Migration Costs, Sorting, and the Agricultural Productivity Gap

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Abstract

We use a unique panel dataset and a policy experiment as an instrument to estimate the impact of policy-induced migration cost reductions on rural-to-urban migration and the associated increase in labor earnings for migrant workers in China. Our estimation shows that there are large migration costs and the observed labor earnings gap between agriculture and non-agriculture is mainly due to a large underlying productivity difference between the two sectors, with sorting plays only a minor role. We construct a general equilibrium household model with endogenous labor supply and migration that not only is consistent with the reduced form results, but also illustrates the channel through which the policy experiment affects migration. We then estimate the general equilibrium model structurally and use the estimated model to quantify the effects of various policies on migration, the labor earnings gap, aggregate productivity, and welfare. We find that the policy that provides transfers to old agents in rural China has positive effects on both GDP and welfare, and scaling up the transfer program would have even larger positive effects on GDP and welfare. However, these policies have relatively small effects on migration and the observed sectoral productivity gap. A policy reform that relaxes restrictions on migration, on the other hand, has larger effects on migration and the observed sectoral productivity gap, and positive effects on GDP and welfare.

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

Keywords: Migration cost; labor supply; sorting; agricultural productivity gap; panel data; China; general equilibrium household model

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1 Introduction

There are large gaps in value-added per worker between the agricultural and non-agricultural sectors in developing countries, a phenomenon known in the literature as the agricultural productivity gap (APG). Sectoral labor productivity gaps remain sizeable, even after controlling for observable sectoral differences in worker characteristics, such as education and working hours (Gollin et al., 2014). Because a large portion of the labor force in poor countries work in agriculture, the APG is also the main reason for the large disparity in aggregate labor productivity between rich and poor countries (Gollin et al., 2002; Caselli, 2005; Restuccia et al., 2008). Therefore, understanding the sources of the APG is important for understanding why developing countries lag behind in aggregate productivity, and for designing policies that may help reduce income disparities between developing and developed countries.

There are two competing explanations for the large APG in developing countries. One explanation refers to differences in unobserved worker characteristics and sorting.[1] Another explanation focuses on barriers to worker mobility between the two sectors, which prevent farmers from migrating to the more productive non-agricultural sector.[2] In the former case, efficient sorting implies that there is little room for policy makers to improve welfare by reallocating workers out of agriculture. In contrast, in the latter case, the APG reflects a combination of the underlying sectoral productivity gap and barriers to switching sectors, and policies that reduce the barriers could help improve aggregate productivity in the developing countries.

Of course, these two explanations are not mutually exclusive. As pointed out by Lagakos (2020) and Donovan and Schoellman (2020), it is likely that both sorting and mobility barriers are important in accounting for the observed APG, and the research challenge is to identify these two sources empirically, to quantitatively estimate their contributions to the APG, and to identify policies that may help reduce the APG and increase aggregate productivity and welfare. We tackle the challenge in this paper. We use a unique large panel dataset and a

[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. (2018), Ngai et al. (2019), Tombe and Zhu (2019), Hao et al. (2020), Lagakos et al. (2020), Imbert and Papp (2020).

policy experiment in China as an instrument to empirically estimate the average migration cost of marginal workers affected by the policy and the underlying average labor productivity difference between the two sectors. We also construct a general equilibrium household model with endogenous labor supply and migration that not only is consistent with the reduced form results, but also illustrates the channel through which the policy experiment affects migration. We then estimate the general equilibrium model structurally and use the estimated model to quantify the effects of various policies on migration, the APG, aggregate productivity, and welfare.

The panel dataset we use is the annual National Fixed Point (NFP) survey of agriculture that tracks around 80,000 rural agricultural workers and rural-to-urban migrant workers from 2003 to 2013 in China. The policy experiment is the gradual county-by-county roll-out of New Rural Pension Scheme (NRPS) between 2009 and 2012. Existing studies show that NRPS increases elderly consumption of healthcare services and reduces their reliance on the eldercare provided by their children (Zhang and Chen, 2014; Eggleston et al., 2016; Chen et al., 2018). The studies also show that NRPS reduces elderly labor supply in farm work and increases their time spent with their grandchildren (Jiao, 2016; Huang and Zhang, 2020). Through these two channels, NRPS helps reduce the migration costs of the elderlies' adult children, but has no direct impact on their labor earnings in the two sectors. Therefore, the policy experiment can serve as an instrument for estimating the migration returns of workers who switched sectors due to the policy—the local average treatment effect (LATE).

The results of our reduced-form empirical analysis can be summarized as follows. First, the OLS cross-sectional regression shows that the observed APG in China is 31 log points, after we control for sectoral differences in observable worker characteristics. Second, in contrast to the recent findings for several other countries, the observed APG is virtually the same if we also control for individual fixed effects. We argue that this is likely due to the high barriers to migration in China, and therefore high returns to migration are needed to induce migration. Third, we estimate the local treatment effect of migration induced by the NRPS policy and find that the incomes of NRPS-induced migrants on average increased by 88 log points, confirming that workers who were affected by the NRPS policy faced large migration costs before the policy implementation. Finally, we also use the NRPS policy as an instrument and a control function approach to estimate the average treatment effect of migration. The estimate implies an APG of 33 log points, which is higher but very close to the OLS estimate of 31 log points. The result suggests that there is negative selection and the selection bias of the observed APG is small in the case of China.

We then extend our analysis by structurally estimating a general equilibrium household model with endogenous labor supply so that we can understand better the channel through which the NRPS policy affects migration and evaluate its aggregate effects. We show that NRPS, by providing income transfers to old agents in rural areas, increase their home production, which in turn allows young agents to increase their labor supply and therefore earn higher income through migration. Our counterfactual analysis of the general equilibrium model shows that the NRPS policy has positive effects on both GDP and welfare, and scaling up the transfer program would have even larger positive effects on GDP and welfare. Our structurally estimated model also shows that China's *hukou* policies impose significant costs to rural-urban migration and our counterfactual analysis show that relaxation of *hukou* policies could have large positive effects on migration, real GDP and aggregate productivity, and negative effect on the APG.

Our study contributes to the literature that examines the roles of labor mobility barriers and sorting in accounting for the observed agricultural productivity gap. See Lagakos (2020) for a recent survey of this literature. In particular, Lagakos and Waugh (2013), Tombe and Zhu (2019), and Hao et al. (2020) use general equilibrium Roy models to quantify the role of selection and migration barriers in accounting for the observed APG. To do so, they impose strong and restrictive assumptions about the distributions of unobserved individual abilities or preferences. Thus the quantitative results could be sensitive to functional form assumptions. To get around this, Herrendorf and Schoellman (2018), Alvarez (2020), and Hamory et al. (2021) try to control for the selection effect by using individual fixed effect regressions to estimate the migration returns of those who did migrate. However, Pulido and Świecki (2018) and Lagakos et al. (2020) point out that controlling for individual fixed effects does not solve the selection problem if individuals' unobserved abilities are different in the two sectors and they sort into the two sectors according to their comparative advantage. One of our paper's main contributions is exploiting a quasi-natural policy experiment as an instrument to solve the identification problem and estimate the average treatment effect (ATE) of migration and the average migration cost of the treated individuals (LATE) without imposing strong functional form assumptions.[3] The empirical methods we use are well known in the labor literature (see, e.g., Heckman and Honore (1990), Card (2001) and Cornelissen et al. (2016)), but have so far not been applied in the APG literature. Our paper helps to bridge the gap.

Another main contribution of our study is developing and estimating a general equilibrium household model with endogenous labor supply and migration. The model helps to clarify the channel through which the NRPS policy affect migration, and we discipline the model by matching key unconditional and conditional moments in the micro data so that our structural model is fully consistent with our reduced-form empirical results. In this regard, our paper is also related to Lagakos et al. (2018), which uses results from a micro field experiment to calibrate its general equilibrium model of migration in Bangladesh.

Finally, our study is also related to the literature on misallocation and aggregate productivity in China. See, e.g., Hsieh and Klenow (2009), Song et al. (2011), Brandt et al. (2013), Ngai et al. (2019), Tombe and Zhu (2019), and Adamopoulos et al. (2022). In particular, Adamopoulos et al. (2022) also uses the NFP panel data and a general equilibrium Roy model to examine misallocation in China. Their focus, however, is on how the frictions within agriculture affect the occupational choices of workers, while our focus is on the effects of rural-to-urban migration costs. Another difference is that they use the household-level data prior to 2003, while we use the data on individual migrant workers for the 10-year period starting from 2003.

2 Institutional Background and Data

2.1 The Hukou System and Origin-based Hukou Index

Under China's household registration system, each Chinese citizen is assigned a *hukou* (registration status), classified as "agricultural (rural)" or "non-agricultural (urban)" 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 tied to having local *hukou* status. Individuals need

[3] There are a small number of recent papers that employ field and natural experiments to identify the return to migration, such as Bryan et al. (2014) and Nakamura et al. (2016). Our study complements these papers, but also highlights how to make use of quasi-experimental variation to identify the underlying APG.

approval from local governments to change their *hukou*'s category (agricultural or non-agricultural) or location, and it is extremely difficult to obtain such approval. Due to these institutional barriers, most rural-to-urban migrant workers are without urban *hukou* and therefore have limited access to local public services, such as health care, schooling, and social security. Consequently, many migrant workers leave their children and elders behind in rural areas. 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 varies across cities.[4]

To capture the spatial and time variation of migration barriers linked to *hukou* policies, we adapt the methodology by Fan (2019) to create an origin-based Hukou Index. This index measures the level of ease with which migrant workers from a particular prefecture can settle in cities, and it is negatively related to the migration barriers faced by migrant workers from that prefecture. (See Appendix A.1 for details.) Table 1 shows that the average and maximum Hukou Index have increased over time, suggesting a general trend of *hukou* policy liberalization. There are also significant variations in migration barriers across different prefectures in China. In 2013, the Hukou Index ranged from 1.045 to 5.247.

Table 1: Hukou Index: Summary Statistics

Year	Mean	Std	Min	Max
2003	2.060	0.641	1.045	4.159
2004	2.421	0.671	1.045	4.247
2005	2.466	0.663	1.045	4.131
2006	2.515	0.657	1.045	4.134
2007	2.663	0.700	1.045	4.804
2008	2.734	0.700	1.045	4.739
2009	3.057	0.679	1.045	4.778
2010	3.203	0.805	1.045	5.168
2011	3.245	0.760	1.045	5.180
2012	3.408	0.810	1.045	5.246
2013	3.606	0.764	1.045	5.247
Total	2.766	0.831	1.045	5.247

[4] Chan (2019) provides a detailed and up-to-date discussion of the system and its reforms, and Hao et al. (2020) presents an up-to-date summary of the internal migration patterns in China based on China's population census data.

2.2 The New Rural Pension Scheme

Historically, the Chinese pension system only covered urban workers. However, in September 2009, the Chinese government initiated the implementation of a pension system for rural workers, known as the New Rural Pension Scheme (NRPS). By the end of 2012, the NRPS had been introduced to all rural counties in mainland China. Figure 1 shows the coverage rate of the NRPS over time in our sample villages, based on data compiled by Huang and Zhang (2020).

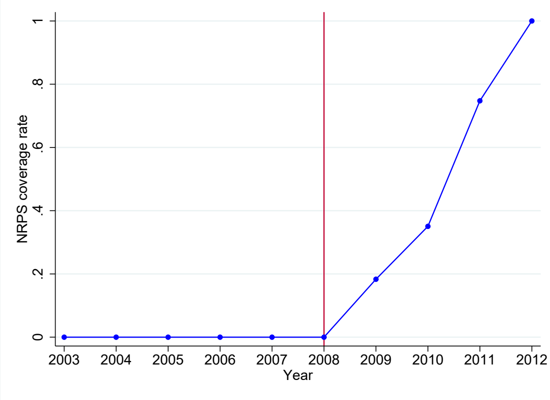
Upon the introduction of the NRPS to a county, all people aged 16 years or older with rural *hukou* in the county can participate in the scheme on a voluntary basis. In order to claim any pension benefits after age 60, enrollees aged 45 and above need to pay premiums continuously until age 60, and enrollees under age 45 need to pay premiums continuously for at least 15 years.[5] 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. According to the arrangement, the central government will fully subsidize the basic pension benefit for central and western provinces, and provide a 50 percent subsidy for eastern provinces. The remaining portion will be subsidized by the provincial government.[6] All enrollees aged 60 years or 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 benefit transfers were effectively direct cash transfers provided by the government, as older workers did not contribute to their pensions in their earlier years. In 2013, when the NRPS had been implemented in all counties, our rural household survey data indicated a significant average share of pension transfers in the annual income of elderly individuals, amounting to 0.68 with a standard deviation of 0.41.

Since many migrant workers leave their children and elders behind in their rural homes, the introduction of the NRPS lowers the intangible migration cost faced by working-age rural workers through the eldercare and childcare channels. The existing literature shows that, with the new pension plan, the elders reallocate time from farm work to non-farm home production and to taking care of their grandchildren (Jiao, 2016; Huang and Zhang, 2020). These channels in effect

[5] Participants can choose from 100, 200, 300, 400 or 500 RMBs as the level of their annual contribution.

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

Figure 1: NRPS Coverage Rate



reduce the migration costs associated with dependent care and non-farm home production. We will use the data on the timing of the introduction of the NRPS as an indicator of policy shocks to migration costs for our empirical analysis.

