital)	Log (machinery service)
	(1)	(2)	(3)	(4)
Panel A: G1 (Households without elderly & young operator)				
$NRPS_{ct}$	0.0920	−0.0425	0.0612	0.0371***
	(0.0671)	(0.0519)	(0.0713)	(0.0097)
N	31,828	31,828	31,828	31,828
R^2	0.6747	0.6905	0.7907	0.4549
Panel B: G21 (Households with elderly & old operator)				
$NRPS_{ct}$	−0.0628	0.1132	−0.0123	0.0096***
	(0.0415)	(0.0702)	(0.0997)	(0.0022)
N	13,099	13,070	13,099	13,099
R^2	0.6603	0.6633	0.6767	0.5614
Panel C: G22 (Households with elderly & young operator)				
$NRPS_{ct}$	0.0541	0.1201	0.2917**	0.0270***
	(0.0563)	(0.0766)	(0.1193)	(0.0088)
N	25,510	25,452	25,510	25,510
R^2	0.6876	0.6956	0.7101	0.4561
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes

Notes: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. G1 represents households without elderly members, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All dependent variables are expressed in logarithmic values. Model specifications include household fixed effects and year fixed effects. Standard errors listed in parentheses are clustered at county level.

6.3. Migration of adult children

By relaxing liquidity constraints, the NRPS can encourage households to send migrants while keeping elderly in agriculture. Table 7 further estimates the effect of NRPS on household members' migration outcomes.[7] It shows that households with elderly as operators experienced increased migration in both extensive and intensive margins. This suggests that when elderly serve as farm operators, their households may get multiple benefits: The migration of young labor from these households also indicates the partial transfer of their land. The reduction in household labor, particularly high-quality labor, challenges the ability of the elderly to manage extensive agricultural work, rendering land transfer an inevitable outcome associated with low productivity. However, the overall balance is improved because the elderly reduce their labor supply and substitute it with agricultural machinery services, thereby maintaining agricultural productivity without significant losses. On the other hand, the younger labor force compensates for the loss of household land transfer by seeking employment externally. Therefore, under the influence of NRPS, all three types of households have achieved more favorable outcomes.

7. Conclusions and policy implications

Rapid population aging and declining fertility rates may cause decreased agricultural productivity and resource misallocation across age groups. This issue poses significant challenges to national economic structural transformation. In response to these challenges, many countries have introduced pension schemes over the past few decades, with China's NRPS being particularly notable. By the end of 2012, the NRPS had encompassed over 200 million rural residents and allocated more than 262 billion yuan (approximately US$41 billion). While the primary objective of these schemes is to support the elderly, they also play a crucial role in redistributing agricultural resources among different age groups. Such redistribution is essential for enhancing productivity and fostering sustainable economic development in the face of demographic shifts, thereby underscoring the importance of addressing these challenges for future growth.

Previous research on this program has revealed its success, particularly in terms of the welfare outcomes for the elderly and the leasing of land when comparing households with and without age-eligible members. However, in the agriculture literature, the focus has largely been on land supplied to the market, with little evidence on where that land goes, how recipient farms adjust their practices, and what happens to productivity. Moreover, the standard age-eligible classification used in agriculture ignores who actually makes production decisions within the household and thus overlooks the central role of the farm operator in shaping intra-household allocation. Our study offers a distinct perspective. We explore the factor reallocation effects of the NRPS on productivity using household data from the National Fixed Points (NFP). We employ a staggered DID approach to explore changes in productivity and how households alter their farming practices with the implementation of NRPS. Crucially, our analysis considers the difference between households with or without elderly members. In addition, for households with elderly members, we further explore the heterogeneous effects based on the identity of farm operator.

[7] In our analysis here, we further match the individual-level NFP data with household-level data to examine the impact of NRPS on the migration of family members. Therefore, the sample size in this analysis is larger compared to the sample size in previous analyses. Additionally, this analysis focuses on households that are still engaged in agricultural operations and the migration of their family members.

Table 6
The heterogeneous impact of NRPS on credit constraints.

VARIABLES	G22 (Households with elderly - young operator)					
	Low credit constraints (yes = 1)			High credit constraints (yes = 1)		
	Log (land area)	Log (capital)	Log (machinery service)	Log (land area)	Log (capital)	Log (machinery service)
	(1)	(2)	(3)	(4)	(5)	(6)
$NRPS_{ct}$	0.0312	0.2125	0.0165	0.0582*	0.3832*	0.0373***
	(0.0385)	(0.1520)	(0.0157)	(0.0323)	(0.1974)	(0.0069)
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	9462	9567	9567	15,758	15,967	15,967
R^2	0.9246	0.8051	0.5228	0.9110	0.7634	0.6196

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G22 represents household with an adult child as farm operator. Specifications are estimated using household fixed effects and year fixed effects. Standard errors listed in parentheses are clustered at county level.

