Rural Pensions, Labor Reallocation, and Aggregate Income: An Empirical and Quantitative Analysis of China

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Abstract

We exploit the implementation of a rural pension policy in China to estimate the average rural-to-urban migration cost for workers affected by the policy and the average underlying sectoral productivity difference. Our estimates, based on a large panel dataset, reveal significant migration costs and substantial sectoral productivity differences, with sorting playing a minor role in accounting for sectoral labor income gaps. We construct and structurally estimate a general equilibrium household model with endogenous labor supply and migration. The results of this model align with the reduced-form findings and illustrate how the rural pension policy influences migration, GDP, and welfare through improving within-household labor allocation. Counterfactual analyses based on the model show that the positive effects of the policy remain even if migration costs were significantly lower, and that scaling up the rural pension policy would lead to even larger improvements in labor allocation, GDP, and welfare.

JEL Classification: E24, J24, J61, O11, O15

Keywords: Rural pensions; labor supply; migration; agricultural productivity gap; panel data; household model; general equilibrium analysis; China.

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1 Introduction

In developing countries, labor productivity in the agricultural sector is significantly lower compared to the non-agricultural sectors, even after accounting for sectoral differences in observable worker characteristics such as education and working hours (Gollin et al., 2014). Despite the disparity in productivity between sectors, a large share of the labor force in developing countries remains in agriculture, resulting in significant lags in aggregate productivity and income (Gollin et al., 2002; Caselli, 2005; Restuccia et al., 2008). What are the sources of sectoral labor productivity gaps? Why do developing countries fail to reallocate labor from the agricultural sector to the non-agricultural sector? Are there policies that could assist these countries in improving labor allocation, thereby increasing aggregate productivity and income? In this paper, we attempt to address these questions in the context of China.

There are two popular explanations for large sectoral productivity gaps in developing countries. One explanation refers to differences in unobserved worker characteristics and sorting.[1] Another explanation focuses on barriers to worker mobility between agricultural and non-agricultural sectors.[2] As pointed out by Lagakos (2020) and Donovan and Schoellman (2022), it is likely that both sorting and mobility barriers are important in accounting for observed productivity gaps; the research challenge is to empirically identify these two channels. We tackle this challenge by using a unique large panel dateset and a policy experiment in China.

Between 2009 and 2012, a new pension program, the New Rural Pension Scheme (NRPS), was rolled out across all rural counties in mainland China. Utilizing the annual National Fixed Point Survey of Agriculture (NFP), a large panel dataset monitoring approximately 80,000 agricultural workers and rural-to-urban migrant workers from 2003 to 2013 in China, we evaluate empirically the impact of the NRPS on labor reallocation across sectors and the resultant returns.

We find that following the implementation of the NRPS, young workers from

[1] See, e.g., Beegle et al. (2011), Lagakos and Waugh (2013), Young (2013), Herrendorf and Schoellman (2018), Alvarez (2020), and Hamory et al. (2021).

[2] See, e.g., Restuccia et al. (2008), Bryan et al. (2014), Munshi and Rosenzweig (2016), Lagakos et al. (2023), Ngai et al. (2019), Tombe and Zhu (2019), Hao et al. (2020), Lagakos et al. (2020), and Imbert and Papp (2020). The migration barrier captures both the pecuniary and non-pecuniary costs of migration. Higher costs of living in the city is another barrier, which can be controlled for by using different living cost indices for rural and urban workers. The sectoral productivity gap could also stem from the mismeasurement of agricultural or non-agricultural output when using aggregate data.

households with pension-eligible elderly members are 4.2 percentage points more likely to be employed in urban non-agricultural sectors compared to their counterparts from households without a pension-eligible elderly member.[3] We also find that the NRPS decreased the labor days of pension-eligible elders while increasing the labor days of young members within their households. These findings point to a potential mechanism through which the NRPS induces migration. The NRPS generates an income effect that allows older workers to reduce their labor supply and dedicate more time to home production. Consequently, young workers in these households can decrease their home production time and increase their labor supply in market production, thereby enhancing the incentive for migration to the non-agricultural sector. Thus, the NRPS effectively reduces the migration costs of young workers in households with pension-eligible family members.[4]

Leveraging the county-by-county rollout of the NRPS and interacting it with the presence of pension-eligible elderly household members as an instrumental variable, we estimate the effect of migration on labor earnings. Our local average treatment effect (LATE) estimate reveals an average increase of 86 log points in daily earnings for NRPS-induced migrants. This result suggests that workers who were affected by the NRPS faced high migration costs prior to the introduction of the pension policy. In addition, using a control function approach and the NRPS as an exogenous shock to migration costs, we estimate the average treatment effect (ATE) of migration, which corresponds to the underlying productivity difference between the agricultural and non-agricultural sectors. We obtain an estimate of 33 log points, indicating a significant underlying agricultural productivity gap (APG) in China. The estimated ATE is close to the OLS estimate of returns to migration (31 log points). Since the difference between the ATE and OLS estimates reflects the selection bias due to labor sorting, their similarity implies that worker sorting plays a minor role in explaining the observed APG in China.

Previous studies have consistently found that pension transfers increase the in-

[3] This result is consistent with the findings of Eggleston et al. (2018) and Huang and Zhang (2021), who use Chinese datasets that are smaller and less comprehensive than ours. Similarly, Ardington et al. (2009) find that pension transfers to the elderly lead to increased employment among prime-age adults in South Africa; this increased employment occurs primarily through labor migration.

[4] The mechanism is supported by evidence from existing studies. For instance, recent research find that the elderly with pensions: (i) tend to increase their consumption of healthcare services while relying less on eldercare provided by their children (Eggleston et al., 2018; Cheng et al., 2018b; Li et al., 2018; Guo et al., 2023); and (ii) allocate more time to taking care of their grandchildren (Jiao, 2016; Li et al., 2018).

come and consumption of the elderly and reduce their savings and labor supply.[5] Some studies also empirically explore the impact of pensions on intra-household arrangements.[6] Our empirical results for China are consistent with the literature. However, we go beyond the reduced-form empirical analysis by introducing a structural model that can help interpret the empirical results and quantify the aggregate effects of rural pensions in China.

Specifically, we consider a model with joint household production in agriculture, shared home production, endogenous labor supply, and labor sorting across sectors. Given that older workers typically have a comparative advantage in home production, our model predicts that the introduction of the NRPS not only encourages migration across sectors, but also drives reallocation of labor supply from older to younger household members, which mitigates within-family labor misallocation, thereby enhancing overall household welfare.

We embed the household model into a general equilibrium framework and use the indirect inference method to structurally estimate the model, ensuring its consistency with our reduced-form empirical results. Our estimated model is able to predict the effects of the NRPS on several untargeted data moments, including the labor supply responses to the NRPS of both young and old workers. Armed with the estimated model, we then quantify the effects of the NRPS on labor allocation, migration, GDP, and welfare.

Our quantitative analysis shows that the NRPS has substantial positive impacts on labor allocation, aggregate income, and welfare. The NRPS increases migrants' labor supply by 6% and GDP by 2.4%, while decreasing the labor supply of elderly rural workers by 34%. Consequently, aggregate welfare, measured by consumption expenditure equivalents, increases by 15%. Given the large positive impacts of the NRPS, we also investigate if scaling up the rural pension transfers would have further positive effects. We conduct a counterfactual experiment by raising the pension transfer amount fivefold. In this case, we find that the scaled-up policy would further increase migrants' labor supply by 6.6% and GDP by 4.2%, while further decreasing the labor supply of elderly rural workers by 73%. As a result, aggregate welfare would further increase by 28.5%.

[5]See, e.g., Jensen (2004), de Carvalho Filho (2008), Kaushal (2014), Unnikrishnan and Imai (2020), and Yang and Chang (2023).

[6]See, e.g., Bertrand et al. (2003), Duflo (2003), Ardington et al. (2009), Jiao (2016), Cheng et al. (2018a), Eggleston et al. (2018), Li et al. (2018), Huang and Zhang (2021), and Guo et al. (2023).

Consistent with our reduced-form results, our structural estimation reveals that high migration costs are the main reason for the large observed APG in China during our sample period from 2003 to 2013, with sorting playing a minor role. The estimation shows that migration costs in China are systematically related to the household registration or *hukou* policy. We consider a hypothetical migration policy reform that allows all cities in China to adopt the most liberal *hukou* policy observed in the data. Our counterfactual analysis suggests that the *hukou* policy reform would increase the migration rate by 2.8 percentage points and GDP by 2.04 percentage points, while lowering the observed APG by 46%.

These quantitative results demonstrate that the effect of the NRPS on GDP is comparable to the effect of a migration policy reform that enables all cities to adopt the most liberal policy observed in the data. However, these two policy reforms exert their effects along different margins. Our decomposition analyses show that the NRPS increases GDP primarily through reducing within-household labor misallocation and increasing aggregate labor supply whereas the migration policy reform affects GDP through sectoral labor reallocation.

Finally, we conduct another counterfactual analysis by eliminating NRPS transfers from the benchmark model and setting each city's *hukou* policy to its 2003 level. We find that the combination of the NRPS and the actual migration policy reforms carried out between 2003 and 2013 increased the migration rate by 6.5 percentage points and GDP by 6.6 percentage points, while lowering the observed APG by more than 40%.

This result is related to, but different from, the findings of Tombe and Zhu (2019) and Hao et al. (2020), who quantify the impact of migration policy changes on GDP using a general equilibrium model. Their model focuses on trade and the spatial misallocation of labor, and is calibrated by matching aggregate moments in the data. In contrast, we emphasize sectoral and within-household misallocation of labor and examine the impact of concrete actionable policies. In addition, we discipline our model by matching both unconditional moments and conditional moments in the microdata. In this regard, our paper is also related to Lagakos et al. (2023), who use results from a micro field experiment to calibrate their general equilibrium model of migration in Bangladesh. Our analysis on labor misallocation is also related to other studies on misallocation in China, e.g., Hsieh and Klenow (2009), Song et al. (2011), Brandt et al. (2013), Ngai et al. (2019), and Adamopoulos et al. (2022).

2 Institutional Background and Data

2.1 The Hukou System and Origin-based Hukou Index

Under China's household registration system, each citizen is assigned a *hukou*, classified as "agricultural" or "non-agricultural" in a specific administrative unit that is at or lower than the county or city level. The system is like an internal passport system where individuals' access to public services is contingent on their *hukou* status. It is generally difficult for individuals to change their *hukou*'s category or location. Due to these institutional barriers, most rural-to-urban migrant workers maintain their rural *hukou*, which limits their access to urban public services, such as health care, schooling, and social security. Consequently, many migrant workers leave their children and elderly parents behind in their rural homes.[7]

In recent years, there have been some policy reforms that relaxed the restrictions imposed by the *hukou* system, but the degree and timing of the liberalization vary across cities. To capture the spatial and time variation of *hukou* policies, we adapt the methodology by Fan (2019) to develop an origin-based *hukou* liberalization index, which we will refer to as the Hukou Index (see Appendix A.1 for details). Figure 1a shows that both the average and maximum Hukou Index have increased over time, suggesting a general trend of liberalization. There are also significant variations in migration policies across different prefectures in China. For instance, in 2013, the Hukou Index ranged from 1.045 to 5.247, where 0 represents the strictest policy and 6 the most liberal.