2.3 Origin-based Panel Data on Migration and Income

2.3.1 Description of the NFP Data

The primary data utilized in this paper is the annual National Fixed Point survey, referred to as NFP for convenience throughout the paper. The survey is 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, population, and more. 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. The data have 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). In Appendix A.2, we show that the workers in the 2005 wave of NFP share similar characteristics with the workers with rural *hukou* in the 2005 China 1% Population Sampling Survey (mini census), and we provide further details of NFP data and assess their quality.

The survey contains village-level, household-level, and, since 2003, individual-level questionnaires. At the household level, it surveys 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 few households migrate to cities as a whole. It is therefore critical to have information about individual household members for studying rural-urban migration in China.

Unique to this study, we have access to annual waves of NFP between 2003 to 2013 that include an individual-level questionnaire in the survey. It asks for information about individuals that includes age, gender, schooling attainment, industry of work, working days, and, most importantly, whether an individual migrated outside the township of her/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, NFP covers approximately 20,000 households and 80,000 individuals from 350 villages in mainland China. In our NFP data, 29% of the individuals can be tracked for one year, 14% for two years, 10% for three years, 8% for four years, and 39% for five or more years.

In examining rural-urban migration, NFP offers several advantages compared to other data frequently used in Chinese internal migration studies. Its strengths lie in its panel structure, and the more comprehensive coverage across both geographical and temporal dimensions. One drawback of NFP data is that they include limited information on migration destinations. Hence, our analysis focuses on migration from the rural agricultural sector to the urban non-agricultural sector, instead of spatial movements among provinces and cities. We compare NFP data with other commonly used data employed in the extant literature in Appendix A.2, and investigate a potential issue of sample attrition in Appendix A.4.

2.3.2 Construction of Key Variables

Now, we formally introduce some key variables constructed from NFP data that are important to our analysis. More details are provided in Appendix A.3.

Sector of Employment and Migration. We define an individual as working in the non-agricultural (na) sector in a particular year if she/he worked more than 180 days out of town during that year, and working in the agricultural (a) sector otherwise. For in-town workers who reported working in the non-agricultural sector, the NFP unfortunately does 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 agriculture. 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 (NBS) of China. In the general equilibrium analysis in section 5, we consider households with potentially more than one young members and define migration as having at least one young member working in the non-agricultural sector.

Nominal Daily Agricultural Earnings. NFP provides detailed information on household agricultural production, including all inputs and output at the crop level. We compute the gross output for each type of crop as the production multiplied by the corresponding market price in that 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 construct individual earnings from agricultural production, we apportion household agricultural income to each household member according to the number of working days they each allocated to agricultural production. The daily agricultural earning is then given by:[7]

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

Nominal Daily Non-agricultural Earnings. NFP 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 earning by the number of working days out of town.

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

[7] In Appendix C.5, 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.

2.3.3 Basic Facts

Our analysis focuses on the sample of individuals aged between 20 and 55 with no more than 12 years of schooling. We make the age restriction because we want to focus on those of the working-age population who have finished schooling but are not close to the eligible age (60) for receiving the rural pension income. We also exclude individuals with more than 12 years of schooling because there are very few of them 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 individual fixed-effect regressions. We also trim the sample at the top 1% and bottom 1% of the annual income distribution in the agricultural and non-agricultural sector, respectively. In the end, we obtain 48,792 individuals, among whom, 10% are tracked for two years, 11% for three years, 11% for four years, and the rest for five or more years.

Table 2 reports summary statistics of the data. About 30% of workers in our sample migrated out of town to work in non-agriculture at some point during the sample period. The means of log daily earnings in agriculture and non-agriculture are 3.70 and 3.43, respectively, which implies that the raw average income gap between the agricultural workers and migrant workers in the non-agricultural sector is 27 log points. The variance of log daily earnings is smaller for the migrant workers than that for the agricultural workers. Note that we are comparing agricultural workers to migrant workers who were born in rural areas, not to the whole population of non-agricultural sector workers, which would also include urban residents. Most of these migrant workers work in low-skill manufacturing and service jobs (see See Figure A.5 in Appendix A), which may explain the lower dispersion of their earnings. Notably, the labor supply in terms of average working days differs significantly between workers in the non-agricultural sector (302 days) and those in the agricultural sector (208 days). Therefore, the sectoral gap in average annual earnings is much larger than the gap in average daily earnings (78 vs. 27 log points).

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

Table 2: Summary Statistics

Sample:	All	Non-agri	Agri
ln Daily wage	3.507	3.695	3.426
	(0.905)	(0.700)	(0.969)
ln Annual income	8.844	9.385	8.609
	(1.011)	(0.687)	(1.039)
Total working days	236.641	302.228	208.166
	(99.323)	(44.207)	(103.059)
Share of working days in:			
Within-town agri production	0.555	0.036	0.780
	(0.434)	(0.077)	(0.316)
Within-town non-agri production	0.122	0.005	0.173
	(0.257)	(0.028)	(0.293)
Out-of-town	0.323	0.959	0.047
	(0.443)	(0.084)	(0.164)
Age	38.485	32.189	41.219
	(10.377)	(9.091)	(9.688)
Years of Schooling	7.193	8.101	6.799
	(2.445)	(2.035)	(2.503)
Female	0.470	0.330	0.531
	(0.499)	(0.470)	(0.499)
Poor health status	0.012	0.004	0.016
	(0.109)	(0.059)	(0.125)
Household with an elderly aged $\geq$60	0.281	0.352	0.250
	(0.449)	(0.477)	(0.433)
Number of observations	229860	69584	160276
Share of workers	1.000	0.303	0.697

Notes: Standard deviation in parentheses.

3 A Framework for Empirical Analysis

In this section, we present a generalized Roy model that examines migration from rural agriculture to urban non-agriculture. The model provides a framework for our reduced-form empirical analysis of migration costs, sorting, and the APG. It helps to clarify the interpretation of different reduced-form estimates of returns to migration, and, by introducing household decisions with endogenous labor supply, sheds light on the channel through which the NRPS policy induces migration of young workers. The model also helps to illustrate how the NRPS policy affects within-household labor allocation and household income.

3.1 A Generalized Roy Model

3.1.1 Technologies and Labor Earnings in the Two Sectors

There are two sectors, agriculture and non-agriculture, indexed by $j = a, na$, which are located in the rural and urban areas, respectively. The production technology in sector j is $Y_j = A_j H_j$, where H_j represents the total efficiency units of labor in sector j. Thus, the real wage per efficiency unit of labor is $w_j = p_j A_j$, where p_j is the price of sector j goods relative to the price of consumption. There are two types of workers, old (o) and young (y).

Each young worker is endowed with a vector of observable characteristics $\boldsymbol{X}$ and a vector of unobserved individual productivity denoted by $\boldsymbol{U} = (U_a, U_{na})$ that is independent of $\boldsymbol{X}$. The latter represents the innate abilities of being a worker in agricultural and non-agricultural sectors, respectively. Without loss of generality, we normalize the mean of $\boldsymbol{U}$ to zero. We assume that an individual young worker's human capital (efficiency units of labor per unit of time) in sector j is determined by $h_{y,j}(\boldsymbol{X}, \boldsymbol{U}) = \exp(\boldsymbol{X}\beta + U_j)$. Let $l_{y,j}$ be the labor supply by the young worker. Then, the worker's potential earnings in sector j are given by

$$e_{y,j}(\boldsymbol{X}, \boldsymbol{U}) = w_j \exp\left(\boldsymbol{X}\beta + U_j\right) l_{y,j}.$$

A young worker can always choose to work in the agricultural sector. If she chooses to work in the non-agricultural sector, however, she has to pay a migration cost, m, that is proportional to her unit labor wage in the non-agricultural sector, $w_{na} h_{y,na} m$. We allow m to depend on individual characteristics $\boldsymbol{X}$ and a vector of some policy variables $\boldsymbol{Z}$.

We assume that old workers always stay in agriculture and their human capital is given by h_o. Hence, an old worker's labor earning is given by $e_o = w_a h_o l_o$, where l_o is the worker's labor supply.

3.1.2 Preferences and Endogenous Labor Supply

Each family consists of one old worker and one young worker, both of whom have the same preferences:

$$\mathcal{U} = \ln(c) + \ln(g),$$

where c is individual good consumption and g is household consumption, which is a public good produced jointly by both old and young workers in home production.

We assume that $g = bk_o + k_y$, where k_o and k_y are the time spent on home production by old and young workers, respectively, and b is a positive number that determines the relative efficiency of the old worker in home production.

The young and old workers in a household play a non-cooperative Nash game. Each of them is endowed with one unit of time, and they allocate it between work and home production to maximize their own utility while taking the time allocation of the other household member as given. We consider a non-cooperative household model rather than a collective household model because the later would predict a negative effect of NRPS on young workers' labor supply, which is inconsistent with the empirical evidence that we will present later. (The proof is available in Online Appendix F.) Thus, the optimization problem of a young worker in sector j is

$$V_{y,j} = \max_{c_{y,j}, l_{y,j}} \ln(c_{y,j}) + \ln(bk_{o,j} + k_{y,j})$$

subject to the budget and time constraints, $c_{y,j} = e_{y,j} = w_j h_j \left(l_{y,j} - m\mathbf{1}_{[j=na]}\right)$ and $l_{y,j} + k_{y,j} = 1$.

Analogously, an old worker's optimization problem is

$$V_{o,j} = \max_{c_{o,j}, l_{o,j}} \ln(c_{o,j}) + \ln(bk_{o,j} + k_{y,j}),$$

subject to the constraints $c_{o,j} = e_{o,j} = w_a h_o l_{o,j} + T$ and $l_{o,j} + k_{o,j} = 1$, where T is any transfer the old worker may receive from the government.

The solutions to the optimization problems are

$$l_{o,j} = \frac{2}{3}\left(\frac{1 + b - m\mathbf{1}_{[j=na]}}{2b} - \frac{T}{w_o h_o}\right) \quad \text{and} \quad l_{y,j} = \frac{1}{3}\left(1 + b + 2m\mathbf{1}_{[j=na]} + \frac{Tb}{w_o h_o}\right). \tag{1}$$

The result reveals that the labor supply of old workers declines with T due to an income effect. This in turn raises the output of home production and induces young workers to allocate more time towards market employment. The result also shows that the labor supply of young workers is higher in non-agriculture than in agriculture due to an income effect associated with the migration cost, and the difference increases with the migration cost.

3.1.3 Migration Decision

Combining the expressions in equation (1) and the budget and time constraints, the value function $V_{y,j}$ can be written as follows

$$V_{y,j} = \ln\left(w_j h_{y,j}\right) + 2\ln\left(\frac{1+b-m\mathbf{1}_{[j=na]}+\frac{T}{w_a h_o}}{3}\right).$$

Thus, the young worker will migrate if and only if

$$V_{y,na} - V_{y,a} = \ln\left(\frac{w_{na}}{w_a}\right) + 2\ln\left(\frac{1+b+\frac{T}{w_a h_o}-m}{1+b+\frac{T}{w_a h_o}}\right) + \left(U_{na}-U_a\right) > 0. \tag{2}$$

Let $R = \ln(w_{na}/w_a)$ be the underlying real wage difference between the agricultural and non-agricultural sectors, which we will simply refer to as the *underlying APG*, and

$$M(\boldsymbol{X},\boldsymbol{Z}) = -2\ln\left(\frac{1+b+\frac{T}{w_a h_o}-m}{1+b+\frac{T}{w_a h_o}}\right). \tag{3}$$

Then, the inequality (2) is equivalent to

$$U_{na} - U_a > M(\boldsymbol{X},\boldsymbol{Z}) - R. \tag{4}$$

That is, a young worker will migrate if her comparative advantage in non-agriculture, $U_{na} - U_a$, is higher than the net migration cost, $M(\boldsymbol{X},\boldsymbol{Z}) - R$. From (3), the net migration cost is decreasing in the amount of cash transfer T. Thus, the model predicts that the introduction of NRPS, which increases T from zero to a positive amount, induces more young workers to switch to the non-agricultural sector. Intuitively, the cash transfers received by old household members increase their home production time, which induce young household members to increase labor supply and hence increase their returns to migration.

3.1.4 Inefficiency of Non-cooperative Labor Supply Decisions

If old and young workers within a household can pool their resources and collectively allocate time to maximize household income, their labor supplies should be determined based on their comparative advantage. Specifically, if the old worker has a comparative advantage in home production (i.e., $bw_{y,j}h_{y,j} > w_o h_o$), the optimal allocation would involve setting $l_{o,j}$ to zero and having the old worker specialize in home production. However, in the non-cooperative Nash game, the old worker typically allocates positive amounts of time to both agricultural and home production, indicating a misallocation of labor within the household. The NRPS transfer, by reducing the labor supply of the old worker and increasing the labor supply of the young worker, helps mitigate this within-household misallocation. Thus, the NRPS policy not only promotes migration but also enhances within-household labor allocation, increases household income, and improves overall welfare.[8]

3.2 Biases of Observed Returns to Migration

If workers are homogeneous with identical labor supply and human capital in both sectors, then the underlying APG, R, is identical to the returns to migration. However, with endogenous labor supply and heterogeneous worker comparative advantage, observed returns to migration are often biased measures of the underlying APG. We will now discuss these potential biases in detail.