Table 7
The impact of NRPS on young members' migration.

VARIABLES	Migration (yes = 1)			Time out(days)		
	G1	G21	G22	G1	G21	G22
	(1)	(2)	(3)	(4)	(5)	(6)
$NRPS_{ct}$	0.0045	0.0149**	−0.0013	1.3507	4.7313**	1.1584
	(0.0054)	(0.0069)	(0.0079)	(1.5434)	(1.9906)	(1.6110)
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	164,883	72,066	133,916	164,883	72,066	133,916
R^2	0.4576	0.5003	0.4669	0.4576	0.5003	0.4669

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All specifications are estimated using household fixed effects and year fixed effects. Standard errors listed in parentheses are clustered at county level.

Our findings suggest that the pension program enhances overall agricultural productivity. Specifically, NRPS has a significantly positive effect on TFP for households without elderly members and households with elderly members but an adult child serve as farm operator. Conversely, NRPS exhibits a slight and statistically insignificant negative effect on the TFP of households with an elderly farm operator.

The mechanism analysis reveals that in households with an elderly farm operator, younger members are more likely to engage in off-farm employment, leading to a reduction in the household labor inputs on agriculture and subsequent land leasing. The rented-out land flows to two other types of households: those without elderly members and those with elderly members and young farm operator, both of which have higher farm productivity. These households experience an increase in TFP. Households without elderly members purchase more machinery services. By comparison, households where adult children serve as farm operator benefit from the pension income received by the elderly, which alleviates their financial constraints and enables them to rent more land, invest more in agricultural tools, and adopt more machinery services.

The outcomes of our analysis carry implications for the design of future pension programs. Specifically, the results demonstrate the potential influence of pension schemes on agriculture. This suggests that when income is transferred to elderly who are serving as farm operators, it can reduce the migration costs for adult children, thereby prompting them to lease out part of their land. This is significant for regions where the proportion of elderly people in the rural labor force is increasing, indicating that providing appropriate support to the elderly can incentivize them to reduce reliance on land for retirement, thereby facilitating land transfers to groups with higher productivity and improving the overall productivity of the agricultural sector. Ultimately, this ensures food security while narrowing productivity gaps between sectors. Last but not least, pension schemes universally entail high costs, deliberating on their benefits to agriculture can greatly facilitate a more precise cost-benefit analysis when crafting pension schemes.

CRediT authorship contribution statement

Shouhan Dai: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Binlei Gong:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Peinan Hu:** Writing – review & editing, Methodology, Formal analysis. **Xiaoyun Wei:** Writing – review & editing, Data curation, Conceptualization.

Disclosure statement

The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

This paper does not involve the collection of data on human subjects.