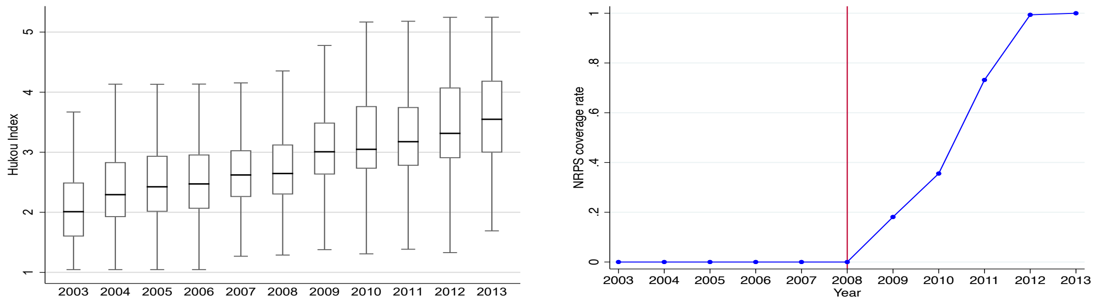
2.2 New Rural Pension Scheme

Historically, the Chinese pension system primarily covered urban residents. In 1992, a rural pension program, the so-called Old Rural Pension Scheme (ORPS), was established as a structured savings program without government contributions. The ORPS came to a standstill after 1998 due to financial mismanagement and the perceived lack of impact (Shi, 2006; Wang, 2006). By 2005, the participation rate in the ORPS had plummeted to below 3 percent, according to the China Agricultural Statistical Yearbooks.

In 2009, the Chinese government introduced a new pension program for rural workers: the New Rural Pension Scheme (NRPS). By the end of 2012, the NRPS

[7] Chan (2019) provides a detailed and up-to-date discussion of the system and its reforms.

Figure 1: Hukou Index and New Rural Pension Scheme



(a) Hukou Index

(b) NRPS Coverage Rate

Notes: In Panel (a), the blue dots show the mean; the boxes represent the 25th and 75th percentiles; and the vertical lines indicate the range.

had been introduced to all rural counties in mainland China. Figure 1b shows the coverage of the NRPS over time in our sample villages, based on data compiled by Huang and Zhang (2021). Citizens aged 16 years or above who have rural *hukou* in counties covered by the NRPS may participate in the scheme on a voluntary basis. To claim pension benefits after the age of 60, enrollees who are 45 and older need to have continuously paid premiums until the age of 60 while enrollees under the age of 45 need to have continuously paid premiums for at least 15 years.

The pension benefits consist of two parts: one is from the accumulated fund in the individual's account and the other is the basic pension benefit. The central government fully subsidizes the basic pension benefit for central and western provinces, and provides a 50 percent subsidy for eastern provinces, with the remaining portion funded by provincial governments.[8] All enrollees who are 60 and older at the start of the NRPS are eligible to receive the basic pension benefit of 660 RMB (about 108 USD) per year, *regardless of their previous earnings or income*. In our sample period, the basic benefits are effectively direct cash transfers from the government, as these workers had not contributed to their pensions as the NRPS was introduced only after these workers had turned 60. In 2013, after the implementation of the NRPS in all counties, our analysis of the rural household survey data reveals that a substantial share of the annual income of elderly individuals is pension transfers. On average, these transfers account for 68% of their income, with a standard deviation of 0.41.

Since many migrant workers leave their children and elderly parents behind

[8] https://www.gov.cn/gongbao/content/2009/content_1417926.htm, last accessed on 2023-10-09.

in their rural hometowns, the introduction of the NRPS effectively lowers the migration costs faced by migrant workers through increasing the home production time of the elderly, thereby allowing migrant workers to supply more labor in the non-agricultural sector. We will use the data on the timing of the introduction of the NRPS in various counties as an indicator of policy shocks to migration costs.

2.3 Origin-based Panel Data on Migration and Income

2.3.1 Description of the NFP Dataset

Our primary dataset is the annual National Fixed Point Survey of Agriculture (NFP). The survey was conducted by the Research Center of Rural Economy (RCRE) of the Chinese Ministry of Agriculture and Rural Affairs. It covers rural households in more than 300 villages from all 31 mainland provinces. The villages were chosen to ensure representativeness across various factors including region, income, cropping pattern, and population. The NFP is designed to be a longitudinal survey, following the same households over time, and has been conducted annually since 1986, with the exceptions of 1992 and 1994 due to funding difficulties. This dataset has recently been used by several researchers studying China's agriculture. See, e.g., Benjamin et al. (2005), Kinnan et al. (2018), Chari et al. (2020), Tian et al. (2020), and Adamopoulos et al. (2022).

The NFP survey uses village-level, household-level, and, since 2003, individual-level questionnaires. At the household level, information is collected on households' agricultural production, consumption, asset accumulation, employment, and income. Most existing studies use the data for the years prior to 2003, which do not include detailed information about individual household members. Due to the restrictions imposed by the *hukou* system, rural-urban migration in China is mostly temporary in nature, and migration of entire households to the city is rare. Hence, in studying rural-urban migration in China, individual-level data provide critical insights that household-level data alone fail to capture.

We have access to the annual waves of the NFP between 2003 and 2013 that include an individual-level questionnaire, which collects individual-level data on age, gender, schooling attainment, industry of work, working days, and, most important, whether an individual migrated outside the township of his *hukou* residence for work during each year of the survey. For those who answered yes, the questionnaire also asks about their earnings from working as a migrant worker. In each year of our sample period, the NFP covers approximately 20,000 households and 80,000 individuals from 350 villages in mainland China. In Appendix A.2, we provide further details about the NFP data and assess its quality. In particular, we show that workers in the 2005 wave of the NFP share similar characteristics with workers possessing rural *hukou* in the 2005 China 1% Population Sampling Survey. We discuss a potential issue of sample attrition in Appendix A.3.

In examining rural-urban migration, the NFP dataset offers two advantages compared to other datasets frequently used in studies of China's internal migration: (i) the NFP has a long panel structure covering 11 years; and (ii) the NFP's geographic scope is extensive, covering agricultural and migrant workers from 350 villages across China. One drawback of the NFP dataset is that there is limited information on migration destinations. Hence, our analysis focuses on rural-urban migration instead of spatial movements across provinces and cities.

2.3.2 Construction of Key Variables

Now, we formally introduce some key variables constructed from the NFP dataset. More details are provided in Appendix A.4.

Sector of Employment and Migration. We define a worker as working in the non-agricultural (na) sector in a particular year if he worked more than 180 days out of town during the year, and working in the agricultural (a) sector otherwise. For in-town workers who reported working in the non-agricultural sector, the NFP data unfortunately do not have information about their non-agricultural earnings. We thus treat them as agricultural workers and assume that they earn the same wages as they would earn in the agricultural sector. Given our definition, we shall use "migration" and "working in the non-agricultural sector" interchangeably in our reduced-form analysis. This classification aligns with the definition of migrant workers by the National Bureau of Statistics of China. In the general equilibrium analysis in Section 4, we define household-level migration as the presence of at least one young member working in the non-agricultural sector.

Nominal Daily Agricultural Earnings. The NFP data provide detailed information on household agricultural production, including all inputs and output at the crop level. To calculate the gross output for each crop type, we multiply the output quantity by the corresponding market price in the given year. Intermediate inputs such as fertilizers and pesticides are also valued by their market prices.

We subtract expenditures on intermediate inputs from the gross output to obtain the value-added for each type of crop. The household-level agricultural income is the sum of value-added across all crops. To obtain individual annual agricultural earnings, we apportion the household-level income to each member according to the number of working days that each person allocated to agricultural production, i.e., $\frac{\text{Individual's working days in } a}{\text{Household's working days in } a} \times$ Household's value-added from a. The measure of individual daily agricultural earnings is then given by:[9]

$$\text{Individual daily earnings in } a = \frac{\text{Household's value-added from } a}{\text{Household's working days in } a}.$$

Nominal Daily Non-agricultural Earnings. The NFP survey also asks each household member the number of days they worked out of town and the corresponding earnings. Non-agricultural daily earning is constructed by dividing the total non-agricultural earnings by the number of out-of-town working days.

Real Earnings. We deflate all nominal earnings into 2003 Beijing prices using province-level spatial price deflators constructed by Brandt and Holz (2006) to obtain measures of real earnings. For the remainder of the paper, all earnings refer to real daily earnings unless stated otherwise.

2.3.3 Basic Facts

Our analysis focuses on the sample of individuals between the ages of 20 and 55 with no more than 12 years of schooling. The age restriction is introduced to allow us to study the working-age population who have completed their schooling but who are at least five years away from being eligible to receive the rural pension income. We also exclude individuals with more than 12 years of schooling due to their limited representation in the data. We additionally restrict the sample to those who can be observed for at least two years, as repeated observations are required for the identification of key parameters in our model. The sample is trimmed at the top 1% and bottom 1% of the annual income distribution in the agricultural and non-agricultural sectors, respectively. Our final sample comprises 48,801 individuals, of which 24.67% are tracked for two years, 17.97% for three years, 13.48% for four years, and the rest for five or more years.

[9] In Appendix C.4, we present an alternative approach for imputing individual agricultural earnings, which takes into consideration the heterogeneity in human capital among members within a household. All our empirical findings remain robust.

Table 1 reports the summary statistics. About 30% of workers in our sample migrated out of town to work in the non-agricultural sector at some point during the sample period. The means of log daily earnings in the agricultural and non-agricultural sectors are 3.70 and 3.43, respectively, which implies that the raw average income gap between agricultural and migrant workers is 27 log points. The variance of log daily earnings is smaller for migrant workers than for agricultural workers. Note that we are comparing agricultural workers to migrant workers who were born in rural areas, not to the entire population of non-agricultural sector workers, which also include urban residents. Most of these migrant workers work in low-skill manufacturing and service jobs (Figure A.4 in Appendix A), which may explain the lower dispersion of their earnings. Notably, the average number of working days differs significantly between agricultural workers (208 days) and migrant workers (302 days). Hence, the sectoral gap in annual earnings is much larger than the sectoral gap in daily earnings (78 vs. 27 log points).

Relative to agricultural workers, migrant workers are generally younger and healthier, and are more likely to have higher educational attainment, be male, and have an elderly household member aged 60 or above. The differences between agricultural and migrant workers suggest that there is sorting along these observable individual and household characteristics. Hence, there is also likely to be sorting along other unobserved or hard-to-measure characteristics. We next present an empirical framework to address the issue of worker sorting in estimating the underlying sectoral productivity gap.

3 Reduced-Form Empirical Analysis

In this section, we empirically study the returns to rural-urban migration in China. We interpret the reduced-form estimates through the lens of a generalized Roy model, where a young rural worker migrates to the urban non-agricultural sector if and only if his returns to migration exceed his cost of migration:

$$R + U_{na} - U_a > M(\boldsymbol{X}, \boldsymbol{Z}, T). \tag{1}$$

Here, U_{na} and U_a denote the unobserved individual productivity in sectors na (non-agricultural) and a (agricultural), respectively; $R = \ln(w_{na}) - \ln(w_a)$ is the *underlying APG*, the difference in log real wage per efficiency unit of labor be-

Table 1: Summary Statistics

Sample:	All	NonAgri	Agri
ln Daily wage	3.5084	3.6949	3.4275
	(0.9025)	(0.6993)	(0.9665)
ln Annual income	8.8450	9.3842	8.6110
	(1.0095)	(0.6860)	(1.0373)
Total working days	236.6606	302.2150	208.2063
	(99.3144)	(44.2010)	(103.0613)
Share of working days in:			
Within-town Agri production	0.5548	0.0356	0.7802
	(0.4343)	(0.0770)	(0.3164)
Within-town NonAgri production	0.1221	0.0049	0.1729
	(0.2567)	(0.0285)	(0.2926)
Out-of-town	0.3231	0.9595	0.0469
	(0.4434)	(0.0844)	(0.1636)
Age	38.4856	32.1853	41.2203
	(10.3787)	(9.0924)	(9.6892)
Years of Schooling	7.1940	8.1015	6.8001
	(2.4454)	(2.0354)	(2.5029)
Female	0.4701	0.3303	0.5307
	(0.4991)	(0.4703)	(0.4991)
Poor health status	0.0121	0.0035	0.0159
	(0.1094)	(0.0592)	(0.1249)
Household with an elderly aged $\geq$60	0.2797	0.3505	0.2489
	(0.4488)	(0.4771)	(0.4324)
Number of observations	229,849	69,570	160,279
Share of workers	1.000	0.3027	0.6973

Notes: Standard deviation in parentheses.

tween the two sectors; $M(\boldsymbol{X}, \boldsymbol{Z}, T)$ represents the effective migration cost faced by the young rural worker, which depends on his individual characteristics ($\boldsymbol{X}$), the migration policies ($\boldsymbol{Z}$), and the NRPS transfers to the young worker's elderly household members (T). Additional details of the estimation strategies and the interpretation of different reduced-form estimators can be found in Appendix B.