First, returns measured using annual earnings are biased because of endogenous labor supply, even if all workers are homogeneous and there is no sorting. Equation (1) shows that young workers' labor supply is higher in non-agriculture than in agriculture as long as the migration cost m is positive. This is consistent with the evidence on working days we presented for China in Table 2 and, more generally, consistent with the cross-country evidence on labor hours presented by Gollin et al. (2014). Our result suggests that the sectoral gap in labor supply itself may be a result of barriers to migration. Due to the gap in labor supply, returns measured using annual earnings overestimate the underlying APG and one should use hourly or daily earnings to avoid the bias.

Second, returns measured using daily earnings may still be biased due to heterogeneous human capital and sorting. Let $y_a(\boldsymbol{X}, \boldsymbol{U}) = w_a h_a(\boldsymbol{X}, \boldsymbol{U})$ and $y_{na}(\boldsymbol{X}, \boldsymbol{U}) = w_{na} h_{na}(\boldsymbol{X}, \boldsymbol{U})$ be the daily wages in the two sectors, respectively. The observed log daily wage is given by

$$\ln y(\boldsymbol{X}, \boldsymbol{U}) = \ln(w_a) + \mathbf{1}(j = na)R + \boldsymbol{X}\beta + U_a + \mathbf{1}(j = na)(U_{na} - U_a). \quad (5)$$

Let R_{OLS} be the observed difference in average log earnings of agricultural and

[8]In Online Appendix F, we further show that, in our simple model, an optimal choice of the transfer (T) can align the non-cooperative labor allocation with the optimal allocation in the collective decision model.

non-agricultural workers, or *observed APG*, and $d = U_{na} - U_a$. We have

$$\begin{aligned} R_{\text{OLS}} &= E\left[\ln\left(y_{na}(\boldsymbol{X}, \boldsymbol{U})\right) | d > M(\boldsymbol{X}, \boldsymbol{Z}) - R\right] - E\left[\ln\left(y_a(\boldsymbol{X}, \boldsymbol{U})\right) | d \leq M(\boldsymbol{X}, \boldsymbol{Z}) - R\right] \\ &= R + E\left[U_{na} | d > M(\boldsymbol{X}, \boldsymbol{Z}) - R\right] - E\left[U_a | d \leq M(\boldsymbol{X}, \boldsymbol{Z}) - R\right] \end{aligned} \tag{6}$$

Due to heterogeneous innate abilities and sorting, the observed APG is generally different from the underlying APG. The last two terms in equation (6) show the selection bias or the effect of sorting on the deviation of the observed APG from the underlying APG. In general, the sign of the bias is ambiguous, depending on both the joint distribution of (U_a, U_{na}) and net migration cost faced by individuals. As a special case, if (U_a, U_{na}) follows a bi-variate normal distribution, we have the following well-known expression for the selection bias (see, e.g., Heckman and Honore, 1990):

$$R_{\text{OLS}} - R = \sigma_{na}\rho_{na,d}\frac{\phi(\frac{R-M(\boldsymbol{X},\boldsymbol{Z})}{\sigma_d})}{\Phi(\frac{R-M(\boldsymbol{X},\boldsymbol{Z})}{\sigma_d})} + \sigma_a\rho_{a,d}\frac{\phi(\frac{R-M(\boldsymbol{X},\boldsymbol{Z})}{\sigma_d})}{1-\Phi(\frac{R-M(\boldsymbol{X},\boldsymbol{Z})}{\sigma_d})}, \tag{7}$$

where σ_a, σ_{na}, and σ_d are the standard deviations of U_a, U_{na}, and d, respectively, and $\rho_{a,d}$ and $\rho_{na,d}$ are the correlations of d with U_a and U_{na}, respectively.

3.3 Empirical Methods

We now turn to the empirical methods for dealing with the selection bias problem. In the literature on APG, there are two commonly used methods in dealing with the selection bias problem. The first method assumes that the distribution of $(\exp(U_a), \exp(U_{na}))$ takes either a multivariate Fréchet or a multivariate log-normal distribution, and uses the moment matching method to estimate the distribution parameters, underlying APG, and migration costs. See, e.g., Lagakos and Waugh (2013), Pulido and Święcki (2018), Tombe and Zhu (2019), Hao et al. (2020), and Adamopoulos et al. (2022). As pointed out by Heckman and Honore (1990), however, the identification of Roy models is not robust to alternative distribution assumptions, and the estimation results are also not robust, depending critically on the functional form assumptions.

More recently, several authors have adopted a second method, using the observed labor returns of new migrants or sector switchers in panel data as estimates of the APGs. See, e.g. Herrendorf and Schoellman (2018), Alvarez (2020), and

Hamory et al. (2021). While this method does not rely on strong functional form assumptions, it is not clear what the observed labor returns of sector switchers really measure. Both Pulido and Świecki (2018) and Lagakos et al. (2020) provide examples showing that these returns may over- or under- estimate the underlying APG if the shocks that caused workers to switch sectors are correlated with individual comparative advantages. Also, Schoellman (2020) argues heuristically that, if the income or migration cost shocks are independent of individual comparative advantages, the estimated return to migration for switchers is not the underlying APG but a measure of the average migration cost faced by the switchers before the shocks hit.

Thus, neither of the two commonly used methods in the APG literature is ideal for dealing with the selection bias problem. We consider a different method in this paper. The model we presented belongs to a class of models that are called generalized Roy models. There is an extensive literature in labor economics and applied econometrics on the identification and estimation of generalized Roy models. See, e.g., Card (2001), Eisenhauer et al. (2015), and Cornelissen et al. (2016). We apply the insights from this literature for identification and estimation of our model. Using the terminology of this literature, the underlying APG is the average treatment effect (ATE) of migration:

$$R = E\left[\ln\left(y_{na}(\boldsymbol{X}, \boldsymbol{U})\right) - \ln\left(y_a(\boldsymbol{X}, \boldsymbol{U})\right)\right].$$

To control for selection bias, the literature suggests using either field or natural experiments. For the case of China, we will use the gradual implementation of NRPS as a policy experiment and a control function approach to estimate the ATE or the underlying APG. Specifically, we estimate equation (5) controlling for proxies for the selection terms $E[U_a|\mathbf{1}(j = na), \boldsymbol{X}, \boldsymbol{Z}]$ and $E[(U_{na} - U_a)|\mathbf{1}(j = na), \boldsymbol{X}, \boldsymbol{Z}]$.

Using the policy experiment, we also estimate the local average treatment effect (LATE) that reveals the average labor return of workers whose migration decisions are marginally affected by the policy. We can show that, under the exclusion assumption of the policy instrument, the LATE estimate of return to migration is also an estimate of the average migration cost faced by these marginal workers. To see this, consider the introduction of the NRPS that changes $T = 0$ to $T > 0$, and hence reduces $M(\boldsymbol{X}, \boldsymbol{Z})$ by ΔM. We prove the following proposition in Appendix B.

Proposition 1: *If the change in migration costs ΔM induced by the introduction of the NRPS is independent of individual comparative advantage in the non-agricultural sector, $d = U_{na} - U_a$, then,*

$$\lim_{\Delta T \to 0} R_{\text{LATE}} = \frac{E\left[m(\boldsymbol{X}, \boldsymbol{Z}) f\left(M(\boldsymbol{X}, \boldsymbol{Z}) - R\right)\right]}{E\left[f\left(M(\boldsymbol{X}, \boldsymbol{Z}) - R\right)\right]},$$

where $f(.)$ is the PDF of d.

Intuitively, a small change in migration costs only induces workers who are ex-ante indifferent between the two sectors to switch. When they switch sectors, the change in incomes reveal their baseline migration costs.

4 Reduced-Form Analysis

Having laid out the empirical framework, we now turn to the empirical analysis of rural-urban migration in China. We start with a simple cross-sectional comparison of the labor productivity in the two sectors.

4.1 Cross-Sectional Estimation of Returns to Migration

We estimate 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 individual and household characteristics, including age, age squared, years of education, a dummy for gender, a dummy for poor health, a dummy indicating whether there is an elderly aged 60 or above residing in the household, and the share of months in year t that the NRPS has been in effect; 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 3 reports the OLS regression results. We find that, conditional on individual characteristics, daily earnings in sector na are on average 31 log points higher than those in sector a. Column (2) includes three indicator variables which are defined based on the migration status in period $t-1$ and t: a-to-na switchers, na-to-a switchers, and sector-na stayers. The stayers in sector a constitute the omitted group. Therefore, the estimates reflect the income gaps relative to the stayers in agriculture. The income gap is 28 log points for a-to-na switchers, and 30 log points for sector-na stayers. This finding suggests that a large portion of the income gains is realized upon migration. Interestingly, relative to sector-a stayers, na-to-a switchers have a lower daily earnings, suggesting that there are factors other than income, such as idiosyncratic shocks to migration costs or preferences, that also affect workers' migration decisions.

Table 3: Sector of Employment and Daily Wage: OLS and Individual FE

Dep. Var.: ln Daily Wage	(1) OLS	(2) OLS	(3) FE	(4) FE
NonAgri	0.3080***		0.3672***	
	(0.0142)		(0.0157)	
a-to-na switchers		0.2808***		0.3372***
		(0.0173)		(0.0197)
na-to-a switchers		-0.1045***		-0.0520***
		(0.0136)		(0.0155)
na stayers		0.2961***		0.3826***
		(0.0165)		(0.0200)
Individual controls	Y	Y	Y	Y
Province× Year FE	Y	Y	Y	Y
Village FE	Y	Y	N	N
Individual FE	N	N	Y	Y
Observations	229,860	154,607	229,858	142,209
R-squared	0.4175	0.4060	0.6663	0.6742

Notes: Individual controls include age, age squared, years of education, a dummy for gender, a dummy for poor health, a dummy indicating whether there is an elderly aged 60 or above residing in the household, and the share of months in year t that the NRPS has been in effect. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1

4.2 Individual Fixed Effect Estimation

Columns (3) and (4) of Table 3 repeat the regression analysis in Columns (1) and (2), but further control for individual fixed effects. This approach has recently been adopted in the APG literature (Herrendorf and Schoellman, 2018; Alvarez, 2020; and Hamory et al., 2021) to address the potential selection bias problem under the assumption that selection on sector of employment is only determined by time-invariant individual characteristics which have the same effect on potential earnings across sectors. If for some reason high-ability workers are more likely to work in the non-agricultural sector, then the observed APG would be due to the difference in average ability of workers in the two sectors, and thus an individual fixed effect regression could control for this selection bias. They therefore argue that the estimated labor return to migration after controlling for individual fixed effects is a better measure of the APG. Using panel data from Brazil, Indonesia, Kenya, and the US, they show that the measured returns to migration after controlling for individual fixed effects are much smaller than the OLS estimates that do not control for individual fixed effects.

In contrast, our result for China in Columns (3) shows that our fixed effect (FE) estimate of the returns to migration is 37 log points, which is actually slightly larger than the OLS estimate. As is argued by Schoellman (2020) and shown by our Proposition 1, if all the sector switches are driven by exogenous shocks to migration costs, the FE estimate measures the average migration cost faced by switchers before the shocks hit. Hence, one interpretation of the difference in the results between China and the other countries studied in the literature is that migration costs are much larger in China than in these other countries due to China's rigid *hukou* system that explicitly restricts rural-to-urban migration.[9]

However, the FE estimate could be biased if sectoral switches are endogenous. To address this problem, we need to find exogenous shocks to migration barriers that are uncorrelated with migrant workers' potential earnings. The gradual county-by-county implementations of NRPS in China constitute such shocks.

4.3 NRPS and IV Estimation

As is discussed in Section 3, the introduction of NRPS decreases (increases) labor supply (home production) of elders, which in turn encourages younger household members to increase labor supply and switch to the non-agricultural sector. Moreover, this NRPS effect on sector choice may vary by household depending on the presence of elderly aged 60 or above who are entitled to the NRPS pension benefit. Therefore, our IV strategy employs $Elder60_{hjt} \times NRPS_{jt}$ to generate exogenous variation in $NonAgri_{ihjt}$.

[9] Appendix C.1 reviews the estimates in the existing literature.

The first-stage regression is

$$NonAgri_{ihjt} = \beta_1 Elder60_{hjt} \times NRPS_{jt} + X_{ihjt}\beta_2 + \varphi_j + \varphi_{pt} + \nu_{ihjt}, \quad (8)$$

where $NRPS_{jt}$ captures the share of months in year t that NRPS covers the elderly in village j. $Elder60_{hjt}$ is an indicator variable that equals one if there is an elderly aged 60 or above residing in the household. 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

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

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

Conceptually, instrumenting for the sector of employment with the interaction term $Elder60_{hjt} \times NRPS_{jt}$ is similar to a triple-difference estimation strategy. A simple difference-in-difference estimation would capture the change in the likelihood of non-agricultural employment induced by the implementation of NRPS, with the identification stemming from the differential timing of the onset of NRPS across regions. The triple-differencing makes an additional comparison between households with and without an elderly aged 60 or above, which adds the advantage of differencing out the village-specific shocks to migration costs or to incomes that coincides in timing with the introduction of NRPS. By employing the triple-difference approach, we address the concern that NRPS may have been rolled out endogenously across the country, and villages that implemented NRPS earlier may have had different trends in income and migration.