Appendix A. Figures

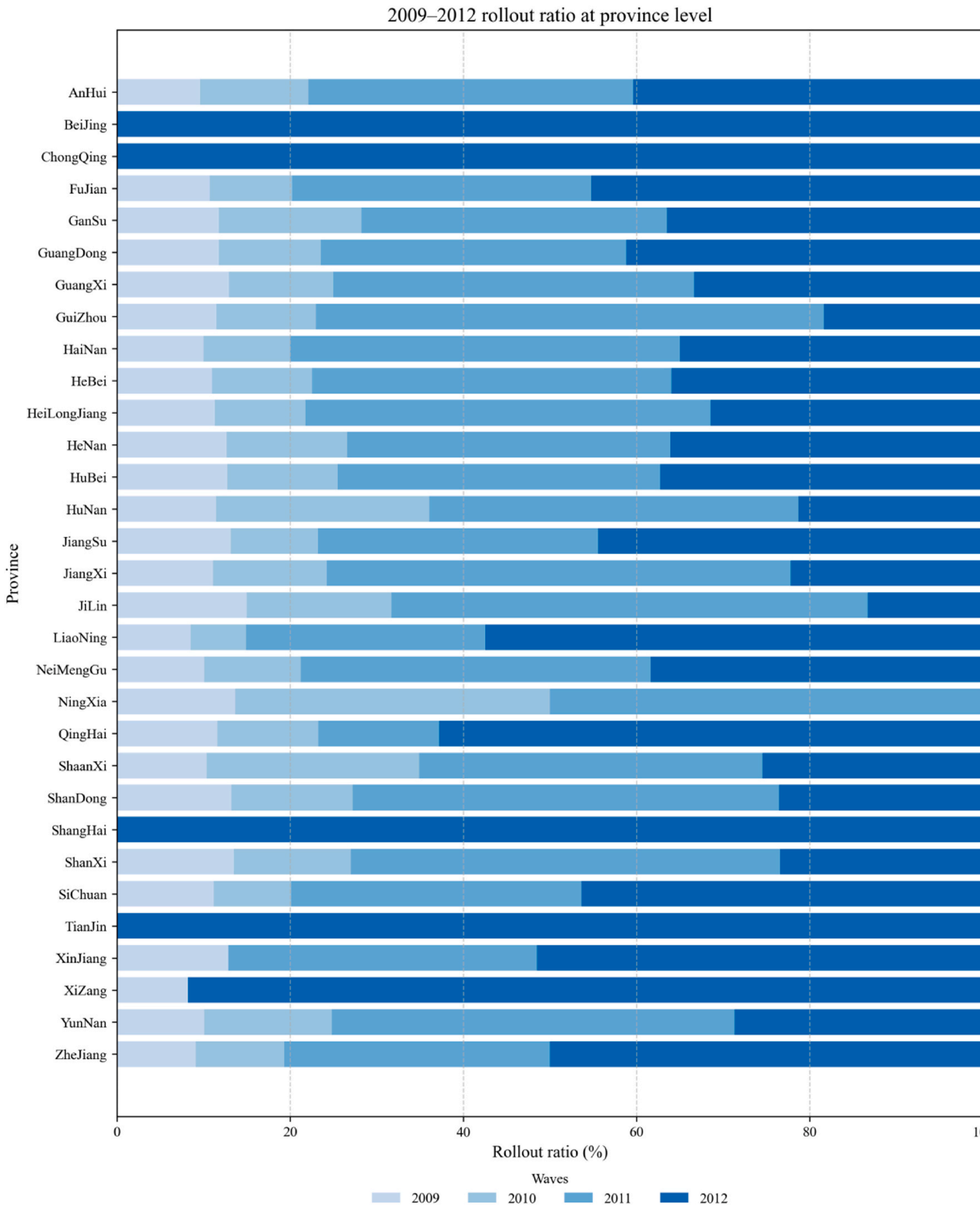

Fig. A1. Rollout ratio at province level
Notes: Bars show the cumulative share of counties within each province that adopted the NRPS by year; lighter to darker shades denote the 2009–2012 waves. The rollout ratio is computed as (counties covered by year t) / (total counties in the province). Apart from a few provinces that implemented near province-wide rollouts early on, the pattern suggests no strong selective pilot placement across provinces.

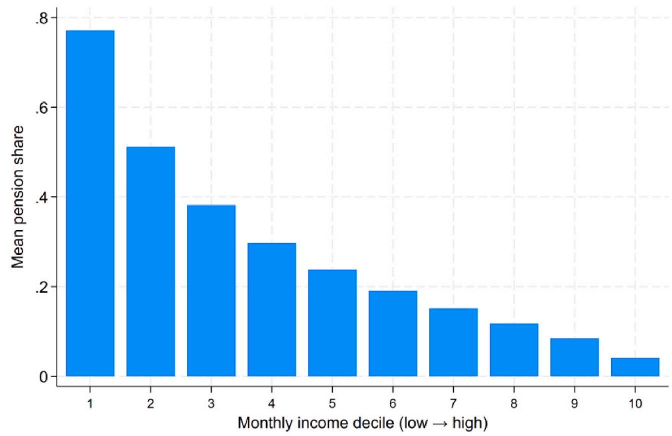

Fig. A2. Mean Pension Share of Rural Elderly by Income Decile, 2008
Notes: The x-axis shows income deciles constructed from per-capita monthly income of rural elderly in 2008, with 1 = lowest and 10 = highest. The y-axis shows the pension share, defined as the ratio of monthly pension income to elderly monthly income per-capita. Source: National Fixed Point (NFP) survey.