This empirical framework is not only connected to the extant literature on migration and selection,[10] but also motivated by the theoretical model that we will present in Section 4.3. Importantly, we allow migration costs to be a function of government transfers to the elderly. As we will illustrate in Section 4.3, the labor supply of older workers decreases with an exogenous increase in pension transfers due to an income effect, leading to increased time spent on home production. This, in turn, induces young workers to allocate more time to market employment and migrate to the na sector. This mechanism aligns with the existing empirical

[10] See, e.g., Heckman and Honore (1990); Card (2001); Cornelissen et al. (2016); Pulido and Święcki (2018); Lagakos et al. (2020).

evidence showing increased migration of young workers to non-farm employment after the introduction of the NRPS, facilitated by eldercare and childcare channels (e.g., Eggleston et al., 2018; Huang and Zhang, 2021; Guo et al., 2023). We will present further empirical evidence regarding the mechanism in Section 3.2.

3.1 Estimation of Returns to Rural-Urban Migration

OLS Estimation We start with a simple OLS estimation of returns to migration with the following regression equation:

$$\ln y_{ihjt} = \gamma_1 NonAgri_{ihjt} + X_{ihjt}\gamma_2 + \varphi_j + \varphi_{pt} + \nu_{ihjt},$$

where y_{ihjt} denotes the year-t daily earnings of individual i who belongs to household h in village j; $NonAgri_{ihjt}$ is a binary indicator for employment in sector na; X_{ihjt} is a vector of control variables, including a dummy indicating whether there is a household member aged 60 or above ($Elder60_{hjt}$), the share of months in year t that the NRPS has been in effect ($NRPS_{jt}$), age, age squared, years of education, a dummy for gender, and a dummy for poor health; and φ_j denotes the village fixed effects, which absorbs all time-invariant village-specific determinants of income. We also include province×year fixed effects, φ_{pt}, which flexibly control for unobserved income shocks at the province level. Standard errors are clustered at the village×year level to account for unobserved shocks that are correlated across individuals residing in the same village in the same year.

Column (1) of Table 2 reports the OLS regression results. Conditional on individual characteristics, daily earnings in sector na are, on average, 31 log points higher than those in sector a.[11] As equation (1) shows, the returns to migration are a function of unobserved individual productivity in sector na relative to that in sector a, $U_{na} - U_a$. Hence, the OLS estimates are susceptible to selection bias and may fail to measure the underlying APG (R). To address this problem, we need to find exogenous shocks to migration barriers that are uncorrelated with workers' potential earnings. The gradual rollout of NRPS in counties across China constitute such shocks.

[11] We also run a regression by additionally controlling for individual fixed effects. This regression yields an estimated return to migration of 38 log points. The details are reported in Appendix B.3.

Table 2: Sector of Employment and Daily Wage: OLS, IV, and Control Function

Dep. Var.:	(1) ln Daily Wage OLS	(2) NonAgri First Stage	(3) ln Daily Wage 2SLS	(4) ln Daily Wage OLS	(5) ln Daily Wage CF
NonAgri	0.3059		0.8614	0.3057	0.3261
	(0.0141)		(0.3532)	(0.0141)	(0.0284)
Elder60 × NRPS		0.0418		0.0232	
		(0.0075)		(0.0145)	
NRPS	-0.0281	0.0113	-0.0423	-0.0360	
	(0.0280)	(0.0100)	(0.0304)	(0.0285)	
Elder60	-0.0006	0.0232	-0.0177	-0.0048	
	(0.0047)	(0.0026)	(0.0119)	(0.0053)	
NonAgri$\times \frac{\phi((Z,W)\hat{\zeta})}{\Phi((Z,W)\hat{\zeta})}$					-0.1358
					(0.0180)
(1-NonAgri)$\times \frac{\phi((Z,W)\hat{\zeta})}{1-\Phi((Z,W)\hat{\zeta})}$					-0.1212
					(0.0173)
Individual controls	Y	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y	Y
Village FE	Y	Y	Y	Y	Y
Observations	229,849	229,849	229,849	229,849	229,236
R-squared	0.4174	0.3611	–	0.4175	0.4191
Kleibergen-Paap F-Stat	–	–	31.02	–	–

Notes: Individual controls include age, age squared, years of education, a dummy for gender, and a dummy for poor health. Robust standard errors are clustered at the village×year level.

IV Approach The introduction of NRPS may induce the elderly to decrease their labor supply and increase their home production time, thereby encouraging younger household members to increase their labor supply and switch to sector *na*. Moreover, the effect of NRPS on sector choice may vary across households depending on the presence of household members aged 60 or above who are eligible for the NRPS pension transfers. Therefore, our IV strategy employs $Elder60_{hjt} \times NRPS_{jt}$ to generate exogenous variation in $NonAgri_{ihjt}$.

The first-stage regression is:

$$NonAgri_{ihjt} = \beta_1 Elder60_{hjt} \times NRPS_{jt} + X_{ihjt}\beta_2 + \varphi_j + \varphi_{pt} + u_{ihjt}. \quad (2)$$

Note that X_{ihjt} contains $NRPS_{jt}$ and $Elder60_{hjt}$ to account for their independent effects on sectoral choice. The second stage of the IV estimation is:

$$\ln y_{ihjt} = \gamma_1 \widehat{NonAgri}_{ihjt} + X_{ihjt}\gamma_2 + \varphi_j + \varphi_{pt} + \nu_{ihjt},$$

where $\widehat{NonAgri}_{ihjt}$ is the predicted value from the first-stage regression.

Instrumenting for the sector of employment with the interaction term $Elder60_{hjt} \times NRPS_{jt}$ is a triple-difference estimation strategy. A simple difference-in-differences estimation would capture the change in the likelihood of non-agricultural employment induced by the implementation of the NRPS, with the identification stemming from the differential timing of the introduction of the NRPS across counties. The triple-differencing enables us to compare households with an elderly NRPS-eligible member and households without such a member. This comparison has an added advantage of differencing out the village-specific shocks to migration costs or to incomes that coincide with the introduction of the NRPS. By employing the triple-difference approach, we address the concern that the NRPS may have been rolled out endogenously across counties, and that early-implementation villages may have had income and migration trends that are different from late-implementation villages. The exclusion restriction for the instrument is

$$Cov(Elder60_{hjt} \times NRPS_{jt}, \nu_{ihjt} | X_{ihjt}, \varphi_j, \varphi_{pt}) = 0.$$

This requires that, conditional on all observables: (i) the NRPS does not directly affect income differently for individuals in households with an elderly NRPS-eligible member and individuals in households without such a member, other than its differential effect on the sector choice; and (ii) the NRPS is uncorrelated with any other village-specific unobserved shocks whose effect on income varies according to the presence of an elderly NRPS-eligible member. The exclusion restriction is plausibly valid in our context — there is little reason to think that cash transfers received by the elderly would change younger household members' innate abilities for working in different sectors.

Column (2) of Table 2 reports the results of the first-stage regression. We find that, in response to the implementation of the NRPS, younger members from households with an elderly NRPS-eligible member are 4.2 percentage points more likely to work in the non-agricultural sector relative to those from households without an elderly NRPS-eligible member. The Kleibergen-Paap F statistic is 31.02, which is well above the Stock-Yogo 10 percent threshold for weak instruments.

Column (3) shows the results of the second-stage regression. The IV estimate implies that working in the non-agricultural sector increases the daily wage by 86 log points. It is an estimate of the local average treatment effect (LATE), which captures the migration returns of the marginal workers whose sector choice was affected by the introduction of the NRPS. We show in Appendix B.2 that the LATE estimate corresponds to the weighted average of the *effective migration* *costs* (measured by $M(\mathbf{X}, \mathbf{Z}, 0)$) among these compliers. Thus, the result indicates that the average migration cost faced by the switchers is around 86 log points. In Appendix C.1, we present evidence that the IV estimate is larger in regions with more restrictive migration policies (i.e., with lower Hukou Indices), implying that migration costs are higher in these regions. As shown in Appendix C.3, compliers are more likely to be workers who face higher baseline migration barriers, such as female workers with young children, which may partially explain the large IV/LATE estimate.

In Column (4), we conduct a mediation analysis by simultaneously including $NonAgri_{ihjt}$ and $Elder60_{hjt} \times NRPS_{jt}$ in the earnings equation. Conditional on the sector of employment, $Elder60_{hjt} \times NRPS_{jt}$ no longer has an independent effect on income; the estimated coefficient is insignificant in both economic and statistical terms. The finding provides supportive evidence for the exclusion restriction, indicating that the NRPS affects earnings only through the channel of sector choice.

Control Function Approach To estimate the underlying APG, we adopt the control function (CF) approach of Card (2001) and Cornelissen et al. (2016) for estimating the average treatment effect (ATE). With the assumption that U_{na} and U_a follow a joint normal distribution, we estimate the following augmented model:

$$\begin{aligned}\ln y_{ihjt} =& \gamma_1 NonAgri_{ihjt} + X_{ihjt}\gamma_2 + \gamma_3 NonAgri_{ihjt} \times \frac{\phi((Z_{ihjt}, W_{ihjt})\hat{\zeta})}{\Phi((Z_{ihjt}, W_{ihjt})\hat{\zeta})} \\ &+ \gamma_4(1 - NonAgri_{ihjt}) \times \frac{\phi((Z_{ihjt}, W_{ihjt})\hat{\zeta})}{1 - \Phi((Z_{ihjt}, W_{ihjt})\hat{\zeta})} + \varphi_j + \varphi_{pt} + \omega_{ihjt},\end{aligned} \tag{3}$$

where Z_{ihjt} corresponds to $Elder60_{hjt} \times NRPS_{jt}$; W_{ihjt} contains all the control variables (including X_{ihjt}, province×year dummies, and village dummies); and $\hat{\zeta}$ is a vector of estimates obtained from the first-stage probit estimation of the selection equation where $Elder60_{hjt} \times NRPS_{jt}$ serves as the excluded instrument. The control functions $NonAgri \times \frac{\phi((Z,W)\hat{\zeta})}{\Phi((Z,W)\hat{\zeta})}$ and $(1 - NonAgri) \times \frac{\phi((Z,W)\hat{\zeta})}{1-\Phi((Z,W)\hat{\zeta})}$ account for the selection bias, with $\phi(\cdot)$ and $\Phi(\cdot)$ denoting the probability density function and cumulative density function of a standard normal distribution, respectively. Hence, theoretically, $\hat{\gamma}_1$ estimates the ATE (Wooldridge, 2015; Cornelissen et al., 2016), which represents the *sectoral real wage gap for the average worker*, denoted as R in equation (1).