The exclusion restriction for the instrument is

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

This requires that, conditional on all the observables, (i) NRPS does not directly affect income differently for individuals in households with an elderly aged 60 or above relative to those without, other than its differential effect on the sector choice across individuals, and (ii) NRPS is uncorrelated with any other village-specific unobserved shocks that affect income differently for individuals in households with an elderly aged 60 or above relative to those without. 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. Despite this consideration, we provide further evidence to substantiate the identification assumptions in the following discussion.

The IV estimate captures the local average treatment effect (LATE), i.e., the difference in potential earnings between the two sectors for a-to-na switchers because of an exogenous reduction in migration barriers induced by the NRPS (i.e., compilers). As we have shown in Section 3, the LATE estimate captures the average (proportional) migration cost of the marginal workers whose sectoral choice was affected by the NRPS policy.

Column (1) of Table 4 reports the first-stage regression result. We find that, in response to the implementation of the NRPS, younger members from households with an elderly aged 60 or above are 4 percentage points more likely to work in the non-agricultural sector relative to those from households without an elderly. Column (2) shows the second-stage regression result. The IV estimate implies that working in the non-agricultural sector increases daily wage by 88 log points, which is even larger than the OLS and individual FE estimates. The result indicates that the baseline average migration cost faced by the switchers is around 88% of the wage rate in the non-agricultural sector. The Kleibergen-Paap F statistic is 29.97, which is above the Stock-Yogo 10 percent threshold for weak instruments. In column (3), we conduct a mediation analysis by including $NonAgri_{ihjt}$ and $Elder60_{hjt} \times NRPS_{jt}$ simultaneously in the earning equation. We show that, 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 only affects earnings through the channel of switching employment sector.

4.4 Control Function Estimation

In this subsection, we adopt the approach of Card (2001) and Cornelissen et al. (2016) to estimate the underlying APG using the control function approach. With the assumption that U_{na} and U_a follow a joint normal distribution, we can estimate

Table 4: Sector of Employment and Daily Wage: IV and Control Function

Dep. Var.:	(1) NonAgri First Stage	(2) ln Daily Wage 2SLS	(3) ln Daily Wage OLS	(4) ln Daily Wage CF
NonAgri		0.8847**	0.3078***	0.3280***
		(0.3627)	(0.0142)	(0.0284)
Elder60 × NRPS	0.0410***		0.0237	
	(0.0075)		(0.0146)	
NRPS	0.0103	-0.0479	-0.0420	
	(0.0101)	(0.0303)	(0.0285)	
Elder60	0.0230***	-0.0197	-0.0064	
	(0.0026)	(0.0120)	(0.0053)	
NonAgri$\times \frac{\phi((Z,X)\beta)}{\Phi((Z,X)\beta)}$				-0.1363***
				(0.0181)
(1-NonAgri)$\times \frac{\phi((Z,X)\beta)}{1-\Phi((Z,X)\beta)}$				-0.1220***
				(0.0174)
Individual controls	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	229,860	229,860	229,860	229,860
R-squared	0.3608	–	0.4175	0.4192
Kleibergen-Paap F-Stat	–	29.97	–	–

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. *** p<0.01, ** p<0.05, * p<0.1

equation (5) by the following regression:

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

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 ζ is a vector of estimates obtained from the first-stage probit estimation of the selection equation. The control functions $NonAgri \times \frac{\phi((Z,W)\zeta)}{\Phi((Z,W)\zeta)}$ and $(1-NonAgri)\times \frac{\phi((Z,W)\zeta)}{1-\Phi((Z,W)\zeta)}$ account for the selection bias.[10] Hence, theoretically, $\hat{\gamma}_1^{CF}$ estimates the ATE (Wooldridge, 2015; Cornelissen et al., 2016).

Column (3) in Table 4 shows our benchmark estimate of γ_1 using the control function (CF) approach. The CF estimate suggests that daily wage of the non-agricultural sector is on average 33 log points higher than that of the agricultural

[10] $(Z, W)\zeta$ maps to $R - M(\boldsymbol{X}, \boldsymbol{Z})$ in the selection terms in equation (7). In particular, M is a function of Z and W, and R is absorbed by the constant term in W.

sector for workers with average characteristics. In Appendix C.3, 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 remains stable.

4.5 Mechanisms: NRPS and Migration

In this subsection, we provide empirical evidence for the mechanisms underlying the effect of NPRS on migration decisions of young workers proposed in our model. We start with investigating labor supply responses of elders to the introduction of NRPS by estimating the following equation:

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

where $WorkingDays_{ojt}$ is the number of working days of an elder o (aged 60 or above) in household h, village j and year t. We restrict the sample to the individuals who live with the young workers in the baseline analysis above.[11] Column (1) in Table 5 shows that 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 NRPS using a Poisson quasi-maximum likelihood (Poisson MLE) count data model and obtain a qualitatively similar result.[12]

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

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

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

[11] We also exclude the elders with disabilities. This is because labor supply is not a relevant margin of adjustment for them: the median (respectively, mean) number of working days is 0 (respectively, 11.7). This group constitutes about 12.7% of the whole elder sample.

[12] The Poisson MLE count data model is generally preferred to alternative count data models (such as the negative binomial model), because the Poisson MLE estimator is consistent even when the error distribution is misspecified (i.e., the true distribution is not Poisson), provided that the conditional mean is specified correctly (Cameron and Trivedi, 2013; Wooldridge, 2002).

[13] We exclude the observations who live with an elder with disabilities.

NRPS decreases labor supply of elders by 9.2 days while increases that of young workers by 3.5 days.[14] In sum, the findings in Table 5 are consistent with the mechanisms proposed by our model in section 3: With cash transfers from NRPS, elderly reduce their labor supply and allocate more time to home production, which in effect lowers migration barriers by increasing labor supply and encouraging migration of young workers. In Appendix C.4, we provide further empirical evidence in support of this interpretation, and explore other possible confounding channels, such as captial investment and credit constraints, through which NRPS may affect potential earnings and influence migration decisions.

Table 5: Effects of NRPS on Labor Supply of the Elder and the Youth

	(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			0.0358***	0.0147**
			(0.0098)	(0.0057)
NRPS	-0.014*	-0.0878**	-0.0126	-0.0073
	(0.008)	(0.0374)	(0.0185)	(0.0116)
Elder60			0.0014	0.0057**
			(0.0042)	(0.0026)
Individual controls	Y	Y	Y	Y
Province×Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	41,194	41,126	219,281	219,281
R-squared	0.2741	–	0.3153	–

Notes: In columns (1) and (2), the sample is restricted to the elders who are not disabled, aged 60 or above, and live with young workers. Individual controls include years of education, a dummy for gender, and dummies of health status. In columns (3) and (4), the sample is restricted to the youth in households without any disabled elderly. 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. *** p<0.01, ** p<0.05, * p<0.1

4.6 Summary of Results from Reduced-form Analysis

We now take stock of what we have learned from our reduced-form estimation results. First, the OLS cross-sectional regression shows that the observed APG in China is 31 log points, after we control for sectoral differences in observable worker characteristics. Note that this is the difference in average labor productivity between migrant and agricultural workers. If we include workers with urban *hukou*, the observed APG would be even higher. Second, in contrast to recent

[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 9.2 ($= 105 \times 0.0878$) and 3.5 ($= 236 \times 0.0147$), respectively.

findings for several other countries, the observed APG is virtually the same if we also control for individual fixed effects. We argue that this is likely due to high barriers to migration in China, and therefore high returns to migration are needed to compensate migration costs. Third, we estimate the local treatment effect of migration induced by NRPS and find that the incomes of NRPS-induced migrants on average increased by 88 log points, confirming that workers who were affected by NRPS faced large migration costs before the policy implementation. Finally, we also use NRPS as an instrument and a control function approach to estimate the average treatment effect of migration. The estimate implies an APG of 33 log points, which is very close to the OLS estimate of 31 log points. The result suggests that the selection bias of observed APG is almost negligible in the case of China.

Why is there a large underlying APG? What are the sources of migration barriers? How would reductions in migration barriers affect the underlying APG, sorting, and aggregate productivity? What is the welfare implication of NRPS? Is there other policies that help increase migration, aggregate productivity, and welfare? To address these questions, we next develop and structurally estimate a general equilibrium Roy model.

5 The General Equilibrium Model

In the general equilibrium model, we enrich the static Roy model from Section 3.1 in several dimensions to better match the data. First, we add the time dimension, introduce idiosyncratic shocks to migration costs and human capital, and allow for differential productivity growth in the two sectors. Second, we introduce household joint production and diminishing returns to labor in the rural area. Third, we use more general utility functions for consumption and labor supply and allow for multiple youth and elderly in a household. Given our focus, we model rural households with micro details, but model urban households as a representative agent.

5.1 Rural Households

There are $N_{r,t}$ number of rural households. Each household has two groups of members, parents and adult children, referred to as old (o) and young (y) agents, respectively. For simplicity, we assume that all household members within a group are identical and act collectively. However, old agents and young agents play a non-cooperative Nash game.

5.1.1 Human Capital

As in Section 3.1, the human capital of agent $i \in \{y, o\}$ in sector $j \in \{a, na\}$ and time t is a function of observable characteristics $\boldsymbol{X_{it}}$ and sector-specific unobserved ability U_j. In addition, the 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 $N(0, \Sigma_\lambda)$: $h_{ijt} = \exp(\boldsymbol{X_{it}}\beta + U_j + \lambda_{jt})$. We assume that all agents make labor supply, migration, and consumption decisions after observing the productivity shocks.

For simplicity, we also assume that 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 elderly do not migrate, to simplify the notation, we use $h_{o,t}$, $h_{y,t}$, and $h_{na,t}$ to denote the human capitals of old agents in the agricultural sector, young agents in the agricultural sector, and young agents in the (urban) non-agricultural sector, respectively.

5.1.2 Household Production in the Rural Area

A household in the rural area can engage in both agricultural production and rural non-agricultural production 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 in sector j, and $h_{fj,t} = h_{o,t}l_{oj,t} + h_{y,t}l_{yj,t}$ is the household's total effective labor supply in sector j, and $h_{i,t}$ and $l_{ij,t}$ is the human capital and labor supply in sector j of agent i in the household, $i = o, y$. We assume that the rural agricultural and non-agricultural sectors use the same human capital, i.e., $h_{i,t}$ for $i \in \{o, y\}$, and that the agricultural and rural non-agricultural TFPs follow the same growth rate g_a,[15] hence $A_{j,t} = e^{g_a t}A_{j,0}$ for $j \in \{a, r\}$.

[15] Since the NFP data do not have information about earnings from rural non-agricultural production, we cannot separately estimate the TFP of the rural non-agricultural sector and therefore make these simplifying identification assumptions.

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

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

subject to

$$l_{ij,t}\geq 0, i=o,y, j=a,r;$$

$$l_{ia,t}+l_{ir,t}=l_{i,t}, i=o,y.$$

We show in Appendix D.1 that the household's production income is

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

where

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

and the agricultural and (rural) non-agricultural output of the household are

$$y_{a,t}=A_{a,t}\left(\frac{p_{a,t}A_{a,t}}{A_{f,t}}\right)^{\frac{\alpha}{1-\alpha}}h_{f,t}^{\alpha} \quad \text{and} \quad y_{r,t}=A_{r,t}\left(\frac{p_{na}A_{r,t}}{A_{f,t}}\right)^{\frac{\alpha}{1-\alpha}}h_{f,t}^{\alpha}.$$

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 of goods. Thus, the effective expenditure that is available for the household to spend on consumption goods is $y_{f,t}/\kappa_{r,t}$. The distribution cost $\kappa_{r,t}$ is exogenous, but varies across provinces and time. We introduce this exogenous distribution cost to account for spatial differences in the average cost of living that we observe in the data.

Finally, we assume that the household production income is allocated according to household members' effective labor input. Thus, the effective income of each old and young agents are:

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

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

5.1.3 Non-agricultural Production in the Urban Area

Like in the simple model, the non-agricultural production in the urban area 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. We assume that $A_{na,t} = e^{g_{na}t} A_{na,0}$. Thus, the wage per efficiency unit of labor is $w_{na,t} = p_{na} A_{na,t}$. When youth work in the non-agricultural sector, their income is $w_{na,t} h_{na,t} l_{na,t}$. where $l_{na,t}$ and $h_{na,t}$ are the labor supply and human capital of the youth in the urban non-agricultural sector, respectively. There is also a distribution cost $\kappa_{u,t}$, which varies by worker location. Therefore, the effective income is $w_{na,t} h_{na,t} l_{na,t} / \kappa_{u,t}$.

5.1.4 Preferences and Time Allocation

Since labor supply and migration decisions are static problems, from now on we omit the time subscript t for the ease of notation.

All members of a household have the same preferences:

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

where c^r is the member's private consumption and G is the public consumption of household production.