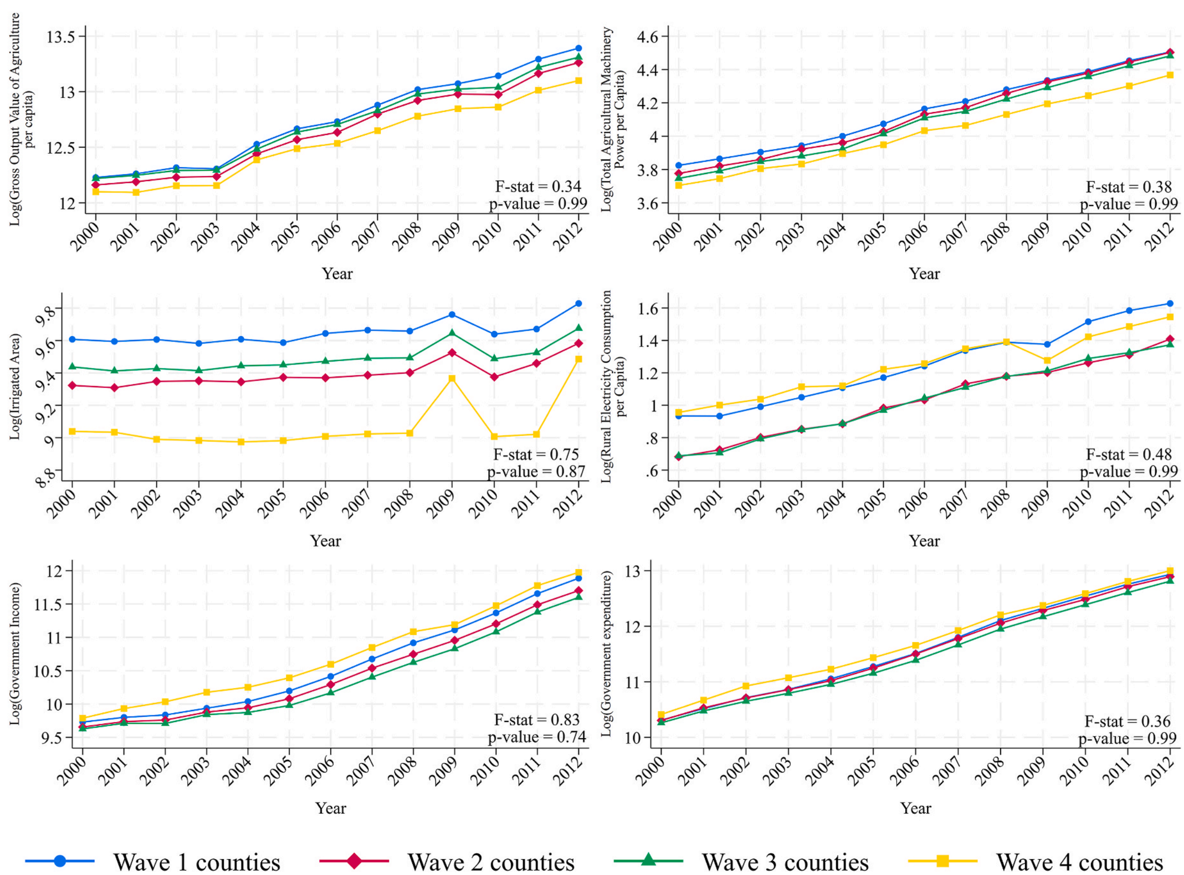

Fig. A3. Examination of pre-trends at county level
Notes: County-level economic indicators are from the China County (City) Social and Economic Statistical Yearbooks. Counties are grouped by their NRPS start year (waves). Each panel plots, for 2000–2012, the wave-level mean of the log of the corresponding indicator. To assess pre-policy comparability, we run regressions on pre-NRPS years only with year fixed effects and wave-by-year interactions, and report in each panel the F-statistic and p-value from the joint F-test that all interaction terms are zero. Failure to reject indicates no significant differential pre-trends across waves.