Column (5) in Table 2 shows our benchmark estimate of γ_1 using the CF approach. The CF estimate suggests that the daily wage of the non-agricultural sector is 33 log points higher than that of the agricultural sector for the average worker. In Appendix C.2, we extend the control function method in several dimensions so that it depends less on functional form restrictions and demands a less stringent identification assumption. The estimate of γ_1 remains stable..

3.2 Mechanisms: NRPS and Labor Supply

In this subsection, we provide empirical evidence that the NRPS primarily affects migration decisions through the labor supply channel. We start by investigating the labor supply responses of the elderly to the introduction of the NRPS by estimating the following equation:

$$\ln(1 + WorkingDays_{ohjt}) = \alpha_1 NRPS_{jt} + X_{ohjt}\alpha_2 + \varphi_j + \varphi_{pt} + \varepsilon_{ojt},$$

where $WorkingDays_{ojt}$ is the number of working days of an elderly NRPS-eligible member o in household h, village j, and year t. We restrict the sample to individuals who live with young workers in the baseline analysis above.[12] Column (1) in Table 3 shows that the NRPS has a significantly negative effect on older workers' labor supply. In Column (2), to account for zero-value observations in the data, we estimate the effect of the NRPS using a Poisson quasi-maximum likelihood (Poisson MLE) model and obtain a qualitatively similar result.

Turning to the labor supply responses of young workers, we estimate the triple-difference specification:

$$\ln(1 + WorkingDays_{ihjt}) = \beta_1 Elder60_{hjt} \times NRPS_{jt} + X_{ihjt}\beta_2 + \varphi_j + \varphi_{pt} + \varepsilon_{ihjt},$$

where $WorkingDays_{ihjt}$ denotes the number of working days of a young worker i in year t who belongs to household h in village j.[13] Column (3) indicates that the introduction of the NRPS increases the labor supply of young workers. This pattern is robust when we adopt the Poisson MLE model in Column (4).

In terms of magnitude, the estimates in Columns (2) and (4) suggest that the

[12] We also exclude elderly household members with disabilities as labor supply is not a relevant margin of adjustment for them. Among this group, the median number of working days is 0 and the mean is 11.7. This group constitutes about 12.7% of the entire sample of elderly individuals.

[13] We exclude young workers who live with a disabled elderly household member who has zero labor supply.

NRPS decreases the labor supply of the elderly by 9.5 days while increasing that of young workers by 3.4 days.[14] In sum, the findings in Table 3 are consistent with the proposed mechanisms: with cash transfers from the NRPS, the elderly reduce their labor supply and allocate more time to home production, which encourages young workers to increase their labor supply and migrate. In Appendix C.3, we provide further empirical evidence to support this interpretation and explore other possible confounding channels, such as savings, capital investments, and liquidity/credit constraints, through which the NRPS may affect potential earnings and influence migration decisions.[15] We find no evidence that these alternative channels play a major role in affecting migration.

Table 3: Effects of the NRPS on the Labor Supply of the Elderly and Young Workers

	(1)	(2)	(3)	(4)
Dep. Var.:	ln(1+Working Days)	Working Days	ln(1+Working Days)	Working Days
	Elder	Elder	Youth	Youth
	OLS	Poisson	OLS	Poisson
Elder60×NRPS			0.0354	0.0145
			(0.0099)	(0.0057)
NRPS	-0.0146	-0.0904	-0.0122	-0.0068
	(0.0077)	(0.0376)	(0.0186)	(0.0117)
Elder60			0.0010	0.0053
			(0.0042)	(0.0026)
Individual controls	Y	Y	Y	Y
Province×Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	41,064	40,996	219,305	219,305
R-squared	0.2767	–	0.2765	–

Notes: In Columns (1)–(2), the sample is restricted to the elderly NRPS-eligible individuals who are not disabled and who live with young workers. Individual controls include years of education, a dummy for gender, and dummies for health status. In Columns (3)–(4), the sample is restricted to young workers in households without a disabled elderly member. Individual controls include age, age squared, years of education, a dummy for gender, and a dummy for poor health. Across all regressions, robust standard errors are clustered at the village×year level.

[14]The average labor supply of older and younger workers in our sample are 105 and 236 days, respectively. Hence, the estimates in Columns (2) and (4) translate to a reduction in working days by 9.5 ($= 105 \times 0.0904$) and 3.4 ($= 236 \times 0.0145$), respectively.

[15]On the one hand, the NRPS cash transfers may allow households to invest more in fixed capital for production, thereby improving potential earnings in the agricultural sector and reducing the incentive to migrate. On the other hand, the transfers may encourage out-migration among individuals who were previously constrained by limited access to credit. The introduction of the NRPS also provides a formal savings channel for households that were previously savings constrained; hence, the NRPS may consequently affect labor supply and migration decisions over the life cycle (Lagakos et al., 2023).

3.3 Summary of Results from Reduced-form Analysis

We summarize the results of our reduced-form estimation. First, the OLS cross-sectional regression shows that the observed APG in China is 31 log points after controlling for sectoral differences in observable worker characteristics. Note that this is the difference in average labor productivity between migrant and agricultural workers. Second, we estimate the LATE of migration induced by the NRPS and find that the daily wages of NRPS-induced migrants increased by an average of 86 log points, confirming that workers who were affected by the NRPS faced high migration costs prior to the implementation of the NRPS. Finally, we use the NRPS as an instrument and a control function approach to estimate the ATE of migration. The estimate implies an underlying APG of 33 log points, which is close to the OLS estimate. The result suggests that the selection bias of observed APG is almost negligible in the case of China.

What is the aggregate implication of the NRPS? Could the economy benefit from scaling up the pension policy? What are the sources of migration barriers? How would reductions in migration barriers affect the underlying APG, sorting, and aggregate productivity? To address these questions, we turn to a general equilibrium analysis.

4 The General Equilibrium Model

In this section, we present a general equilibrium model with joint household production in agriculture, shared home production in rural areas, endogenous labor supply, and migration. The model guides the interpretation of our reduced-form empirical results and can be estimated and used to quantify the effects of rural pensions on labor allocation, migration, GDP, and welfare.

4.1 Rural Households

There are $N_{r,t}$ rural households. Each household has two groups of members: parents (old (o) agents) and adult children (young (y) agents). We assume that all household members within a group are identical and act collectively, but old agents and young agents play a non-cooperative Nash game. As we discuss in Appendix D, our non-cooperative household model predicts that the pension transfer increases the labor supply of young agents, which is consistent with what we documented in Section 3.2. In contrast, a collective household model would imply a decrease in the labor supply of young agents, which contradicts our empirical results. Let $n_{o,t}$ and $n_{y,t}$ denote the number of old and young agents within a family. Each agent is endowed with one unit of time. Thus, $n_{o,t}$ and $n_{y,t}$ are also the total time endowments of old and young agents, respectively.

Human Capital The human capital of agent $i \in \{y, o\}$ in sector $j \in \{a, na\}$ and time t is a function of the observable characteristics $\boldsymbol{X_{it}}$ and sector-specific unobserved ability U_j. In addition, human capital is subject to a sector-specific productivity shock λ_{jt}, which is i.i.d. across households, sectors, and time, and follows a bi-variate normal distribution $N(0, \Sigma_\lambda)$: $h_{ijt} = \exp(\boldsymbol{X_{it}}\beta + U_j + \lambda_{jt})$. All agents make decisions on labor supply, migration, and consumption after observing the productivity shocks.

Members within a rural household share the same unobserved agricultural ability U_a, which captures not only their innate ability in agricultural production but also the household's land endowment and land quality. Since the elderly do not migrate, to simplify the notation, we use $h_{o,t}$, $h_{a,t}$, and $h_{na,t}$ to denote the human capital of the old agents in the agricultural sector, of the young agents in the agricultural sector, and of the young agents in the urban non-agricultural sector, respectively.

Household Production in Rural Areas A rural household can engage in both agricultural production (a) and rural non-agricultural production (r) with the following production technologies:

$$y_{j,t} = A_{j,t} \left(h_{fj,t}\right)^{\alpha}, 0 < \alpha \leq 1, j = a, r.$$

Here, for $j = a, r$, $A_{j,t}$ is the TFP, $h_{fj,t} = h_{o,t}l_{oj,t} + h_{a,t}l_{yj,t}$ is the household's total effective labor supply in sector j, and $l_{ij,t}$ is the labor supply in sector j of agent $i = o, y$ in the household.

Given the total labor supply of old and young agents in a rural area, $l_{o,t}$ and $l_{y,t}$, and output prices $p_{a,t}$ and $p_{na,t}$, the household allocates labor between the agricultural sector and the rural non-agricultural sector to maximize total household income:

$$\max_{l_{oa,t}, l_{or,t}, l_{ya,t}, l_{yr,t}} \left\{p_{a,t}A_{a,t} \left(h_{o,t}l_{oa,t} + h_{a,t}l_{ya,t}\right)^{\alpha} + p_{na,t}A_{r,t} \left(h_{o,t}l_{or,t} + h_{a,t}l_{yr,t}\right)^{\alpha}\right\}$$

subject to the constraints: $l_{ij,t} \geq 0, i = o, y, j = a, r$; and $l_{ia,t} + l_{ir,t} = l_{i,t}, i = o, y$.

Let $A_{f,t}$ and $h_{f,t}$ be defined as follows:

$$A_{f,t} = \left[(p_{a,t} A_{a,t})^{\frac{1}{1-\alpha}} + (p_{na,t} A_{r,t})^{\frac{1}{1-\alpha}} \right]^{1-\alpha}, \quad \text{and} \quad h_{f,t} = h_{o,t} l_{o,t} + h_{a,t} l_{y,t}.$$

We show in Appendix E.1.1 that the household's production output in sector $j = a, r$ is

$$y_{j,t} = A_{j,t} \left(\frac{p_{j,t} A_{j,t}}{A_{f,t}} \right)^{\frac{\alpha}{1-\alpha}} h_{f,t}^{\alpha},$$

and total production income is $y_{f,t} = A_{f,t} h_{f,t}^{\alpha}$. Here, $p_{r,t} = p_{na,t}$ by definition.

Given income $y_{f,t}$, a household has to incur an iceberg distribution cost $\kappa_{r,t}$ before it can spend the income on consumption. The cost, $\kappa_{r,t}$, is exogenous but varies across provinces and time. We introduce $\kappa_{r,t}$ to account for spatial differences in the average cost of living in the data. Thus, the effective expenditure that is available for the household to spend on consumption goods is $y_{f,t}/\kappa_{r,t}$.

Finally, we assume that the household production income is allocated according to household members' effective labor input. Thus, the effective incomes of an old agent and a young agent are, respectively,

$$e_{o,t} = \left(\frac{h_{o,t} l_{o,t}}{h_{f,t} n_{o,t}} y_{f,t} + p_{a,t} T \right) / \kappa_{r,t}, \quad \text{and} \quad e_{y,t} = \frac{h_{y,t} l_{y,t}}{h_{f,t} n_{y,t}} y_{f,t} / \kappa_{r,t},$$

where T is the pension payment, which becomes positive after the introduction of the NRPS. We assume that the transfer is indexed to the agricultural price and, in our benchmark analysis, financed by a lump-sum tax on urban households.

Non-agricultural Production in Urban Areas The non-agricultural production technology in urban areas is linear, $Y_{na,t} = A_{na,t} H_{na,t}$, where $H_{na,t}$ is the effective units of labor in the urban non-agricultural sector in year t and $A_{na,t}$ is the TFP of the urban non-agricultural sector. The non-agricultural wage per efficiency unit of labor is $w_{na,t} = p_{na} A_{na,t}$. Thus, when young agents work in the non-agricultural sector, their income is $w_{na,t} h_{na,t} l_{na,t}$. There is also a distribution cost, $\kappa_{u,t}$, in urban areas. Therefore, the effective income is $w_{na,t} h_{na,t} l_{na,t} / \kappa_{u,t}$.