The private consumption c^r is determined by a non-homothetic CES utility function:

$$\varphi_a^{\frac{1}{\varepsilon}} \left(c^r\right)^{\frac{1-\varepsilon}{\varepsilon}} c_a^{\frac{\varepsilon-1}{\varepsilon}} + \varphi_{na}^{\frac{1}{\varepsilon}} \left(c^r\right)^{\frac{1-\varepsilon}{\varepsilon}\mu} c_{na}^{\frac{\varepsilon-1}{\varepsilon}} = 1. \tag{9}$$

φ_a is the preference weight on agricultural consumption, $\varphi_{na} = 1 - \varphi_a$, and ε is the elasticity of substitution between agricultural and non-agricultural consumption goods. The parameter μ determines how the relative demand for the non-agricultural good consumption changes with income. If $\mu > 1$, then the utility yields the Engel curve effect: the relative consumption demand for non-agricultural good consumption increases with income.

Let n_o and n_y be the total number of old and young agents of the household. Each agent is endowed with one unit of time, so n_o and n_y are also the time endowments of the old and young agents. 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

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

where η is a parameter that determines the utility of public consumption or disutility of labor supply, and ξ is the relative household production efficiency of elderly, with that of youth normalized to one.

Since very few parents migrate in our data, we assume that parents can only work in the rural area and do not make migration decisions. Only adult children 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 l_o and l_y are the total labor supply of old and young agents in the rural area, respectively, l_{na} is the labor supply of young agents in the urban non-agricultural sector, and j is the migration decision of young agents with $j = na$ means they migrate to the urban non-agricultural sector. Note that even if they decide to migrate, they can still provide some labor in household agricultural or rural non-agricultural production. Old and young agents separately choose their labor supply in the rural area and and urban non-agricultural sector (for young agents only). Their leisure time jointly produces household public goods.

Once old and young agents choose their total labor supply in the rural area, the household jointly decides how to allocate their labor supply in the rural agricultural and non-agricultural sectors:

$$l_o = l_{oa} + l_{or} \quad \text{and} \quad l_y = l_{ya} + l_{yr},$$

where l_{ia} and l_{ir} are the labor supply in the rural agricultural and non-agricultural sector for agent i, respectively. Therefore, an individual member's utility can also be written as

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

5.1.5 Consumption Allocation

Let e be the effective expenditure of an agent, the agent's consumption allocation problem is $\max_{c_a, c_{na}} c^r$ subject to the constraint (9) and the budget constraint: $p_a c_a + p_{na} c_{na} = e$. As shown in Yao and Zhu (2021), the optimal consumption allocation is given by the following two equations:

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

and c^r is the solution to the equation below:

$$\varphi_a p_a^{1-\varepsilon} \left(c^r\right)^{1-\varepsilon} + \varphi_{na} p_{na}^{1-\varepsilon} \left(c^r\right)^{(1-\varepsilon)\mu} = e^{1-\varepsilon}. \tag{10}$$

We denote the solution as $c(e)$. We can also easily show the following:

$$c'(e) = \frac{e^{-\varepsilon}}{\varphi_a p_a^{1-\varepsilon} \left(c(e)\right)^{-\varepsilon} + \varphi_{na} \mu p_{na}^{1-\varepsilon} \left(c(e)\right)^{(1-\varepsilon)\mu - 1}}.$$

5.2 Labor Supply and Migration Decisions of Rural Households

We now state households' decisions on labor supply in the case of no migration and migration, and their migration decisions. The details about solutions to these problems are presented in Appendix D.2.1 and D.2.2.

Case of No Migration:

The parent's optimization problem is

$$\max_{l_o \in [0, n_o]} n_o \left\{ \frac{1}{1-\gamma} c\left(e_o\right)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \frac{\left(\xi l_o + l_y\right)^{1+\frac{1}{\phi}}}{\left(n_o + n_y\right)^{1+\frac{1}{\phi}}} \right\}.$$

The child's optimization problem is

$$V_a = \max_{l_y \in [0, n_y]} n_y \left\{ \frac{1}{1-\gamma} c\left(e_y\right)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \frac{\left(\xi l_o + l_y\right)^{1+\frac{1}{\phi}}}{\left(n_o + n_y\right)^{1+\frac{1}{\phi}}} \right\}.$$

Case of Migration:

If the child migrates, the effective income of old and young agents are:

$$e_o = \left(\frac{h_o l_o}{h_f n_o} y_f + p_a T \right) / \kappa_r,$$

and

$$e_y = \frac{h_y l_y}{h_f n_y} y_f / \kappa_r + \frac{\frac{w_{na}}{n_y} h_{na} l_{na} - (m_o + m_1 \frac{l_{na}}{n_y}) w_{na} h_{na}}{\kappa_u}.$$

Here, m_1 is the migration cost related to the share of migrants in the household ($\frac{l_{na}}{n_y}$). m_0 is the migration cost for the youth related to other household characteristics.

$$m_1 = \exp((\boldsymbol{X_y}, \boldsymbol{Z_y})\zeta),$$

where $\boldsymbol{X_y}$ includes the same set of observed individual characteristics as in the human capital equation for the youth, and $\boldsymbol{Z_y}$ includes a constant term and a Hukou Index that captures the weighted average of the lenience of *hukou* policies of potential destination cities.

The parent's optimization problem in this case is

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

The child's optimization problem is

$$V_{na} = \max_{l_y + l_{na} \leq n_y} n_y \left\{ \frac{1}{1-\gamma} c\left(e_y\right)^{1-\gamma} - \frac{\eta}{1+\frac{1}{\phi}} \frac{\left(\xi l_o + l_y + l_{na}\right)^{1+\frac{1}{\phi}}}{\left(n_o + n_y\right)^{1+\frac{1}{\phi}}} \right\}.$$

Migration Decision:

The migration decision of the young household member is given by the following condition:

$$V_{na} - V_a > U_c.$$

where U_c is an idiosyncratic migration cost shock that follows a normal distribution $N(0, \sigma_c^2)$.

5.3 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 is h_u. Their wage income is then $w_{na}h_u l_u = p_{na}A_{na}h_u l_u$. 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 urban households' location, $\bar{\kappa}_u$ is the national average urban distribution cost.

Urban household members also have the same non-homothetic CES preferences over the agricultural and non-agricultural goods as the rural agents. The optimization problem of urban workers is

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

5.4 Definition of Key Macro Variables

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

First, the total effective output (after distribution cost) of the agricultural production is

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

the total effective output of rural non-agricultural production is

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

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

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

Now, we have the following defintions:

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

2. <u>*Human capital gap*</u> is defined as $\ln[H_m/L_m] - \ln[(H_a + H_r)/(L_a + L_r)]$. By definition, we have *observed APG = underlying APG + human capital gap.*

3. <u>*Underlying APG*</u> is defined as $\ln[Y_m/H_m] - \ln[(Y_a + Y_r)/(H_a + H_r)]$, where

H_m, H_a, and H_r are the effective labor supply of migrants, rural agricultural, and rural non-agricultural workers, respectively.

4. Real GDP is defined as

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

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

5. Total effective labor is defined as $H = H_a + H_r + H_{na}$. and the Aggregate productivity is defined as Y/H.

5.5 General Equilibrium Conditions and Solution

A full definition of the equilibrium is given in Appendix D.3. Here, we just state a key condition that is crucial for calibration and counterfactual analysis—the market clearing condition for the agricultural good:

$$Y_a = \chi_r N_r \int p_a c_a(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}) + \chi_u N_u \varphi_a p_a^{1-\varepsilon} \left(c\left(e_u\right)\right)^{1-\varepsilon} e_u^{\varepsilon}, \tag{11}$$

where the second term on the right-hand side of the equation is the demand for agricultural goods by urban households, and $e_u = \left(p_{na} A_{na} h_u l_u - p_a \tau\right) / \kappa_u$. χ_r and χ_u are the population-to-worker ratio in the rural and urban areas, respectively. The equilibrium condition states that the total output of agricultural goods produced by agricultural workers equals the total demand for agricultural goods from rural and urban populations.

Given the prices p_a and p_{na}, the government transfer T and tax rate τ, and the values of all the other parameters of the model, equation (11) can be used to calibrate the value of h_u, the human capital level of urban households, so that the market clearing condition holds.

In any counterfactual exercise, we can first solve the government tax rate τ from the government's budget constraint

$$\tau = \frac{N_r}{N_u} T \int n_o dF(\boldsymbol{X}, \boldsymbol{U}, \boldsymbol{\lambda}, \boldsymbol{n}, \boldsymbol{Z}),$$

and, then, holding p_{na} fixed,[16] we again use the market clearing condition (11) to solve for the new equilibrium price p_a.

6 Calibration and Estimation

In this section we discuss how the values of model parameters are determined. Broadly speaking, we determine the values of most preference parameters by calibration and estimate the parameters of individual ability distribution, migration costs, and household production using micro-data.

6.1 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). For the parameters of the non-homothetic CES consumption aggregator, we calibrate them by using data on prices and household expenditures. The details about the construction of prices and the calibration procedures are reported in Appendix E. The calibration results are summarized in Table 6 below:

Table 6: Calibration Results

	Estimated using expenditure shares:	
ϵ	elasticity of substitution	0.349
μ	income elasticity of NonAgr goods	2.475
φ_a	preference weight on Agr goods	0.669
	Taken from literature:	
γ	1/intertemporal elasticity of substitution	1.2
ϕ	Frisch elasticity of labor supply	0.5

6.2 Identification and Estimation

For the parameters of individual ability distribution, migration costs, and household production that are key in determining the APG, we estimate them structurally using the micro-data. More specifically, we use Indirect Inference method

[16]By Walras 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.

to estimate them 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 of the rural non-agricultural 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 within a sector, 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 shock. 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 sector ability. Likewise, the serial correlation in daily earnings for households that have members switching sectors identify 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. We regress the migration rate on household averages of sex, years of schooling, age, age squared, and the origin-based hukou index and match the regression coefficients to identify the parameters in the migration cost function. We also match the average annual working days of young agents in the rural and urban areas, for households with and without migrants, 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), as higher migration costs will encourage workers to work longer in the urban area. The average migration rate helps to identify the standard deviation of migration cost shock (σ_c), and the average annual working days of old agents in rural areas helps to identify the efficiency of home production for the elderly (ξ).

Lastly, we match the effect of 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 between households with and without NRPS, focusing on those containing both youth and elderly individuals. This identifies the parameter in the household production in the rural agricultural sector, α. NRPS affects migration through the home production channel by increasing parents' time in home production and adult children's labor supply, which will increase migration. The strength of this effect is affected by the diminishing returns to labor: when young workers move to the city, the labor productivity in the rural area will increase, which will dampen the incentive to migrate. The smaller α is, the stronger the diminishing returns to labor, and therefore the smaller the effect of NRPS on migration.

6.3 Estimation Results

Table 7 shows the parameter estimates. The initial TFP levels in 2003 of rural agricultural, rural non-agricultural, and urban non-agricultural sectors are 2.253, 2.176, and 4.083, respectively. The TFP in the urban non-agricultural sector has a higher growth rate than that in the rural sectors (0.119 vs. 0.063), which implies that, holding labor allocation constant, the underlying productivity gap between agriculture and urban non-agriculture would increase over time.

The upper panel of Table 7 also shows the estimated values of the parameters of the innate ability distribution. Agricultural ability has a larger standard deviation than non-agricultural ability (0.862 vs. 0.481), and there is a positive correlation between agricultural and non-agricultural abilities (0.561). The productivity shock also has a larger standard deviation in agriculture than in non-agriculture (0.673 vs. 0.523). This, together with the larger standard deviation of agricultural ability, explains the larger variance in agricultural income in the data.

The rest of the upper panel reports the parameters related to household agricultural production and home production. The estimated value of α is 0.898, confirming that agricultural production exhibits diminishing returns to labor. The estimated values of η and ξ are 2.213 and 4.114, respectively. $\xi > 1$ implies that the home production efficiency/disutility of labor supply is higher for elderly workers than for young workers.

The middle panel of Table 7 reports the coefficients in the human capital equation. The human capital premium for men (compared to women) is 7.2 log points. The return to education is 2.8 log points. The life-cycle human capital has a hump shape, with a peak at age 40.

Table 7: Estimation Results

Parameter	Meaning	Estimate	Standard error
A_a	TFP level of Agr in 2003	2.253	0.0012
A_r	TFP level of rural NonAgr in 2003	2.176	0.0011
A_{na}	TFP level of urban NonAgr in 2003	4.083	0.0041
g_a	TFP growth rate of Agr and rural NonAgr	0.063	0.0000
g_{na}	TFP growth rate of urban NonAgr	0.119	0.0000
σ_u^a	std of Agr ability	0.862	0.0002
σ_u^{na}	std of NonAgr ability	0.481	0.0008
ρ	correlation of Agr and NonAgr ability	0.561	0.0002
σ_e^a	std of Agr productivity shock	0.673	0.0002
σ_e^{na}	std of NonAgr productivity shock	0.523	0.0002
σ_c	std of migration cost shock	0.200	0.0002
α	labor share in Agr	0.898	0.0001
η	disutility of labor supply	2.213	0.0024
ξ	relative home productivity efficiency of the elderly	4.114	0.0016
β	coefficients in human capital equation		
β_1	female	-0.072	0.0001
β_2	years of schooling	0.028	0.0000
β_3	age	0.079	0.0000
β_4	age squared	-0.001	0.0000
m_0	constant in migration cost	0.033	0.0000
ζ	coefficients in marginal migration costs		
ζ_0	constant	-1.678	0.0010
ζ_1	female	2.342	0.0010
ζ_2	years of schooling	-0.139	0.0001
ζ_3	age	1.410	0.0003
ζ_4	age squared	-0.017	0.0000
ζ_5	Hukou Index	-0.406	0.0004
	overall average migration cost (% of NonAgr earnings)	70.2%	
	linear time trend in yearly average migration cost	-2.29%	

The bottom panel of Table 7 shows the parameter estimates related to migration costs. We find that the migration costs are lower for men, highly educated workers, and younger workers. Since households vary by their demographics and labor supply, we calculate the average migration costs across all individuals and years in the model. It is 70% of non-agricultural earnings. The structural estimate of the average migration cost faced by all households is lower than the LATE estimate of the average migration cost of the households who were affected by NRPS (70% vs. 88%). We also find that the Hukou Index has a profound effect on migration costs. Between 2003 and 2013, the Hukou Index on average increased from 2.06 in 2003 to 3.61 due to relaxation of *hukou* policies. As a result, the yearly average of migration costs across all individuals decreased by 2.29

percentage points a year.