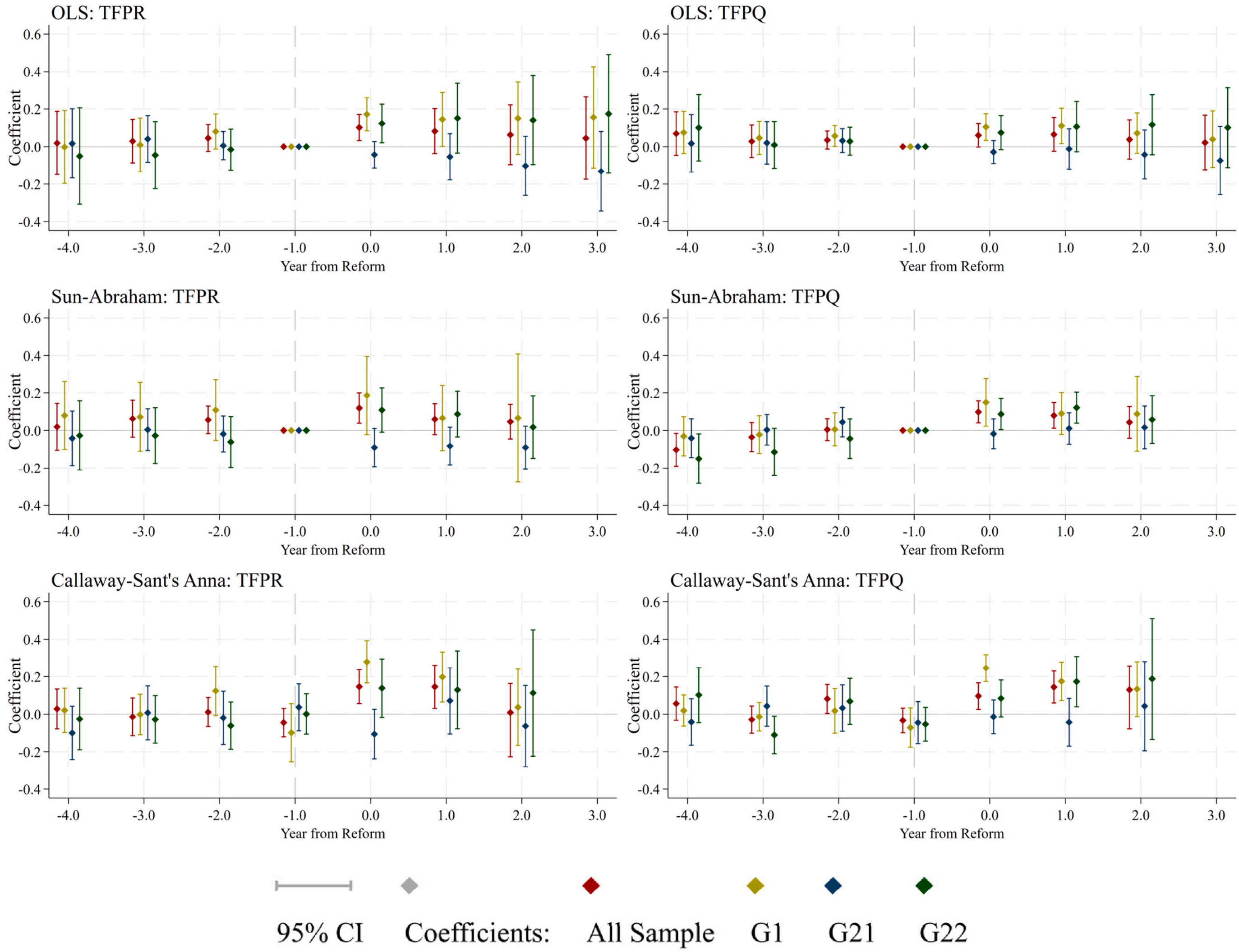

Fig. A4. Test for Parallel Pre-trends
Notes: G1 represents households without elderly, G21 represents household with an elderly farm operator, G22 represents household with an adult child as farm operator. Each panel plots event-time coefficients. −1 is the omitted category. Outcomes are log TFPR (revenue-based productivity) and log TFPQ (quantity-based productivity).

Appendix B. Tables

Table B1
Estimating the Staggered DID design using Alternative Methods.

	Point Estimate	Standard error	Lower Bound 95 % Confidence Interval	Upper Bond 95 % Confidence Interval
Panel A: overall				
OLS	0.0980***	0.0328	0.0334	0.1626
Callaway and Sant'Ana	0.0937*	0.0552	−0.0145	0.2020
Sun and Abraham	0.0635**	0.0286	0.0073	0.1197
de Chaisemartin and D'Haultfeuille	0.1001**	0.0462	0.0095	0.1906
Panel B: G1				
OLS	0.1458***	0.0443	0.0585	0.2329
Callaway and Sant'Ana	0.1716***	0.0546	0.0645	0.2788
Sun and Abraham	0.1289*	0.0744	0.2453	−0.0475
de Chaisemartin and D'Haultfeuille	0.1410**	0.0627	0.0181	0.2639
Panel C: G21				
OLS	−0.0273	0.0378	−0.1016	0.0470
Callaway and Sant'Ana	−0.0225	0.0654	−0.1507	0.1058
Sun and Abraham	−0.0072	0.0378	−0.0816	0.0673
de Chaisemartin and D'Haultfeuille	0.0084	0.0483	−0.0863	0.1031
Panel D: G22				
OLS	0.1189**	0.0492	0.0222	0.2156

(*continued on next page*)

Table B1 (*continued*)

	Point Estimate	Standard error	Lower Bound 95 % Confidence Interval	Upper Bond 95 % Confidence Interval
Callaway and Sant'Ana	0.1273	0.0995	−0.0677	0.3223
Sun and Abraham	0.0785**	0.0349	0.0098	0.1472
de Chaisemartin and D'Haultfeuille	0.1461**	0.0577	0.033	0.2592

*Notes:**, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. In this table, we estimate the effects of NRPS on agricultural TFP using different methods proposed in the literature to address the potential bias in a staggered DID design. The model specifications follow Equation (8) and are the same as Table 2. Most of the methods generate estimates similar to the baseline OLS estimates. Robust standard errors clustered at the county level are shown in parentheses.