Preferences and Time Allocation Since labor supply and migration decisions are static problems, henceforth, we omit the time subscript t for ease of notation.

All members of a household have the same preferences:

$$\mathcal{U}_r = \frac{1}{1-\gamma} (c)^{1-\gamma} + G.$$

where c is an individual household member's private consumption and G is the public consumption of home production.

Private consumption c is determined by a non-homothetic CES utility function. Let e be the effective expenditure of an agent; the agent's consumption allocation problem is

$$\max_{c_a, c_{na}} c$$

subject to the following constraints

$$p_a c_a + p_{na} c_{na} = e, \quad \text{and} \quad \varphi_a^{\frac{1}{\varepsilon}} (c)^{\frac{1-\varepsilon}{\varepsilon}} c_a^{\frac{\varepsilon-1}{\varepsilon}} + \varphi_{na}^{\frac{1}{\varepsilon}} (c)^{\frac{1-\varepsilon}{\varepsilon}\mu} c_{na}^{\frac{\varepsilon-1}{\varepsilon}} = 1.$$

Here, φ_a represents the preference weight on agricultural consumption, $\varphi_{na} = 1 - \varphi_a$, and ε denotes the elasticity of substitution between agricultural and non-agricultural consumption. The parameter μ determines how the relative demand for non-agricultural consumption changes with income. If $\mu > 1$, the relative demand for non-agricultural consumption increases with income, known as the Engel curve effect. Let $c(e)$, $c_a(e)$, and $c_{na}(e)$ denote the solutions to the consumption maximization problem.

The public consumption G depends on the time input of both old (k_o) and young (k_y) members of the household. We assume that

$$G = -\frac{\eta}{1+\frac{1}{\phi}} \frac{(\xi(n_o - k_o) + n_y - k_y)^{1+\frac{1}{\phi}}}{(n_o + n_y)^{1+\frac{1}{\phi}}},$$

where η is a parameter that determines the utility of public consumption or disutility of labor supply, and ξ is the relative home production efficiency of the elderly.

Since very few old agents migrate in our data, we assume that old agents only work in rural areas and do not make migration decisions. Only young agents can supply labor in the urban non-agricultural sector. Given the total time endowments n_o and n_y, we have

$$l_o + k_o = n_o, \quad \text{and} \quad l_y + l_{na} \mathbf{1}_{\{j=na\}} + k_y = n_y,$$

where j is the migration decision of young agents and $j = na$ means they migrate to the urban non-agricultural sector. Note that even if young agents decide to migrate, they can still provide some labor in household agricultural production or rural non-agricultural production. Therefore, an individual member's utility can also be written as:

$$\mathcal{U}_r = \frac{1}{1-\gamma}(c)^{1-\gamma} + G(k_o, k_y) = \frac{1}{1-\gamma}(c)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \frac{\left(\xi l_o + l_y + l_{na}\mathbf{1}_{\{j=na\}}\right)^{1+\frac{1}{\phi}}}{(n_o + n_y)^{1+\frac{1}{\phi}}}.$$

4.2 Labor Supply and Migration Decisions

We now state households' decision problems on labor supply and migration.

Labor Supply Decisions: The labor supply decision problem of old agents is:

$$V_o = \max_{l_o \in [0, n_o]} \left\{ \frac{1}{1-\gamma} c\left(e_o\right)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \frac{\left(\xi l_o + l_y + l_{na}\mathbf{1}_{\{j=na\}}\right)^{1+\frac{1}{\phi}}}{(n_o + n_y)^{1+\frac{1}{\phi}}} \right\},$$

and the labor supply decision problem of young agents is, for $j = a, na$:

$$V_j = \max_{l_y, l_{na} \in [0, n_y], l_y + l_{na}\mathbf{1}_{\{j=na\}} \leq n_y} \left\{ \frac{1}{1-\gamma} c\left(e_{y,j}\right)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \frac{\left(\xi l_o + l_y + l_{na}\mathbf{1}_{\{j=na\}}\right)^{1+\frac{1}{\phi}}}{(n_o + n_y)^{1+\frac{1}{\phi}}} \right\},$$

An old agent's income is $e_o = \left(\frac{h_o l_o}{h_f n_o} y_f + p_a T\right)/\kappa_r$ and a young agent's income is

$$e_{y,j} = \frac{h_y l_y}{h_f n_y} y_f / \kappa_r + \frac{\frac{w_{na}}{n_y} h_{na} l_{na} - (m_o + m_1 \frac{l_{na}}{n_y}) w_{na} h_{na}}{\kappa_u} \mathbf{1}_{\{j=na\}}.$$

Here, $m_0 + m_1 \frac{l_{na}}{n_y}$ is the proportional migration cost; m_0 is a constant; and $m_1 = \exp((\boldsymbol{X_y}, \boldsymbol{Z_y})\zeta)$, where $\boldsymbol{X_y}$ includes the same set of observed individual characteristics as the human capital equation for young agents, and $\boldsymbol{Z_y}$ includes a constant term and the Hukou Index constructed in Section 2. Thus, the migration costs of young agents depend on both their individual characteristics and the *hukou* policy they face.

Migration Decision The migration decision of young agents is given by the the condition $V_{na} - V_a > U_c$, where U_c is an idiosyncratic migration cost shock that follows a normal distribution $N(0, \sigma_c^2)$.

The solutions to these problems are presented in Appendix E.1.2. To illustrate the impact of rural pensions on labor allocation and migration, we now consider a special case of our model, in which we can analytically characterize the labor allocation and migration decisions.

4.3 An Illustrative Special Case

Consider a special case of our general model in which each family has one old agent and one young agent (i.e., $n_o = n_y = 1$), $\kappa_r = \kappa_u = 1$, and $\eta = 2^{\frac{1+\phi}{\phi}}$. In addition, we assume that $c(e) = e$, $\alpha = 1$, $A_r = 0$, $\gamma = 1$, $m_1 = 0$, $\lambda_j = 0$, and $U_c = 0$. In this case, we have

$$e_{o,j} = w_a h_o l_{o,j} + p_a T; \quad e_{y,j} = w_a h_a l_y \mathbf{1}_{\{j=a\}} + w_{na} h_{na} \left(l_{na} - m_0\right) \mathbf{1}_{\{j=na\}}.$$

where $l_{o,j}$ is the old agent's labor supply when the young agent chooses to work in sector j. Therefore, the old agent's labor supply decision problem becomes

$$V_{o,j} = \max_{l_{o,j} \in [0,1]} \left\{ \ln\left(w_a h_o l_{o,j} + p_a T\right) - \frac{1}{1+\frac{1}{\phi}} \left(\xi l_{o,j} + l_y \mathbf{1}_{\{j=a\}} + l_{na} \mathbf{1}_{\{j=na\}}\right)^{1+\frac{1}{\phi}} \right\}.$$

For $j = a$, the young agent's labor supply decision problem is

$$V_a = \max_{l_y \in [0,1]} \left\{ \ln\left(w_a h_a l_y\right) - \frac{1}{1+\frac{1}{\phi}} \left(\xi l_{o,a} + l_y\right)^{1+\frac{1}{\phi}} \right\},$$

and for $j = na$, the young agent's labor supply decision problem is

$$V_{na} = \max_{l_{na} \in [0,1]} \left\{ \ln\left(w_{na} h_{na} (l_{na} - m_0)\right) - \frac{1}{1+\frac{1}{\phi}} \left(\xi l_{o,na} + l_{na}\right)^{1+\frac{1}{\phi}} \right\}.$$

Let $\tilde{T} = \frac{p_a T}{w_a h_0}$, and $l_y^*(\tilde{T})$, $l_{o,a}^*(\tilde{T})$, $l_{na}^*(m_0, \tilde{T})$, and $l_{o,na}^*(m_0, \tilde{T})$ be the interior solutions to the first-order conditions of the respective labor supply problems. In addition, let $\tilde{T}^*(m_0)$ be defined by the condition $\xi \tilde{T}^*(m_0)(\xi \tilde{T}^*(m_0) + m_0)^{\frac{1}{\phi}} = 1$. It can be easily shown that $\tilde{T}^*(m_0) \leq \xi^{-1}$ for any $m_0 \geq 0$ and the equality holds if and only if $m_0 = 0$. In Appendix E.2.1, we prove the following proposition about the household's labor allocation.

Proposition 1 *The household's labor allocation* $\{l_y, l_{oa}, l_{na}, l_{o,na}\}$ *is determined as follows:*

(i) If $\tilde{T} < \tilde{T}^*(m_0)$*, then* $l_y = l_y^*(\tilde{T}) \in (0,1)$*,* $l_{o,a} = l_{o,a}^*(\tilde{T}) \in (0,1)$*,* $l_{na} = \min\left\{1, l_{na}^*(m_0, \tilde{T})\right\}$*, and* $l_{o,na} = l_{o,na}^*(m_0, \tilde{T}) \in (0,1)$*;*

(ii) If $\tilde{T}^*(m_0) \leq \tilde{T} < \xi^{-1}$*, then* $l_y = l_y^*(\tilde{T})$*,* $l_{o,a} = l_{o,a}^*(\tilde{T})$*,* $l_{na} = 1$*, and* $l_{o,na} = 0$*;*

(iii) If $\tilde{T} \geq \xi^{-1}$*, then* $l_y = l_{na} = 1$ *and* $l_{o,a} = l_{o,na} = 0$*.*

In addition, $\frac{dl_{o,a}^*(\tilde{T})}{d\tilde{T}} < 0$*,* $\frac{\partial l_{o,na}^*(m_0,\tilde{T})}{\partial \tilde{T}} < 0$*,* $\frac{dl_y^*(\tilde{T})}{d\tilde{T}} > 0$*,* $\frac{\partial l_{na}^*(m_0,\tilde{T})}{\partial \tilde{T}} > 0$*,* $\frac{\partial l_{na}^*(m_0,\tilde{T})}{\partial m_0} > 0$ *and* $l_{na}^*(0, \tilde{T}) = l_y^*(\tilde{T})$*.*

Proposition 1 states that government transfers to old agents lower the labor supply of old agents through an income effect, and increase the labor supply of young agents through a substitution effect. When old agents reduce their labor supply, they allocate more time to home production, enabling young agents to reallocate their time from home production to market production. This proposition is consistent with our reduced-form empirical result in Section 3.2.

Part (i) of Proposition 1 also indicates that in the absence of government transfers (i.e., $\tilde{T} = 0$), old agents always exhibit positive labor supply, even if they have a comparative advantage in home production. This inefficient allocation of labor within the household arises from the non-cooperative nature of labor supply decisions between old and young agents. In Appendix D, we demonstrate that in our illustrative case, if old agents have a comparative advantage in home production, i.e., $w_a h_o < \xi w_a h_a$ and $w_a h_o < \xi w_{na} h_{na}$, and if old and young agents can pool their incomes and collectively allocate their labor supply, old agents will specialize in home production while young agents will specialize in market production. Part (iii) of Proposition 1 demonstrates that efficient labor allocation can be achieved if the government chooses the appropriate amount of transfers to old agents (i.e., $\tilde{T} = \xi^{-1}$).

Finally, the last part of Proposition 1 implies that due to the fixed-cost nature of the migration cost, a young worker's labor supply increases when he migrates to the non-agricultural sector. Therefore, when estimating returns to migration, it is important to use daily rather than annual incomes to avoid an upward bias induced by endogenous labor supply.