6.4 Model Fit

Panel A of Table 8 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 un-targeted moments. The model predicts that the average observed APG across the whole sample period is 0.259, which is slightly higher than the corresponding moment in the data (0.209). The yearly observed APG exhibits a linear trend, increasing by 0.043 a year in the model and 0.046 a year in the data, respectively. The key reason for the rising APG is the higher TFP growth in the non-agricultural sector that we reported in Table 7.

As shown in Section 4.5, the mechanism through which NRPS affects migration costs is by reducing the labor supply of elderly and increasing the labor supply of youth. The model's prediction of these effects of NRPS is consistent with the data. The model is also consistent with data in predicting a positive linear trend in the migration rate without assuming an exogenous reduction in the average migration cost. There are two forces in the model that lead to a rise in the migration rate. First, migration costs decline due to increases in the average Hukou Index (relaxation of *hukou* policiwa) and the implementation of NRPS. Second, the returns to migration increase due to higher TFP growth in the non-agricultural sector.

7 Counterfactual Analysis

In this section, we examine various counterfactual experiments. The baseline case is China in 2013 with the implemented NRPS. The counterfactual experiments include eliminating the NRPS transfers, scaling them up, replacing them with unconditional transfers to rural workers, a *hukou* policy reform, and rolling back local *hukou* policies to the policies in 2003.

Before conducting the counterfactual analysis, we need to specify the values of some exogenous variables in the baseline case. First, we normalize the number of rural households N_r to be 1. According to the 2010 census, the ratio of the number of urban workers to the number of rural households is 0.612. Hence, we set N_u to be 0.612. Then, we use the 2010 census to calibrate the population-to-worker ratio in the urban area, which implies that χ_u is 1.311. In addition, we

Table 8: Model Fit

Moments	Data	Model
A. Targeted Moments		
The average of log daily urban NonAgr earnings	3.682	3.712
The average of log daily rural Agr earnings	3.416	3.391
Linear trend of log daily urban NonAgr earnings	0.114	0.120
Linear trend of log daily rural Agr earnings	0.067	0.065
The variance of log daily urban NonAgr earnings	0.671	0.656
The variance of log daily rural Agr earnings	0.999	1.048
Serial correlation in log daily household earnings for rural stayers	0.704	0.653
Serial correlation in log daily household earnings for urban stayers	0.614	0.598
Serial correlation in log daily household earnings for switchers from rural to urban	0.531	0.574
Regression of log daily urban NonAgr earnings on		
age	0.067	0.071
age squared	-0.001	-0.001
female	-0.092	-0.103
years of education	0.041	0.035
Regression of migration dummy on		
age	-0.057	-0.052
age squared	0.001	0.001
female	-0.159	-0.143
years of education	0.012	0.014
hukou index	0.054	0.043
Average migration rate	0.603	0.603
Effect of NRPS on migration rate for families with elderly	0.021	0.022
Average working days of youth in rural for households with migrants	0.281	0.274
Average working days of youth in urban for households with migrants	0.409	0.383
Average working days of youth in rural for households without migrants	0.577	0.614
Average working days of elderly in rural	0.280	0.308
Share of rural workers in the rural non-agricultural sector	0.130	0.130
B. Untargeted Moments		
Observed APG	0.209	0.259
Linear trend in observed APG	0.046	0.043
Linear trend in migration share	0.016	0.013
Effect of NRPS on youth labor supply (rural + urban)	0.008	0.012
Effect of NRPS on elderly labor supply in rural	-0.020	-0.064

use the NFP data to calibrate the population-to-worker ratio in the rural area in 2010, which implies that χ_r is 1.396. Finally, the human capital for urban workers, h_u, is calibrated by solving the goods market clearing condition (11), yielding a result of 7.431. This value is significantly higher than the average human capital for migrant workers, which stands at 2.956. These figures imply a gap in average wages between urban residents and migrant workers of 2.5:1, which is close to, but smaller than, the reported 3:1 average income gap between urban and rural households in 2013 according to the China Statistical Yearbook.[17] Therefore, in addition to the APG between the migrant and rural agricultural workers, there exits a productivity gap between urban residents and migrant workers.

[17]See Table 6-4 of the 2014 edition of the Chinese Statistical Yearbook. Since rural household income includes both agricultural and migrant workers, the income gap is naturally larger than the gap between urban residents and migrant workers.

7.1 Effects of NRPS and Other Transfer Programs

Table 9 presents the effects of NRPS and other transfer programs on the migration rate, real GDP, total effective labor, and aggregate productivity. Row two is the baseline case. Except for the migration rate, the value of all other four variables are normalized to 1 in the baseline case. Row one shows the counterfactual results if no county has NRPS. Comparing the results from the first two rows, we find that NRPS increases the migration rate by 0.9 percentage points, total effective labor by 0.9 percent, and real GDP by 1 percent. Thus, most of the real GDP increase is due to the increase in total effective labor, with only a 0.1 percent change in aggregate productivity.

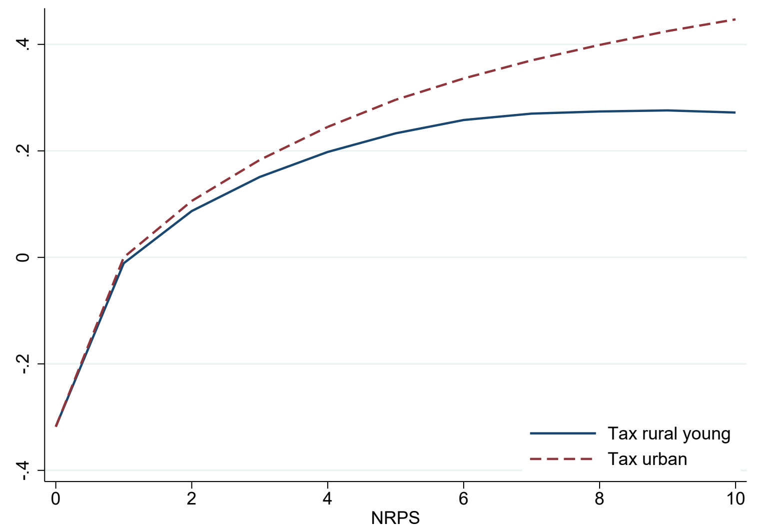
The third and fourth rows show the results when we increase the amount of transfers to old agents to 2 times and 5 times the amount under NRPS, respectively. These additional increases in transfers have only small positive effects on migration but significant positive effects on labor supply and GDP. Doubling the NRPS amount results in 1 percent increase in real GDP, while raising the amount to 5 times the NRPS amount leads to a 3.8 percent increase in real GDP. The increases in real GDP in these two scenarios are entirely due to the increases in total effective labor.

Table 9: Effects of NRPS and other transfers on migration, GDP, and productivity

	Migration rate	Real GDP	Total effective labor	Aggregate productivity	Welfare		
					rural young	rural old	urban
No NRPS	0.675	0.990	0.991	0.999	-0.172	-0.687	0.004
NRPS (baseline)	0.684	1.000	1.000	1.000	0.000	0.000	0.000
2 times NRPS	0.688	1.010	1.011	1.000	0.092	0.122	-0.003
5 times NRPS	0.687	1.038	1.038	0.999	0.212	0.332	-0.011
5 times NRPS (tax rural young)	0.692	1.044	1.045	0.999	0.105	0.330	0.001
8 times NRPS (tax rural young)	0.694	1.062	1.064	0.999	0.050	0.449	0.001
Equal transfer	0.676	0.993	0.993	1.000	0.107	0.013	-0.016

Figure 2 shows the effects of transfers to elderly on total welfare, which is defined as the sum of individual utilities. It plots the expenditure equivalent of total welfare increases. In our baseline analysis, we have assumed that transfers are financed by a lump-sum tax on urban households. We also consider an alternative financing scheme of taxing rural young workers only. In both cases, NRPS has a significant positive welfare effect: The welfare consequence of eliminating the NRPS transfer in 2013 is equivalent to a 30% proportional reduction in the income of all workers. In our sample, some rural elderly lived in extreme poverty, and the pension transfer amounts to 100% or more of their labor income. Consequently,

Figure 2: Expenditure equivalent of different transfer levels



NRPS has a large impact on the welfare of these individuals, thereby resulting in a significant overall welfare impact on the population, no matter which of the two financing schemes is used.

In the baseline case when transfers are financed by taxing urban households, we find that the total welfare always increases in the transfer amount, even if the transfer amount is ten times the current NRPS amount. This is because urban households earn much more than rural households and therefore there is a large welfare gain from transferring income from urban households to rural households. If transfers are financed by taxing rural young workers only, we find that, up to 5 times the amount of NRPS, the welfare of both young and old agents in the rural area increases in the amount of transfers, and the welfare of urban households does not decline with the transfer amount. (See the last three columns of Table 9.) Furthermore, when the transfer amount is 5 times the amount under NRPS, the aggregate real GDP increases by 4.2 percent.

Therefore, a policy that provides large transfers to old rural agents and finances the transfers with a lump-sum tax on rural young agents would improve the welfare of both old and young agents and result in a large increase in real GDP. As we illustrated in the simple model in Section 3.1.4, the reason for the large real effects of the transfers to old is that there is a friction in within-family labor allocation between old and young agents. With the two type of agents play a non-cooperative Nash game, young agents spend too much time in home production and old agents spend too much time in agricultural production. This is inefficient because old agents have a comparative advantage in home production. Income transfers to old agents help to reduce the within-family misallocation of labor by allowing old agents spend more time in home production and young agents spend more time in goods production.

Further increasing the transfer amount to a level beyond 5 times the amount under NRPS, however, would lead to a decline in the welfare of rural young agents. When the amount reaches 8 times the amount under NRPS, the total welfare would also decline.

The last row of Table 9 presents a case where young rural workers receive the same transfers as rural old workers did under NRPS. In this case, welfare of rural agents increases, but the migration rate, total effective labor, and real GDP all decrease compared to the baseline case where only old agents receive the transfers. The increase in income of young workers reduces their market labor supply, leading to lower benefits of migration and a deterioration of within-family labor allocation. As a result, fewer young workers migrate and rural households' labor supply and labor income both decline.

Table 10: Effects of NRPS and other transfers on APG and Human Capital Gap

	APG (migrants vs rural workers)		Human capital
	Observed	Underlying	gap
No NRPS	0.410	0.538	-0.128
NRPS (baseline)	0.381	0.526	-0.145
2 times NRPS	0.360	0.527	-0.166
5 times NRPS	0.325	0.527	-0.203
5 times NRPS (tax rural young)	0.330	0.544	-0.214
8 times NRPS (tax rural young)	0.314	0.542	-0.228
Equal Transfer to Old and Young	0.382	0.514	-0.131

Table 10 reports the observed APG in the baseline model and the counterfactual experiments, and the decomposition of the observed APG into the underlying APG and human capital gap. In all scenarios, the observed APG is lower than the underlying APG due to a negative human capital gap between migrants and rural workers, indicating a negative selection in human capital for migrants. The negative selection is driven by selection on unobservables, while the selection on the observable component of human capital is positive. As pointed out by Borjas (1987), whether the selection on unobservales is positive or negative depends on the variance-covariance structure of the unobservables. In our structural model, the unobserved human capital in sector j comprises a time-invariant component

U_j and an i.i.d shock λ_{jt}. Based on the estimates provided in Table 7, the standard deviation of unobserved human capital is 1.904 for the agricultural sector and 0.711 for the non-agricultural sector. The large difference in the dispersion of unobserved human capital between two sectors and a relatively low correlation between the unobserved human capital in the two sectors (0.299) implies that migrants are negatively selected relative to the human capital distribution of the agricultural sector. Relative to the underlying APG, the human capital gap is small and therefore the observed APG is still significantly positive.

When the NRPS is eliminated, rural effective labor declines, and therefore, real labor productivity in the rural sector increases (due to diminishing returns in rural production technology). However, the reduction in migration also leads to a decline in non-agricultural output, causing the relative price of the non-agricultural good to increase. This price effect dominates, resulting in an overall increase in the underlying APG. In cases where the amount of transfers to old rural agents increases beyond the NRPS level, rural effective labor increases, but rural labor productivity decreases. In these cases, migration changes little, leading to minimal relative price change. Consequently, the underlying APG increases. However, as the transfer amount increases, negative selection in human capital also becomes stronger, resulting in a decrease in the observed APG.