Table B2
The Impact of NRPS on TFPQ by Age Group

VARIABLES	Log TFPQ				
	All sample	Sub-sample			
		Household without elderly	Household with elderly		
		Young operator	Young & Old	Old operator	Young operator
		G1	G2 = G21+G22	G21	G22
	(1)	(2)	(3)	(4)	(5)
$NRPS_{ct}$	0.0782**	0.1188***	0.0449	−0.0244	0.1016**
	(0.0305)	(0.0397)	(0.0307)	(0.0277)	(0.0395)
HH FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
N	70,103	31,783	38,320	13,002	25,318
R^2	0.6102	0.7472	0.6650	0.6701	0.7078

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly members, G2 represents households with elderly members, G21 represents households with an elderly farm operator, and G22 represents households with an adult child as farm operator. Dependent variables are expressed in logarithmic values. TFPQ is computed using crop output quantities as the dependent variable. Model specifications include household fixed effects and year fixed effects. Standard errors listed in parentheses are clustered at county level.

Appendix C. Details description of TFP Measurement

We follow Adamopoulos et al. (2024) to use household panel data and construct estimates of farm outputs, inputs.

Gross output value. We focus on the cropping sector and exclude the sideline agricultural activities (animal husbandry, aquaculture, and forestry). For each household farm, we calculate total gross output as the sum of the sales value of all crops produced, covering five major cereals (wheat, rice, corn, soybeans, and potatoes) and ten cash crops (cotton, oil crops, sugar crops, hemp, tobacco, fruits, tea, sericulture, medicinal herbs, and vegetables).

Gross output. Crop production is reported in physical quantities. To construct real farm-level gross output for TFPQ, we aggregate across all crops using common and constant crop prices. Specifically, for each household that sells to the market, we observe both reported quantities and revenues by crop, which allow us to back out unit prices. For each crop, we then compute the median price across all households in 2005 and use these constant prices to value crop quantities, yielding a real measure of gross output at the household level.

Labor. NFP data record the working days of self-employed and hired labor by households for each crop. We first aggregate the two types of labor days for each crop, and then sum them to obtain the total agricultural labor input for the household.

Land. Land input is measured as the total cultivated area of crops and orchards. We rely on cultivated rather than sown area, since a given plot may be planted more than once within a year.

Intermediate inputs. We measure the value of intermediate inputs as the total expenditure on fertilizer, seeds, diesel fuel, pesticides, and related items.

Capital. We adopt the perpetual inventory method to deal with the capital stock. The original data used are the year-end values of productive fixed assets owned by households, including draught animals, large and medium-sized iron and wood agricultural tools, agricultural machinery, and production houses and facilities. We use the perpetual inventory method to handle nominal capital stock to obtain real capital. The specific method is as follows: for samples after the first period in the panel data, the nominal investment amount for the current period is obtained by subtracting the previous period's fixed asset value from the current period's fixed asset value, and then adjusted for inflation. Finally, the real capital stock is calculated based on the perpetual inventory method and depreciation information.

Appendix D. Robustness Checks

Robustness Check 1: *Rule Out the Impact of Operator Shifts*

The farm operator may change over time. In the classical model of farm succession, senior operators in their later working years are often replaced by adult children, who take over the farm decision (Glauben et al., 2004; Dudek, 2016). In the context of the NRPS, elderly operators may transfer farm decision-making to younger household members, which could increase TFP due to improved capacity. Conversely, if adult children hand decision-making back to elderly parents while engaging in off-farm work, TFP could decline. In either case, operator shifts may confound our estimates, as changes in TFP could reflect alterations in farm management rather than the causal effects of the NRPS.

To address this concern, we first quantify the prevalence of operator changes. Using 2009 as the baseline year, we calculate that only 12.70 % of households experience an inter-generational shift (defined as an age difference >20 years) in operator identity over the sample period (Table D1). Meanwhile, we use 2006 as the baseline, the corresponding rate for 2006–2008 is 11.85 %. Taken together, this implies that the systematic operator changes attributable to the NRPS shock are very limited.