Now consider the household's migration decision. Note that

$$\begin{aligned} V_{na} - V_a &= \ln\left(w_{na}h_{na}(l_{na} - m_0)\right) - \frac{1}{1+\frac{1}{\phi}}\left(\xi l_{o,na} + l_{na}\right)^{1+\frac{1}{\phi}} \\ &- \ln\left(w_a h_a l_y\right) + \frac{1}{1+\frac{1}{\phi}}\left(\xi l_{o,a} + l_y\right)^{1+\frac{1}{\phi}}, \end{aligned}$$

where l_y,l_{na}, $l_{o,a}$, and $l_{o,na}$ are the agents' optimal labor supply. Let

$$M(m_0, \tilde{T}) = \ln\left(\frac{l_y}{l_{na} - m_0}\right) - \frac{1}{1+\frac{1}{\phi}}\left[\left(\xi l_{o,a} + l_y\right)^{1+\frac{1}{\phi}} - \left(\xi l_{o,na} + l_{na}\right)^{1+\frac{1}{\phi}}\right]. \quad (4)$$

Then, we have $V_{na} - V_a = \ln\left(\frac{w_{na}}{w_a}\right) + \ln\left(\frac{h_{na}}{h_a}\right) - M(m_0, \tilde{T})$. Thus, the young agent will migrate if $V_{na} - V_a > 0$, or

$$\ln\left(\frac{h_{na}}{h_a}\right) > M(m_0, \tilde{T}) - \ln\left(\frac{w_{na}}{w_a}\right). \quad (5)$$

Here, $M(m_0, \tilde{T})$ can be interpreted as an effective migration cost, which is influenced by the government transfers to the old agent, $\tilde{T}$. In Appendix E.2.2, we prove the following proposition regarding the effective migration cost.

Proposition 2 *The effective migration cost, $M(m_0, \tilde{T})$, has the following properties: (i) $M(0, \tilde{T}) = 0$; (ii) $\partial M(m_0, \tilde{T})/\partial m_0 > 0$; and (iii) $\partial M(m_0, \tilde{T})/\partial \tilde{T} < 0$.*

Proposition 2 demonstrates that the effective migration cost $M(m_0, \tilde{T})$ is a monotonically increasing function of the migration cost m_0, but is also influenced by government transfers to the elderly. The great the government transfers, the lower the effective migration cost. This result explains our empirical finding in Section 3.1 that rural pensions in China increase the migration rate of young workers with elderly parents.

Equation (5) demonstrates the selection issue. The young agents who migrate are those with relative human capital in the non-agricultural sector that exceeds the net migration cost $M(m_0, \tilde{T}) - \ln(w_{na}/w_a)$. By influencing the effective migration cost without affecting the potential earnings of young agents, government transfers to the elderly can serve as an instrument to address the selection issue in the OLS regression.[16]

[16]In Appendix B.1, we provide a more detailed discussion of the connection between our illustrative model and the empirical framework used in our reduced-form empirical analysis in

4.4 Urban Households

There are N_u number of urban workers. They have a time endowment of 1 and choose their labor supply in the urban non-agricultural sector. We assume their human capital to be h_u. Hence, their wage income is $w_{na}h_u l_u = p_{na}A_{na}h_u l_u$. The government levies a lump-sum tax $p_a\tau$ on urban household members to finance the NRPS. Thus, the effective expenditure of an urban household member is $e_u = (p_{na}A_{na}h_u l_u - p_a\tau)/\bar{\kappa}_u$. Since we are not modeling the location of urban households, $\bar{\kappa}_u$ is the national average urban distribution cost. Urban household members have the same non-homothetic CES preferences as rural agents over agricultural and non-agricultural goods.

The optimization problem of urban workers is

$$V_u = \max_{l_u \in [0,1]} \left\{ \frac{1}{1-\gamma} c\left(e_u\right)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \left(l_u\right)^{1+\frac{1}{\phi}} \right\}.$$

4.5 Definition of Key Macro Variables

We define some key aggregate variables of interest: the APG, (real) GDP, total effective labor, and aggregate productivity.

Let the total effective output of agricultural production be

$$Y_a = N_r \int \kappa_r^{-1} p_a y_a(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}),$$

the total effective output of rural non-agricultural production be

$$Y_r = N_r \int \kappa_r^{-1} p_{na} y_r(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}),$$

and the total effective output of non-agricultural production by migrants be

$$Y_m = N_r \int \kappa_u^{-1} p_{na} A_{na} h_{na}(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}) l_{na}\left(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}\right) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}).$$

We define the following:

1. <u>*Observed APG*</u>: $\ln\left[Y_m/L_m\right] - \ln\left[\left(Y_a + Y_r\right)/\left(L_a + L_r\right)\right]$, where L_m, L_a, and L_r are the labor supply of migrant workers, rural agricultural workers, and rural non-agricultural workers, respectively.

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2. *Underlying APG*: $\ln\left[Y_m/H_m\right] - \ln\left[\left(Y_a+Y_r\right)/\left(H_a+H_r\right)\right]$, where H_m, H_a, and H_r are the effective labor supply of migrant workers, rural agricultural workers, and rural non-agricultural workers, respectively.

3. *Human capital gap*: $\ln\left[H_m/L_m\right] - \ln\left[\left(H_a+H_r\right)/\left(L_a+L_r\right)\right]$. By definition, *observed APG = underlying APG + human capital gap*.

4. *GDP*:

$$
\begin{aligned}
Y &= N_r \int \bar{p}_a y_a(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) \\
&+ N_r \int \bar{p}_{na} y_r(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) + \bar{p}_{na} A_{na} H_{na},
\end{aligned}
$$

   where $\bar{p}_a$ and $\bar{p}_{na}$ are the 2003 prices of agricultural and non-agricultural goods, respectively; $H_{na} = H_m + H_u$; and H_u is the effective labor of urban residents.

5. *Total effective labor*: $H = H_a + H_r + H_{na}$.

6. *Aggregate productivity*: Y/H.

4.6 General Equilibrium Conditions and Solution

The total demand for agricultural goods is

$$D_a = \chi_r N_r \int p_a c_a(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) + \chi_u p_a c_a^u N_u$$

where the second term is the demand for agricultural goods by urban households and χ_r and χ_u are the population-to-worker ratios in rural and urban areas, respectively. Similarly, the total demand for non-agricultural goods is:

$$D_{na} = \chi_r N_r \int p_{na} c_{na}(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) + \chi_u p_{na} c_{na}^u N_u$$

The market clearing conditions for the agricultural goods market and the non-agricultural goods markets, are, respectively,

$$D_a = Y_a \quad \text{and} \quad D_{na} = Y_r + Y_m. \tag{6}$$

where Y_a, Y_r, and Y_m are the total effective outputs of rural agricultural goods, rural non-agricultural goods, and urban non-agricultural goods, as defined in Section 4.5.

The government's budget constraint is

$$\left[N_r \int n_o dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z})\right] p_a T = N_u p_a \tau. \tag{7}$$

It implies that the total pension transfers to the rural elderly equal the total taxes collected from the urban workers.

Given the prices, p_a and p_{na}, government transfer, T, and tax rate, τ, and the values of all the other parameters of the model, the market-clearing condition in the agricultural sector can be used to calibrate the value of h_u, the human capital level of urban households.

In any counterfactual exercise, we can first solve the government tax rate, τ, from the government's budget constraint in equation (7). Then, holding p_{na} fixed, we again use the market-clearing condition in the agricultural sector to solve for the new equilibrium price, p_a.[17]

5 Calibration and Estimation

In this section, we discuss how the parameters of the model are determined. We utilize micro-data and the indirect inference method to estimate the parameters of production technologies, the ability distribution, migration costs, and home production. Meanwhile, the values of the preference parameters are determined through calibration.

5.1 Calibration

For the inverse of the elasticity of intertemporal substitution (γ) and the Frisch elasticity of labor supply (ϕ), we take the values directly from the macro-labor literature and set $\gamma = 1.2$ and $\phi = 0.5$. See, e.g., Bick et al. (2022) and Heathcote et al. (2014). The parameters of the non-homothetic CES consumption aggregator are calibrated using data on prices and household expenditures. The details about the construction of prices and the calibration procedures are reported in Appendix F. The calibration results are summarized in Table 4 below.

[17]By Walras's law, only the relative price, p_a/p_{na}, is determined in equilibrium. Thus, we can fix the value of p_{na} at its value in the data in our counterfactual analysis.

Table 4: Calibration Results

	Estimated using expenditure shares:	
ε	elasticity of substitution	0.342
μ	income elasticity of non-agricultural goods	2.446
φ_a	preference weight on agricultural goods	0.698
	Taken from the literature:	
γ	1/intertemporal elasticity of substitution	1.2
ϕ	Frisch elasticity of labor supply	0.5

5.2 Identification and Estimation

The parameters of production technologies, the individual ability distribution, migration costs, and home production are estimated structurally using micro-data and the indirect inference method by matching unconditional and conditional moments related to earnings, migration, and labor supply in the NFP data. Before presenting the estimation results, we discuss intuitively how each of these parameters is identified in our structural estimation.

The average level, trend, and variance of daily earnings in the agricultural and urban non-agricultural sectors help identify the levels of TFP, the trends in TFP, and the variances of productivity shocks in the two sectors, respectively. We then use the share of labor supply in the rural non-agricultural sector to recover the TFP in that sector. To identify the parameters in the human capital function, we match the coefficients of a Mincer regression of urban non-agricultural daily earnings on sex, years of schooling, age, and age squared in the model to those in the data.

The serial correlations of daily earnings for individuals staying in the agricultural and non-agricultural sectors help to identify the variances of agricultural and non-agricultural ability, respectively. For individual workers who stay in a sector (i.e., stayers), the variance of earning residuals after accounting for observable characteristics arises from two sources: the variance of ability in the sector and the variance of i.i.d. productivity shocks. If the variance of ability is substantial, we would expect to observe a strong persistence in earnings over time. Consequently, the serial correlation in daily earnings of stayers identifies the variance of ability in the sector. Likewise, the serial correlation in daily earnings for household members who switch sectors identifies the correlation between agricultural and non-agricultural abilities.

We define migration rate at the household level as an indicator of whether a household has at least one migrant. Then, we regress the migration rate on household averages of sex, years of schooling, age, age squared, and the origin-based Hukou Index. Then we match the regression coefficients to identify the parameters in the migration cost function. To identify the disutility of labor supply (η), the constant term in the migration cost (m_0), and the constant term in the marginal migration cost (ζ_0), we match the average number of annual working days of young agents in the rural and urban areas, for households with and without migrants. In particular, the fixed cost of migration, m_0, affects the non-agricultural labor supply of migrant families, while ζ_0, which captures the variable cost of migration, affects the difference between agricultural and non-agricultural labor supply in migrant families. The average migration rate helps to identify the standard deviation of the migration cost shock (σ_c), and the average number of annual working days of old agents in rural areas helps to identify the efficiency of home production of the elderly (ξ).

Lastly, we match the effect of the NRPS on migration by utilizing the triple-difference specification introduced in the reduced form analysis. In the model, we simulate the counterpart by comparing the migration share of households with and without the NRPS, focusing on those containing both young workers and elderly individuals. This identifies the parameter in the household production in the rural agricultural sector, α. The NRPS affects migration through the home production channel by increasing elderly parents' time in home production and adult children's labor supply and migration rate. The strength of this effect is influenced by the diminishing returns to labor: when young workers move to the city, labor productivity in rural areas will increase, which will dampen the incentive to migrate. The smaller α is, the stronger the diminishing returns to labor, and hence the smaller the effect of the NRPS on migration.