7.2 Effects of Migration Policies

Migration policy varies 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 origin location. In 2013, the value of this index varies from 1.0 to 5.2 (see Table 1). As our estimation results in Table 7 show, the Hukou Index has a strong negative effect on migration costs. We consider a hypothetical policy reform in 2013 that makes all destination cities adopt the most liberal *hukou* policy, which effectively sets the Hukou Index to a value of 6 for migrants from all origin locations. Table 11 shows that, under this reform, the migration rate increases by 2.1 percentage points. As migration reduces sectoral misallocation of labor, the aggregate productivity increases by 1%. The total effective labor also increases by 0.6% and therefore the real GDP increases by 1.7%. Not surprisingly, the *hukou* policy reform increases the welfare of rural agents, but decreases the welfare of urban agents.

We also conduct a simulation by eliminating the NRPS transfers and setting Hukou Index to its 2003 value for all Chinese cities. This counterfactual shows what would happen if there had been no *hukou* policy reform between 2003 and 2013 and no NRPS. In this case, the migration rate would be 5.4 percentage points lower, and total effective labor and aggregate productivity would be 3.1% and 1.6% lower, respectively. As a result, the real GDP would be 4.6% lower. In other words, relaxation of migration policies between 2003 and 2013 and NRPS contributed to 5.4 percentage points increase in migration and a 4.6% increase in real GDP.

Table 11: Effects of migration costs on migration, GDP, and productivity

	Migration rate	Real GDP	Total effective labor	Aggregate productivity	Welfare		
					rural young	rural old	urban
Baseline	0.684	1.000	1.000	1.000	0.000	0.000	0.000
Hukou reform	0.705	1.017	1.006	1.010	0.127	0.009	-0.013
2003 hukou and no NRPS	0.630	0.954	0.969	0.984	-0.347	-0.764	0.018

In related work, Tombe and Zhu (2019) and Hao et al. (2020) also examined the impact of migration cost reductions on real GDP growth in China. In particular, 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, between 2003 and 2013. In Table 9 of their paper, they showed that the reduction of costs to out-of-county agriculture-to-nonagriculture migration contributed to 8.3% increase in real GDP in China. This effect is larger than the 4.6% increase in real GDP we find from policy changes between 2003 and 2013. There are three reasons for the difference in results. Firstly, they consider all potential changes in migration costs that help their structural model account for the observed changes in migration rates, while we consider two explicit police changes, relaxation of *hukou* policies and NRPS. Secondly, our estimation using micro data shows that there is a significant productivity gap between migrant and urban workers. They assumed that migrant workers and urban workers have the same productivity and therefore likely overestimated 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 reallocaiton of labor between sectors.

Table 12 shows the effect of migration costs on the observed APG and decomposes it into the effect on the underlying APG and human capital gap. The

Table 12: Effects of migration costs on APG and human capital gap

	APG (migrants vs rural workers) Observed	Underlying	Human capital gap
Baseline	0.381	0.526	-0.145
Hukou reform	0.183	0.372	-0.190
2003 hukou and no NRPS	0.670	0.726	-0.055

hukou reform reduces the underlying APG for two reasons. First, by inducing more young workers to migrate, it reduces labor supply in rural production and therefore increases rural labor productivity. Second, as labor supply in agricultural production declines, relative price of the agricultural good increases and therefore relative wage in agriculture increases. The *hukou* reform also increases negative selection in human capital. Thus, the reduction in observed APG is even larger than the reduction in the underlying APG (19.8 log points vs. 15.4 log points). Rolling back *hukou* policies to the policies in 2003 and eliminating the NRPS, on the other hand, would lead to a much larger underlying APG of more than 70 log points. In this case of high migration costs, there is little selection in human capital, with the human capital gap being less than 6 log points. Thus, the observed APG is also high, at 67 log points. These counterfactual experiments show that the role of selection in accounting for the observed APG is affected by migration costs, and selection plays a smaller role when migration costs are higher, which helps to explain why our reduced form estimation using data for the entire period of 2003 to 2013 found small selection effect.

8 Conclusion

In this paper, we utilize nationally representative long-term panel data to examine the influence of migration costs and sorting on the agricultural productivity gap in China. To address selection bias, we employ a policy experiment as an exogenous instrument and estimate the average cost of policy-induced migration as well as the sectoral productivity disparity in China. Our reduced-form estimation findings reveal high average migration costs and significant sectoral productivity differences in the period of 2003 to 2013. It also shows that selection plays a minor role in explaining the observed agricultural productivity gap in the period due to high migration costs.

We then construct a general equilibrium household model with endogenous labor supply and migration that is not only consistent with the reduced form results but also illustrates the channel through which the policy experiment affects migration. We then estimate the general equilibrium model structurally and use the estimated model to quantify the effects of two types of policies: income transfers to old rural agents and relaxation of migration policies. We find that the NRPS policy, which provides transfers to old agents in rural China, has positive effects on both GDP and welfare. Scaling up the transfer program would have even larger positive effects on GDP and welfare. These positive effects mainly result from the reduction in within-household misallocation of labor in rural families, but they have a small impact on migration and the observed sectoral productivity gap. On the other hand, a policy reform that relaxes restrictions on migration has a large positive effect on GDP by improving both within-family and between-sector allocation of labor through increasing migration and reducing the sectoral productivity gap.

Analysis based on our micro data also reveals a large gap in average labor income between migrant workers and urban residents, which limits the gain from rural-urban migration in China. A detailed analysis of this migrant-resident productivity gap is an interesting question that we leave for future research.

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ONLINE APPENDIX

A Data Appendix

A.1 Hukou Index

We extend the prefecture-level *hukou* policy liberalization index constructed by Fan (2019) to 2013. Specifically, we search and review all *hukou*-related official news articles, and laws and regulations at the prefecture level from Peking University's Law Information Database and Baidu. Following the narrative approach by Fan (2019), we rate each document describing *hukou* policies on a score of 0 to 6, with 0 being the most stringent and 6 being most open.[18] The average policy liberalization index increased from 2.04 in 2003 to 3.31 in 2010, and to 3.74 in 2013. This *hukou* index in general captures a migrant's job stability and the prospect of long-term settlement at a particular destination city in a particular year. Using the 2000 and 2010 population censuses, as well as the 2005 population mini-census, Fan (2019) finds that a one-point increase in the destination-based *hukou* index leads to a 19%-21% rises in the number of inward migrants in the destination prefectures. These findings highlight the association between the *hukou* index and migration patterns.

To construct an origin-based annual *hukou* index faced by potential out-migrants from different localities, we proceed as follows. First, for each prefecture, we use the 2000 Population Census to calculate the shares of out-migrants to different destination prefectures. Second, employing the predetermined migration shares as weights, we calculate the average of *hukou* policy liberalization indices across different destination prefectures. This measure is negatively related to the migration barriers faced by potential out-migrants in different origins, and is named Hukou Index in the paper. Lastly, with the mapping of villages and prefectures, we assign the prefecture-level Hukou Index measures to the villages.

In Table A.1, we employ the NFP data to examine the impact of *hukou* policy liberalization in destination prefectures, as indicated by an increase in the origin-based *hukou* index, on out-migration flows from different orgins. We employ a

[18] See the details of the rating criteria in the appendix of Fan (2019). In the data, for each prefecture-year observation, there is at most one document of *hukou* policy. If such a document exists, the score of the document is the *hukou* index for the prefecture in a given year. If there is no new document introducing new *hukou* reforms, we adopt the measure from the preceding year.

difference-in-differences analysis to assess this relationship. The dependent variable in columns (1) is our baseline measure of migration, which is equal to one if an individual worked more than 180 days out of town during the year, and zero otherwise. Our findings reveal a positive and statistically significant effect of the *hukou* index on migration. Specifically, a one-standard deviation increase in the *hukou* index leads to a 2 percent increase in the probability of migration.[19] In column (2), we additionally control for the effects of the NRPS and individual characteristics, and the estimate for the *hukou* index remains robust. In columns (3) and (4), we repeat the analysis while replacing the dependent variable by the number of working days spent out of town. Based on the estimate in column (3), we find that a one-standard deviation increase in the *hukou* index leads to a significant increase of 6.9 working days spent out of town.

A.2 The NFP Data: Details

Overview. The inception of the The National Fixed Points (NFP) Survey dates back to 1984-85 when the Central Rural Policy Research Office (CRPRO) undertook a nationwide socio-economic survey to evaluate the impacts of reforms in rural areas. This extensive survey covered a sample of 37,422 farming households in 272 villages across 28 provinces. In 1986, the CRPRO made the decision to designate the surveyed villages from the 1984-1985 survey as long-term fixed points for continuous and comprehensive observation, with a planned duration of up to 50 years. The NFP system was established, and has been serving two main objectives since then: (i) to provide a comprehensive understanding of the grassroots situation in rural areas, and (ii) to evaluate rural policies. During its early years, the NFP survey was primarily conducted at the village and household levels. Since 2003, the NFP survey included an individual-level questionnaire as an integral part of the data collection process. the NFP survey periodically updated and rotated the samples within villages, and incorporated new villages into the survey to enhance its coverage and representativeness. We utilize the data spanning the period from 2003 to 2013 in this study.

Authenticity and quality are the primary requirements of the NFP survey. Several designs of the survey help enhance the credibility of the data. First, it is centrally managed by the Chinese Ministry of Agricultural and Rural Affairs, which ensures the direct reporting of data. The management structure comprises

[19] The standard deviation of *hukou* index across individuals and years is 0.678.

four levels, encompassing 31 provincial supervisory departments, 68 county-level supervisory departments, over 2,000 county and village investigators, and over 1,000 village assistant investigators. Direct reporting to the central government effectively mitigates the risk of data manipulation or falsification by provincial or municipal governments. Second, since its introduction in 1986, the bookkeeping system has played a crucial role in ensuring the accuracy of the original data. More specifically, bookkeeping books are issued to farmers (see Figure A.1), allowing them to actively and timely engage in the bookkeeping process. The information recorded in these books is then utilized and transferred to the corresponding record sheets and survey sheets. Third, assistant investigators, often village officials or farmers familiar with the community, are employed and trained to improve the quality of the survey. They conduct regular checks, verify farmers' bookkeeping activities, and guide farmers who need assistance to maintain their accounts. They also collaborate with county-level investigators to compile the data timely. Lastly, the system rewards farmers and investigators with excellent bookkeeping records, which encourages continued adherence to best practices.

Comparing the NFP and Other Datasets. Relative to repeated cross-sectional data, such as the population census, the panel structure of the NFP better serves identification purposes. Another advantage of the NFP over the population censuses is that the NFP provides detailed information on individual income, whereas only the 2005 mini population census includes income information. Different from other longitudinal surveys, such as the Longitudinal Survey on Rural Urban Migration in China (RUMiC) and the China Family Panel Study (CFPS), the NFP has a much more comprehensive sample coverage in both geographic and time dimensions. It tracks both rural residents and migrants annually over a 14-year period that encompasses the introduction of the NRPS. In particular, given that the NFP is an origin-based survey, its attrition rate is much lower than the destination-based surveys of migrants such as the RUMiC.

One drawback of the NFP data is that they include limited information on migration destinations. We can only know whether a migrant is within home county, within home province, or outside home province. For the surveys after 2009, we know the destination provinces but not the destination cities. For analyzing spatial allocation of labor, population census data are more suitable.

To evaluate the representativeness and quality of the NFP data, we compare the 2005 wave of survey with a randomly selected 10% sample from the 2005

China 1% Population Sampling Survey (mini census). As is reported in Table A.2, the observations in the NFP data exhibit similar characteristics to those of individuals holding rural *hukou* in the mini census, particularly with regards to educational attainment, labor force participation, the proportion of elderly individuals, and the share of agricultural employment.[20] We also aggregate up the NFP data to facilitate a comparison with the national-level data reported by the National Bureau of Statistics (NBS). Given that the NFP was established in 1986 and its sample selection was primarily based on rural development at that time, it is reasonable to expect potential disparities in the levels of the two data series. Nevertheless, as depicted in Figure A.2, the two data series demonstrate comparable trends throughout the sample period.

A.3 Construction of Key Variables: Details

Sector of Employment and Migration. The NFP provides the following information, which can be used to infer sector of employment and earnings for each sector: (i) number of working days in each of within-town agricultural and non-agricultural sectors, (ii) number of working days out of town, (iii) net income from agricultural production at the household level, and (iv) income earned out of town at the individual level. Table A.3 shows that out-migration status and non-agricultural employment are highly correlated. On the one hand, those who work more than 180 days out of town only spend 3.6% of working days in agricultural production on average, and 91.8% of these workers report non-agriculture as their sector of employment. On the other hand, for those who spend less than 180 working days out of town, the share of working days allocated to agricultural production is 78% (i.e, the weighted average of the statistics in columns (1) and (2)), and the share of workers reporting non-agriculture as their sector of employment is only 19.4%. Column (2) shows that the majority of workers with out-of-town working days within the range $(0, 180]$ still report agriculture as their sector of employment.

Based on these observations, this paper does not distinguish between sector choice and location choice. We loosely define sector of employment as follows: an individual is affiliated with the *na* sector if she works out of town for more

[20]We repeat the analysis by comparing the 2010 wave of survey with a randomly selected 1% sample from the 2010 Population Census, and we obtain consistent findings (results available upon request).

than 180 days, and in the a sector otherwise.[21] Panel A of Figure A.3 shows the distributions of working days allocated to within-town agriculture, within-town non-agriculture, and out of town for workers who are grouped into the a sector. We find that for workers in the a sector, 64.8% have zero working day in the within-town na sector and 90.8% spend zero working day out of town. Analogously, Panel B reveals that, for workers in the na sector, 72.7% have zero working days in the within-town a sector and 95.1% have zero working days in the within-town na sector.