Table D1
Robustness check 1

Operator change	Age Differences Before and After Change			
Panel A:(2009 as base, 2009–2013)				
	>5	>10	>15	>20
Yes	17.32 %	14.52 %	13.86	12.70 %
No	82.68 %	85.48 %	86.14 %	87.30 %
Panel B:(2006 as base, 2006–2008)				
	>5	>10	>15	>20
Yes	16.40 %	13.58 %	12.89 %	11.85 %
No	83.60 %	86.42 %	87.11 %	88.15 %

Notes: This table documents the prevalence of farm-operator shifts before and after the NRPS rollout. Panel A takes 2009 as the baseline and compares subsequent operator identities in 2009–2013 with those in 2009. Panel B instead uses 2006 as the baseline and compares operator identities in 2006–2008. A household is flagged as "Yes" (operator change) when the absolute age gap exceeds 5/10/15/20 years; otherwise it is "No."

As an additional robustness check, we exclude all households flagged as inter-generational shifts and re-estimate our models, the results are reported in Table D2. Overall, the results are unchanged in both magnitude and significance relative to the baseline.

Table D2
Robustness check 1

VARIABLES	Log TFP			
	All sample	G1	G21	G22
	(1)	(2)	(3)	(4)
$NRPS_{ct}$	0.0912***	0.1473***	−0.0407	0.1104*
	(0.0334)	(0.0452)	(0.0379)	(0.0563)
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	58,860	27,072	12,037	19,751
R^2	0.6917	0.7636	0.7468	0.7666

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All the dependent variables are expressed in logarithmic values. Specifications are estimated using household fixed effects and year fixed effects. Standard errors in parentheses are clustered at county level.

Robustness Check 2: *Rule Out Impact of the Entry and Exit of Farm*

Another concern is households' entry and exit in the sample. Attrition may reflect migration, which can be correlated with farming capability. If capability differs systematically between movers and stayers, TFP estimates may be biased. To mitigate composition changes without discarding too much data, we re-estimate the models on increasingly restrictive pseudo-balanced panels, defined by the number of survey waves in which a household appears: Number >4, >5, and >6. Table D3 shows that the results are qualitatively unchanged across thresholds: the overall effect continues to have a positive and statistically significant impact on TFP for G1 and G22 households.

Table D3
Robustness check 2

VARIABLES	Log TFP			
	All sample	G1	G21	G22
	(1)	(2)	(3)	(4)
	Number>4			
$NRPS_{ct}$	0.1201***	0.1768***	−0.0116	0.1559**
	(0.0435)	(0.0542)	(0.0639)	(0.0772)
N	17,933	8205	3367	6361
R^2	0.7486	0.8303	0.8014	0.8389
	Number>5			
$NRPS_{ct}$	0.1396***	0.2032***	0.1123	0.2162*
	(0.0520)	(0.0606)	(0.1160)	(0.1159)
N	10,662	4906	1973	3783
R^2	0.7981	0.8763	0.8535	0.8666
	Number>6			
$NRPS_{ct}$	0.1463**	0.2053**	0.2299	0.2847*
	(0.0663)	(0.1037)	(0.2221)	(0.1640)
N	5128	2404	921	1803

(*continued on next page*)

Table D3 (*continued*)

VARIABLES	Log TFP			
	All sample	G1	G21	G22
	(1)	(2)	(3)	(4)
R^2	0.8691	0.9250	0.9050	0.9285
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All the dependent variables are expressed in logarithmic values. Specifications are estimated using household fixed effects and year fixed effects. Standard errors in parentheses are clustered at county level. Standard errors listed in parentheses are clustered at county level.

Robustness Check 3: *Rule Out the Impact of Migration Trend*

The natural migration of rural inhabitants could lead to a reallocation of agricultural input factors, significantly influencing land distribution and productivity dynamics. Our sample period spans from 2006 to 2013, a time of rapid urbanization in China, marked by substantial rural-to-urban labor migration. This large-scale movement of labor is likely linked to additional variability related to the pilot waves of the NRPS, potentially confounding our analysis of NRPS's impact on land reallocation and overall productivity. To ensure the robustness of our estimates and isolate the causal effect of the NRPS policy, we exclude the top 20 % of counties with the highest ratios of population migration relative to their total population. These high-mobility counties might experience land reallocation and productivity changes driven more by external migration dynamics than by NRPS implementation. By focusing on counties with moderate mobility, we aim to reduce noise from unrelated factors, enhancing the reliability of our findings. The results are listed in Table D4. The coefficients of interest remain largely consistent with the baseline results, indicating that the estimated impact of NRPS on TFP enhancement holds even after accounting for high population mobility regions.