5.3 Estimation Results

Table 5 shows the parameter estimates. We assume that, for $j = a, r$, $A_{j,t} = e^{g_a t} A_{j,0}$, and $A_{na,t} = e^{g_{na} t} A_{na,0}$. The initial TFP levels in 2003, $A_{a,0}$ and $A_{na,0}$, are estimated to be 2.230 and 4.083, respectively. The TFP in the urban non-agricultural sector has a higher growth rate than the TFP in the rural sector (0.110 vs. 0.057). Thus, holding labor allocation constant, the underlying productivity gap between sectors na and a would increase over time.

The upper panel of Table 5 shows the estimated values of the parameters of the ability distribution. Agricultural ability has a larger standard deviation than non-agricultural ability (0.741 vs. 0.472), and agricultural and non-agricultural abilities are positively correlated (0.552). The productivity shock also has a larger standard deviation in the agricultural sector than in the non-agricultural sector (0.570 vs. 0.541). These facts explain why agricultural income has a larger variance than non-agricultural income in the data.

The rest of the upper panel reports the parameters related to household agricultural production and home production. The estimated values of α and η are 0.990 and 2.200, respectively. The estimated value of ξ is 5.075, which implies that the home production efficiency/disutility of labor supply is higher for elderly workers than for young workers.

The middle panel of Table 5 reports the coefficients in the human capital equation. The human capital premium for men (relative to the premium for women) is 4.3 log points. The return to education is 3.3 log points. The life-cycle human capital is hump-shaped, with a peak at age 46.

The bottom panel of Table 5 shows the parameter estimates related to migration costs. Migration costs are lower for workers who are male, more educated, and younger. Since households vary by their demographics and labor supply, we calculate the average migration cost across all individuals and across all years in the model, and find that the average migration cost is 76% of non-agricultural earnings. We also find that the Hukou Index has a profound effect on migration costs. The Hukou Index, on average, increased from 2.06 in 2003 to 3.61 in 2013 due to the relaxation of *hukou* policies. As a result, the yearly average migration costs across all individuals decreased by 2.56 percentage points a year in that period.

5.4 Model Fit

Panel A of Table 6 reports the targeted moments in the data and the corresponding values in the model. Overall, the model fits the targeted moments well. Panel B reports the model fit of some untargeted moments. The model predicts that the average observed APG over the whole sample period is 0.195, which is slightly higher than the corresponding moment in the data (0.140). The yearly observed APG exhibits a linear trend, increasing by 0.045 a year in the model and 0.051 a year in the data, respectively. The key reason for the rising APG is the higher TFP growth in the non-agricultural sector, as reported in Table 5.

Table 5: Estimation Results

Parameter	Meaning	Estimate	Standard error
A_a	TFP level of Agri in 2003	2.300	0.0002
A_{na}	TFP level of urban NonAgri in 2003	4.083	0.0010
g_a	TFP growth rate of Agri and rural NonAgri	0.057	0.0000
g_{na}	TFP growth rate of urban NonAgri	0.110	0.0001
σ_u^a	std of Agri ability	0.741	0.0010
σ_u^{na}	std of NonAgri ability	0.472	0.0003
ρ	correlation of Agri and NonAgri ability	0.552	0.0003
σ_e^a	std of Agri productivity shock	0.570	0.0005
σ_e^{na}	std of NonAgri productivity shock	0.541	0.0007
σ_c	std of migration cost shock	0.180	0.0000
α	labor share in Agri	0.990	0.0003
η	disutility of labor supply	2.200	0.0004
ξ	relative home productivity efficiency of the elderly	5.075	0.0019
β	coefficients in human capital equation:		
β_1	female	-0.043	0.0002
β_2	years of schooling	0.033	0.0002
β_3	age	0.073	0.0001
β_4	age squared	-0.001	0.0000
m_0	constant in migration cost	0.077	0.0001
ζ	coefficients in marginal migration costs:		
ζ_0	constant	-1.749	0.0002
ζ_1	female	1.721	0.0005
ζ_2	years of schooling	-0.107	0.0001
ζ_3	age	1.260	0.0002
ζ_4	age squared	-0.014	0.0000
ζ_5	Hukou Index	-0.407	0.0006
	overall average migration cost (% of NonAgri earnings)	75.9%	
	average annual change in migration cost	-2.68%	

As shown in Section 3.2, the NRPS affects migration costs by reducing the labor supply of the elderly and increasing the labor supply of young workers. The model's prediction of these effects of the NRPS is consistent with the data. The model is also consistent with the data in predicting a positive linear trend in the migration rate without assuming an exogenous reduction in the average migration cost. The migration rate increases in the model for two reasons: (i) a decline in migration costs due to an increase in the average Hukou Index (i.e., the relaxation of *hukou* policies) and the implementation of the NRPS; and (ii) an increase in returns to migration due to higher TFP growth in the non-agricultural sector.

6 Counterfactual Analyses

In this section, we use the data in 2013 with the implemented NRPS as our baseline and conduct a series of counterfactual analyses to quantify the impact of the rural

Table 6: Model Fit

Moments	Data	Model
A. Targeted Moments		
Average of log daily urban NonAgri earnings	3.680	3.518
Average of log daily rural Agri earnings	3.416	3.201
Linear trend of log daily urban NonAgri earnings	0.113	0.112
Linear trend of log daily rural Agri earnings	0.067	0.066
Variance of log daily urban NonAgri earnings	0.670	0.663
Variance of log daily rural Agri earnings	0.998	0.978
Serial correlation in log daily household earnings for rural stayers	0.704	0.654
Serial correlation in log daily household earnings for urban stayers	0.614	0.588
Serial correlation in log daily household earnings for rural-to-urban switchers	0.530	0.572
Regression of log daily urban NonAgri earnings on		
age	0.067	0.067
age squared	-0.001	-0.001
female	-0.093	-0.093
years of education	0.041	0.041
Regression of migration dummy on		
age	-0.057	-0.054
age squared	0.001	0.001
female	-0.158	-0.156
years of education	0.012	0.012
Hukou Index	0.053	0.053
Average migration rate	0.602	0.548
Average working days of young workers in rural areas for households with migrants	0.280	0.265
Average working days of young workers in urban areas for households with migrants	0.409	0.380
Average working days of young workers in rural areas for households without migrants	0.577	0.612
Average working days of elderly in rural areas	0.281	0.273
Effect of NRPS on migration rate for families with elderly members	0.022	0.022
B. Untargeted Moments		
Average observed APG	0.140	0.195
Linear trend in observed APG	0.051	0.047
Linear trend in migration share	0.017	0.018
Effect of NRPS on the labor supply of young workers (rural + urban areas)	0.008	0.038
Effect of NRPS on the labor supply of elderly workers in rural areas	-0.019	-0.092

pensions and *hukou* policy reforms on labor allocation, migration, the APG, GDP, and welfare.

For the baseline case, we specify the values of some exogenous variables as follows. We normalize the number of rural households N_r to be 1. We set the ratio of the number of urban workers to the number of rural households, N_u, to be 0.612 and the population-to-worker ratio in urban areas, χ_u to be 1.311 according to the 2010 census. We set the rural population-to-worker ratio, χ_r, to be 1.396 based on the 2010 NFP data. Finally, we calibrate the human capital for urban workers, h_u, by solving the goods market-clearing condition (equation (6)), yielding a human capital value of 8.164. This value is significantly higher than the average human capital for migrant workers, $\bar{h}_{na}$, which stands at 2.947. These figures imply an average wage gap of 2.8:1 between urban residents and migrant workers, which is close to the reported 3:1 average income gap between urban and rural households in 2013 according to Table 6-4 of the 2014 China Statistical

Yearbook. Therefore, in addition to the APG between the migrant workers and the rural agricultural workers, there exists a productivity gap between urban residents and migrant workers.

The effects of the rural pension and *hukou* policies on aggregate GDP are shown in Table 7. Since the changes in aggregate GDP can be decomposed into changes in aggregate productivity, average human capital, and aggregate labor supply,

$$\Delta \ln(Y) = \Delta \ln(Y/H) + \Delta \ln(H/L) + \Delta \ln(L); \tag{8}$$

these changes are also reported in Table 7.

Aggregate productivity and average human capital can be further decomposed as follows:

$$\frac{Y}{H} = \bar{w}_a \left(1 - \frac{H_{na}}{H}\right) + \bar{w}_{na}\frac{H_{na}}{H}; \tag{9}$$

$$\frac{H}{L} = \bar{h}_o\frac{L_o}{L} + \bar{h}_a\frac{L_y}{L} + \bar{h}_{na}\frac{L_{na}}{L} + h_u\frac{L_u}{L}. \tag{10}$$

Here, $\bar{w}_a$ and $\bar{w}_{na}$ denote the real value-added per unit of effective labor in the rural and urban sectors, respectively; $\bar{h}_o$, $\bar{h}_a$, $\bar{h}_{na}$, and h_u denote the average human capital of old rural workers, young rural workers, migrant workers, and urban residents, respectively.

In the baseline case, $\bar{w}_a = 19.92$ and $\bar{w}_{na} = 27.23$. Given the large difference in labor productivity between the two sectors, the effective allocation of labor between the two sectors is critical in determining aggregate productivity. In the baseline case, the average human capital values are $\bar{h}_o = 1.57$, $\bar{h}_a = 2.94$, $\bar{h}_{na} = 2.95$, and $h_u = 8.16$. Thus, among workers with rural *hukou*, the human capital gap between old and young agricultural workers is large, but the gap between young agricultural workers and migrants is small. Therefore, the reallocation of labor supply from old workers to young workers has an important effect on the average human capital of the whole economy. We report the effects of the rural pension and *hukou* policies on labor allocation and migration in Table 8, and on the APG and human capital gap in Table 9.

6.1 Effects of the NRPS

Row (2) of Table 7 shows the counterfactual results if the NRPS had not been implemented in any county in 2013. Compared to the baseline case, aggregate GDP is 2.241 log points lower without pension transfers; this is mainly due to a

2.029 log-points reduction in aggregate labor supply. As shown in Rows (1)–(2) of Table 8, in the absence of the NRPS, elderly rural workers would have increased their labor supply, and young rural workers and migrants would have decreased their labor supply to an even greater degree, such that aggregate labor supply would have declined. The reallocation of labor from young workers to old workers also reduces average human capital as well as the non-agricultural sector's share of effective labor (H_{na}/H). The decline in (H_{na}/H), in turn, decreases aggregate productivity. These two effects, however, are quantitatively small relative to the effect on aggregate labor supply. Table 8 also shows the impact of the NRPS on between-sector labor allocation. Comparing the numbers in Row (1) to those in Row (2), we can see that the NRPS increases the migration rate by a modest half a percentage point. The effect of the NRPS on migrants' share of employment (L_{na}/L) is three times as large at 1.5 percentage points.

Table 7: Effects of the Rural Pension and *Hukou* Policies on GDP and Its Components

Log difference in: (relative to the baseline, log points)	GDP	Aggregate productivity	Average human capital	Aggregate labor supply
(1) Baseline: with NRPS in 2013	0.000	0.000	0.000	0.000
(2) Without NRPS	-2.241	-0.136	-0.076	-2.029
(3) NRPS scaled up fivefold	4.173	0.076	0.829	3.268
(4) *hukou* reform	2.039	0.905	1.596	-0.462
(5) *hukou* reform without NRPS	-0.006	0.761	1.537	-2.304
(6) 2003 hukou without NRPS	-6.556	-1.498	-3.145	-1.913

Notes: The table reports the changes in GDP, aggregate productivity, human capital, and aggregate labor supply relative to the baseline case under six counterfactual scenarios. The changes are measured in log points.