Table D4
Robustness check 3

VARIABLES	Log TFP			
	All sample	G1	G21	G22
	(1)	(2)	(3)	(4)
$NRPS_{ct}$	0.1139***	0.1593***	−0.0214	0.1411***
	(0.0333)	(0.0453)	(0.0386)	(0.0505)
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
N	62,505	25,844	11,175	22,999
	0.6909	0.7314	0.7477	0.7576

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All the dependent variables are expressed in logarithmic values. Specifications are estimated using household fixed effects and year fixed effects. Standard errors in parentheses are clustered at county level.

Robustness Check 4: *Anticipation effect*

From a policy-design perspective, anticipation effects should be limited. The State Council's 2009 guidance (Guo Fa [2009] No. 32)[8] specified that only about 10 % of counties would start in 2009, with phased expansion and "basic nationwide coverage by 2020." Thus, during 2009–2011, households in non-pilot counties reasonably expected coverage to occur years later rather than within 2–3 years. Therefore, rural households had little reason to anticipate the rollout of the NRPS.

Nevertheless, we conduct empirical tests to directly rule out this possibility. Geographic proximity could matter if counties adjust behavior in response to neighboring counties' adoption. Table D5 (Panels A–C) evaluates this channel by redefining treatment to include neighboring counties or by treating neighbors as exposed even when their own county has not yet adopted. Across all specifications, the neighbor-exposure coefficients are small and statistically insignificant, indicating little evidence of geographic anticipation. These findings suggest that geographic anticipation effects do not bias our estimates.

[8] "Guo Fa 2009 No. 32" refers to the State Council's Policy Circular No. 32 of 2009, the document can be accessed here: [https://www.gov.cn/zhengce/zhengceku/2009-09/04/content_7280.htm].

Table D5
Robustness Check 4

VARIABLES	Log TFP			
	All sample	G1	G21	G22
	(1)	(2)	(3)	(4)
Panel A: Control for whether neighboring counties are treated				
$NRPS_{ct}$	0.0971***	0.1620***	0.0459	0.1103**
	(0.0315)	(0.0418)	(0.0365)	(0.0478)
Neighbor_treat	0.0026	−0.0541	0.0391	0.0213
	(0.0314)	(0.0484)	(0.0364)	(0.0482)
N	70,103	31,783	38,320	25,318
R^2	0.6875	0.7590	0.7275	0.7581
Panel B: Neighbors treated, excluding real treated group, others as control group				
$NRPS_{ct}$	0.0091	−0.0162	0.0209	−0.0310
	(0.0449)	(0.0676)	(0.0511)	(0.0669)
N	46,516	22,772	23,744	15,946
R^2	0.7325	0.7770	0.7915	0.8279
Panel C: Define treatment to include both adopting counties and their neighbors				
$NRPS_{ct}$	0.0426	0.0478	0.0466	0.0480
	(0.0364)	(0.0549)	(0.0430)	(0.0555)
N	70,103	31,783	38,320	25,318
R^2	0.6871	0.7581	0.7274	0.7578
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All the dependent variables are expressed in logarithmic values. Specifications are estimated using household fixed effects and year fixed effects. Standard errors in parentheses are clustered at county level. Standard errors listed in parentheses are clustered at county level.

Robustness Check 5: *Excluding Provinces with Clustered Implementation*

To address the concern that there are other dynamics in the province with clustering adoption of NRPS driving our results, we exclude provinces in which adoption is highly concentrated in a single year (>75 % or >50 % of counties adopt in the same year). As shown in Table D6 (Panels A–B), the estimated coefficients are basically unchanged and of same magnitude to the baseline across the full sample and three subgroups, indicating that our findings are not driven by province-specific implementation dynamics.

Table D6
Robustness Check 5

VARIABLES	Log TFP			
	All sample	G1	G21	G22
	(1)	(2)	(3)	(4)
Panel A: excluding provinces with >75 % of counties adopting in the same year				
$NRPS_{ct}$	0.1103***	0.1615***	−0.0161	0.1270***
	(0.0316)	(0.0428)	(0.0366)	(0.0488)
N	68,641	31,235	12,599	24,807
R^2	0.6866	0.7579	0.7437	0.7570
Panel B: excluding provinces with >50 % of counties adopting in the same year				
$NRPS_{ct}$	0.1191***	0.1600***	0.0021	0.1409***
	(0.0325)	(0.0443)	(0.0384)	(0.0482)
N	59,941	26,843	10,954	22,144
R^2	0.6907	0.7617	0.7525	0.7575
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes

Notes: *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. G1 represents households without elderly, G21 represents households with an elderly farm operator, G22 represents households with an adult child as farm operator. All the dependent variables are expressed in logarithmic values. Specifications are estimated using household fixed effects and year fixed effects. Standard errors in parentheses are clustered at county level. Standard errors listed in parentheses are clustered at county level.

Data availability

The authors do not have permission to share data.

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