Table 8: Effects of the Rural Pension and *Hukou* Policies on Labor Allocation

	Migration rate	L_{na}/L	H_{na}/H	L_o	L_y	L_{na}
(1) Baseline: with NRPS in 2013	0.637	0.377	0.637	0.089	0.975	0.848
(2) Without NRPS	0.632	0.362	0.634	0.134	0.935	0.800
(3) NRPS scaled up fivefold	0.635	0.389	0.639	0.024	1.052	0.904
(4) *hukou* reform	0.665	0.393	0.647	0.095	0.924	0.880
(5) *hukou* reform without NRPS	0.661	0.379	0.645	0.134	0.891	0.834
(6) 2003 *hukou* without NRPS	0.572	0.326	0.612	0.133	1.023	0.719

Notes: The table reports the migration rate, migrants' share of labor, the non-agricultural sector's share of effective labor, and the labor supply of rural workers and migrants in the baseline case and under six counterfactual scenarios.

Table 9 reports the observed APG, underlying APG, and the human capital gap between migrants and agricultural workers in the baseline case and under six

Table 9: Effects of the Rural Pension and *Hukou* Policies on the APG and Human Capital Gap

	Observed APG	Underlying APG	Human Capital Gap
(1) Baseline: with NRPS in 2013	35.6	31.5	4.1
(2) Without NRPS	39.9	32.9	7.0
(3) NRPS scaled up fivefold	33.2	30.8	2.4
(4) *hukou* reform	19.2	16.5	2.7
(5) *hukou* reform without NRPS	23.8	18.2	5.6
(6) 2003 *hukou* without NRPS	62.2	52.6	9.7

Notes: The table reports the observed APG, underlying APG, and human capital gap between migrants and agricultural workers in the baseline case and under six counterfactual scenarios. The gaps are measured in log points.

counterfactual scenarios. Row (1) shows the baseline case: the observed APG is 35.6 log points while the underlying APG is slightly lower at 31.5 log points. The 4.1-log-point difference between the observed APG and the underlying APG is the average human capital gap between migrant workers and agricultural workers. Thus, most of the observed APG is accounted for by the underlying productivity difference, with selection playing a minor role. This result remains true under all six counterfactual scenarios and is consistent with our reduced-form empirical result in Section 3.1. A comparison of Row (1) and Row (2) indicates that the NRPS reduces the underlying APG by 1.4 log points and the human capital gap by 2.9 log points. Therefore, the observed APG declines by 4.3 log points.

In summary, the NRPS policy has a significant positive effect on aggregate output, primarily through reducing within-household labor misallocation and increasing the labor supply of young workers in both agricultural and non-agricultural sectors. Additionally, the policy enhances between-sector labor allocation and decreases the APG, although these effects are quantitatively modest. Having established the outcomes of the rural pension policy, we next examine the impacts of scaling up said policy.

6.2 Effects of Scaling Up the NRPS

Row (3) of Table 7 displays the effects of increasing the pension transfer amount fivefold. In this case, aggregate GDP would further increase by 4.173 log points, primarily because of an increase in aggregate labor supply. Moreover, under the scaled-up policy, the reallocation of labor supply from elderly rural workers to young rural workers also leads to a quantitatively significant increase in the average human capital of 0.829 log points.

Row (3) of Table 8 shows that, under the scaled-up pension policy, the migration rate decreases slightly. This is because the significant reduction in the labor supply of old workers leads to an increase in the marginal product of labor among young rural workers in the agricultural sector, making it more likely for some young workers to remain in that sector. However, the young workers who do migrate will increase their labor supply significantly. As a result, migrants' share of the total labor supply increases despite the minor reductions in the migration rate. These findings underscore the importance of examining labor allocation not only at the extensive margin but also at the intensive margin when assessing the impact of rural pension policies. Finally, the scaled-up pension policy leads to additional small reductions in both the underlying APG and human capital gap.

Table 10 presents the effects of rural pension policies on the welfare of elderly rural workers, young rural workers, urban workers, and the total population, alongside their impact on GDP.

Table 10: Effects of the Rural Pension Policies on GDP and Welfare

	GDP	Welfare				
		Rural old	Rural young	Urban	Total	Total (exp. equiv)
(1) Baseline: with NRPS in 2013	0.000	0.000	0.000	0.000	0.000	0.000
(2) Without NRPS	-2.241	-0.196	-0.201	0.004	-0.394	-14.8
(3) NRPS scaled up fivefold	4.173	0.344	0.214	-0.012	0.546	28.5
(4) NRPS scaled up fivefold, tax rural young workers	4.656	0.343	0.080	0.004	0.427	21.3

Notes: The table reports the effects of rural pension policies on GDP (in log points) and welfare (in utiles) of elderly rural workers, young rural workers, urban workers, and the total population. The last column reports the expenditure-equivalent percentage changes in total welfare.

Rows (1)–(3) of Table 10 demonstrate that in addition to boosting aggregate GDP and the welfare of elderly rural workers, the rural pension policies also enhance the welfare of young rural workers. As illustrated in the simple model in Section 4.3, there exists friction in allocating labor between old workers and young workers within a family. Young workers dedicate excessive time to home production, while old workers spend too much time in agricultural activities, leading to inefficiencies as old workers possess a comparative advantage in home production. By providing pension transfers to old workers, the within-family labor misallocation diminishes, enabling old workers to focus more on home production and young workers on market production, thereby benefiting both types of rural workers.

In our baseline case, we assumed that transfers are funded through a lump-sum tax on urban households. Unsurprisingly, these policies have a detrimental impact on the welfare of urban workers. However, given the substantial income disparity between rural workers and urban workers, the overall welfare of the entire population experiences a significant boost. We also explore an alternate financing scheme that taxes only young rural workers. Row (4) of Table 10 delineates the effects of scaling up the NRPS on GDP and welfare under this different financing scheme. If young rural workers were to bear the burden of financing pension transfers at five times the NRPS level, their welfare would still be higher than it is under the current NRPS policy. GDP would further increase due to a rise in the labor supply of young rural workers. Urban workers would benefit as well because the relative price of non-agricultural goods will increase.

In essence, a policy entailing substantial transfers to elderly rural workers and funded through a lump-sum tax on young rural workers would enhance the welfare of elderly rural workers, young rural workers, and urban workers. This policy would lead to an almost 4.7% GDP increase, presenting a viable strategy for driving significant economic growth and welfare gains.

6.3 Effects of Migration Policies

Migration policies vary significantly across Chinese cities. As a result, migrants who move to different cities face different migration costs. Our origin-based Hukou Index measures the expected degree of migration policy liberalization in destination cities faced by migrants from a particular location. In 2013, the value of this index varied from 1.0 to 5.2 (see Figure 1a, the higher the number, the more liberal the policy). As our estimation results in Table 5 show, the Hukou Index has a strong negative effect on migration costs.

We consider a hypothetical policy reform in 2013 where all destination cities adopt the most liberal *hukou* policy, which effectively sets the Hukou Index to be 6 for all destination cities and reduces the migration costs for many rural households. Row (5) of Table 8 shows that, under the hypothetical *hukou* reform, the migration rate, the migrants' share of labor supply, and the non-agricultural sector's effective labor supply increase by 2.8, 1.6, and 1 percentage point(s), respectively. Row (5) of Table 7 shows that, due to the sectoral labor reallocation, the hypothetical *hukou* reform leads to a 1.596-log-points increase in average human capital and a 0.905-log-point increase in aggregate productivity. Aggregate labor supply, however, decreases by 0.462 log points. Overall, the hypothetical *hukou* reform increases GDP by 2.039 log points, which is close to the 2.241 log-points increase in GDP under the NRPS policy. However, the two policies affect GDP through two different channels. While the rural pension policy increases GDP primarily through reducing within-household labor misallocation and increasing aggregate labor supply, the hypothetical *hukou* reform increases GDP through sectoral labor reallocation, which in turn improves aggregate productivity and average human capital.

The significant sectoral labor reallocation under the hypothetical *hukou* reform also leads to large reductions in both the underlying APG and human capital gap between migrants and agricultural workers. A comparison of Row (5) and Row (1) of Table 9 reveals that the hypothetical *hukou* reform decreases the underlying APG by 15 log points and the human capital gap by 1.4 log points. Consequently, the observed APG declines by 16.4 log points under the hypothetical *hukou* reform. To estimate the quantitative effect of the NRPS in an environment with a much lower APG, we conduct a counterfactual experiment that implements the hypothetical *hukou* reform in 2013 but eliminates the NRPS transfers. The results are reported in Row (6) of Tables 7–9. A comparison of Row (5) and Row (6) of Table 7 shows that, similar to the baseline case, eliminating the pension transfers under the hypothetical *hukou* reform would reduce GDP by 2.045 log points, mainly due to a 1.842-log-points reduction in aggregate labor supply. In other words, the impact of the rural pension policy remains important even if migration costs and the APG are much lower than those observed in China in 2013.

Finally, we conduct a counterfactual experiment by eliminating the NRPS transfers from the baseline case and setting each region's Hukou Index to its 2003 value. Relative to the baseline case, we find that the combination of NRPS and the actual *hukou* policy reforms that have taken place between 2003 and 2013 increased migration by 6.5 percentage points and raised aggregate productivity, average human capital, and aggregate labor supply by 1.498, 3.145, and 1.913 log points, respectively. Consequently, the actual policy reforms between 2003 and 2013 led to a 6.556% increase in GDP.

In related work, Tombe and Zhu (2019) and Hao et al. (2020) also examined the impact of migration cost reductions on GDP in China. Hao et al. (2020) updated the analysis of Tombe and Zhu (2019) to the period between 2005 and 2015, which is very close to the period of our analysis (2003–2013). In Table 9 of their paper, they show that the reduction of costs to out-of-county agriculture-to-nonagriculture migration contributed to an 8.3% increase in GDP. This effect is larger than the 6.556% increase in GDP we find stemming from policy changes between 2003 and 2013. There are three reasons for the difference in estimates. First, Hao et al. (2020) consider all potential changes in migration costs that help their structural model account for the observed changes in migration rates; meanwhile, we consider only two explicit policy changes: the relaxation of *hukou* policies and the NRPS. Second, our estimation using microdata shows that there is a significant productivity gap between migrants and urban workers. Meanwhile, Hao et al. (2020) assume that migrants and urban workers have the same productivity and therefore likely overestimate the gains from migration. Finally, their model is a spatial model in which migration helps to reduce both sectoral and spatial misallocation of labor, while our model abstracts from spatial variation and focuses only on the gains from reallocating labor between sectors.

7 Conclusion

This study sheds light on the potential barriers to the reallocation of labor away from agriculture in developing countries. We find that the New Rural Pension Scheme (NRPS) in China effectively decreases the labor supply of elderly workers while increasing the labor supply of younger household members in the non-agricultural sector, leading to higher earnings and better resource allocation within households and across sectors.

We further demonstrate the considerable positive aggregate effects of the rural pension policy on labor allocation, GDP, and welfare using a structural model and quantitative analyses. The results show that the absence of adequate old-age security in rural regions acts as a barrier to labor reallocation across sectors in developing countries, and that implementing rural pension programs can facilitate enhanced labor allocation, thereby boosting aggregate income and welfare in developing countries.

Our empirical analysis shows that high migration costs, rather than labor sorting, predominantly explain the observed agricultural productivity gap (APG) in China. Furthermore, our analysis reveals a large gap in the average labor income between migrants and urban residents, which limits the gain from rural-urban migration in China. Further investigation into the factors contributing to this migrant-resident productivity gap is an interesting avenue for future research.

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