Deflating Nominal Earnings to Real Earnings. We deflate all nominal earnings into 2003 Beijing prices using province-level spatial price deflators constructed by Brandt and Holz (2006). Specifically, for workers in agriculture, we deflate their daily earnings by the rural price index of the province in which their village is located. For out-of-town non-agricultural workers within their home province, we deflate daily earnings by the urban price index of the same province. For workers in the out-of-province non-agricultural sector, their migration destination is unobserved during the period of 2003-2008. To deflate their incomes, we proceed as follows. First, we use the 2000 Population Census to calculate the shares of out-migrants to different provinces for each prefecture. Second, we map the villages to prefectures, and based on the predetermined migration shares, construct the weighted average of urban price indices across different destination provinces for each village. The daily earnings of out-migrants is deflated by this weighted urban price index.

A.4 Sample Attrition in the NFP

To ensure effective tracking of migrants, the NFP employs a variety of methods. Firstly, surveys are strategically conducted after December each year, aligning with the Chinese Spring Festival when most migrants return to their hometowns. Secondly, the local investigators are acquainted with the surveyed households, having access to essential information and contact details. As telephones and cell phones have become increasingly prevalent in China, these investigators can maintain communication with migrants through various means. These measures and strategies play a crucial role in facilitating successful follow-up visits to rural

[21] The National Bureau of Statistics of China adopts a cutoff of 180 days to define migrant workers.

households and their members, particularly migrants.

To gain a better understanding of sample attrition in the NFP and its underlying factors, we compute the attrition rates for both households and individuals, respectively. The NFP data assigns unique codes to households, but not to individual household members. Hence, we utilize the household code to track the status of households, while the gender and age of members in 2003 serve as identifiers for individual tracking. The yearly attrition rate is defined as:

$$\text{Raw attrition rate}_t = 1 - \frac{\text{\# of these observations tracked at t+1}}{\text{\# of observations at t.}}$$

To account for the possibility that respondents may reappear in subsequent periods even after being lost in the immediate follow-up, we adjust the measure of attrition rate according to:

$$\text{Adjusted attrition rate}_t = 1 - \frac{\text{\# of these observations tracked in any period after t}}{\text{\# of observations at t.}}$$

This alternative measure reflects the overall tracking situation for the entire sample period.

Panel A in Figure A.4 finds that, between 2003 and 2012, the raw and adjusted attrition rates at the household level are on average 8.01% and 3.89%, respectively. The sample attrition rate at the individual level is higher than that at the household level. The raw and adjusted rates are 20.26% and 15.26%, respectively.[22] As is revealed in Panel B, there is no discernable difference in attrition rates between migrants and stayers. To benchmark the sample attrition rates in the NFP, we make a comparison with the CFPS which is widely adopted in the extant studies, such as Lagakos et al. (2020). The CFPS employs an internationally accepted survey methodology that assigns a unique identification code to each observed household and individual. Using the aforementioned definitions, the CFPS exhibits raw and adjusted household-level attrition rates of 17.03% and 12.51% over the period of 2010 to 2018, respectively. Similarly, at the individual level, the corresponding rates are 23.19% (raw) and 15.66% (adjusted).

If sample attrition is selective, our empirical identification based on sectoral switchers could be biased. For example, if individuals with higher abilities are more likely to migrate and attrit from the sample, we may underestimate the in-

[22]Note that the lack of unique codes assigned to NFP household members may result in inaccuracies in identifying follow-up samples, leading to an overestimate of sample attrition.

come gap between the agricultural and non-agricultural sectors. To investigate this potential issue, we compare the characteristics in year $t-1$ between samples that were successfully tracked and those that were not tracked in year t. The results are presented in Table A.4. We find that a higher proportion of individuals who could not be successfully tracked are female, have poor health, and are elderly. Furthermore, among individuals in the labor force who were not successfully tracked, there is a tendency towards higher education levels, a higher proportion working in non-agricultural sectors, and a greater likelihood of outmigration, while engaging in less agricultural work. Concerning migrant workers, the number of working days is similar between tracked and untracked migrants, but the latter earn more than the former. Based on these findings, we conclude that the sample attrition in NFPS is likely to bias our fixed-effects estimates towards zero. However, it is important to note that the magnitude of this bias is likely to be small, considering the relatively low attrition rate discussed earlier.

Figure A.1: The NFP Bookkeeping System

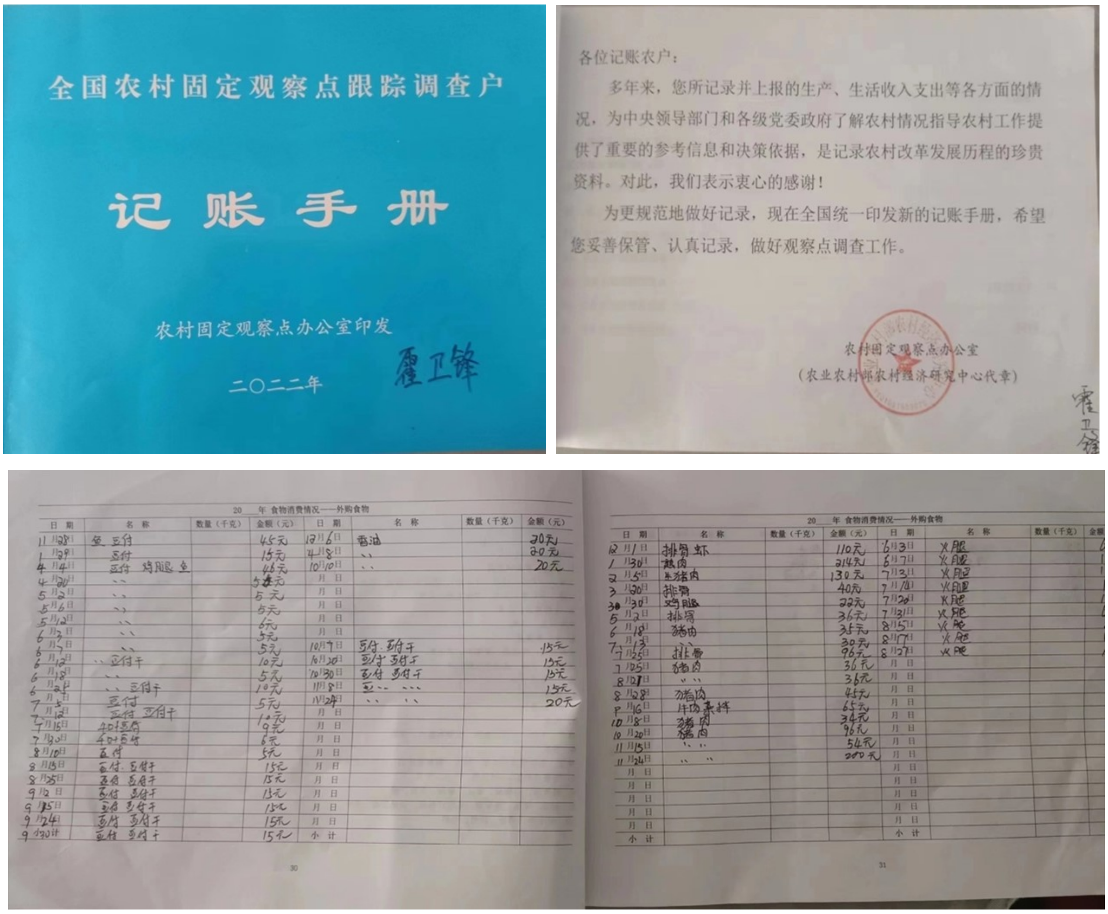
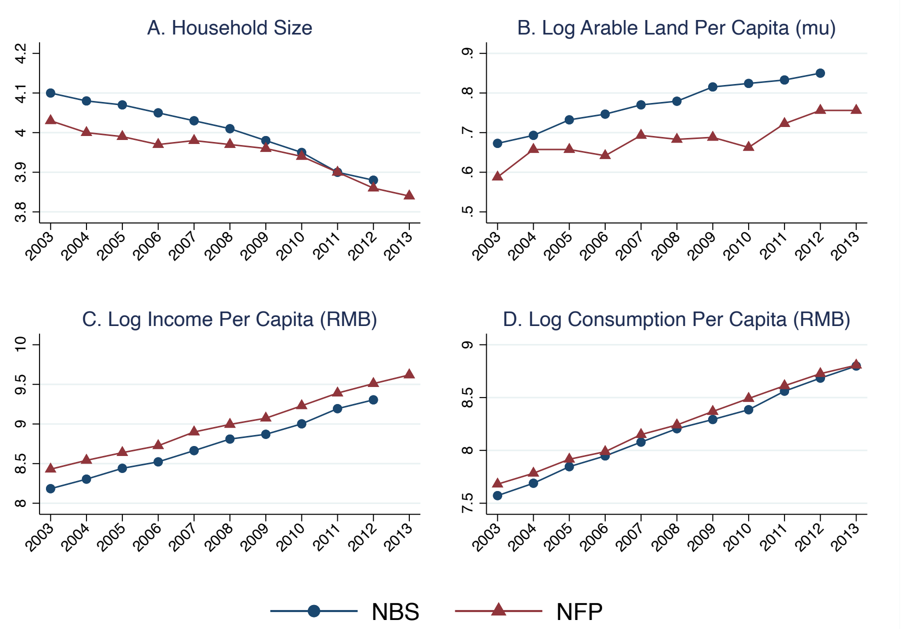
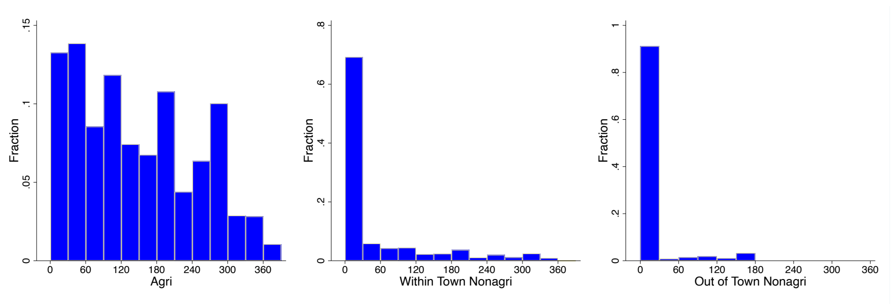


Figure A.2: NBS versus NFP

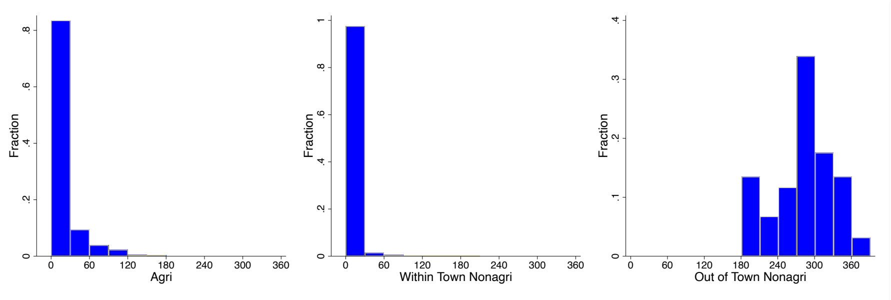


Notes: The figure compares several variables aggregated from the NFP with those from the China Rural Statistical Yearbooks published by the National Bureau of Statistics (NBS). In 2013, the NBS stopped reporting the data on household size, arable land per capita, and income per capita in rural areas.

Figure A.3: Distribution of Working Days for Agri/NonAgri Workers



Panel A. Working days in different sectors for Agri workers



Panel B. Working days in different sectors for NonAgri workers

Figure A.4: Attrition Rates

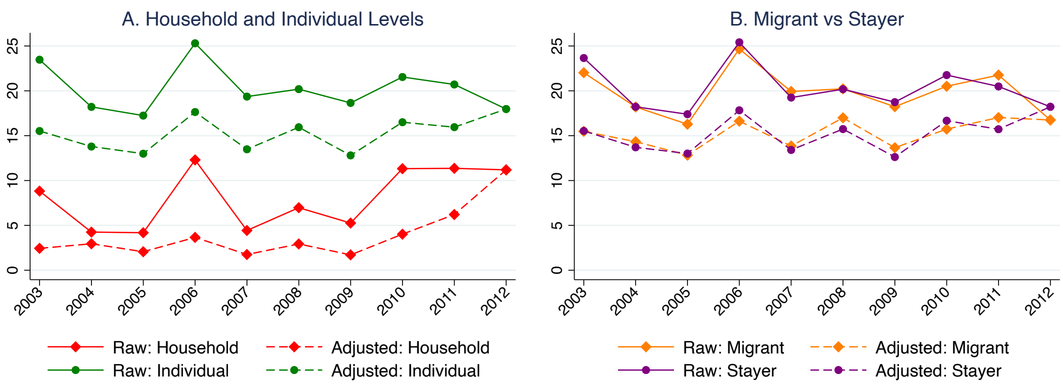
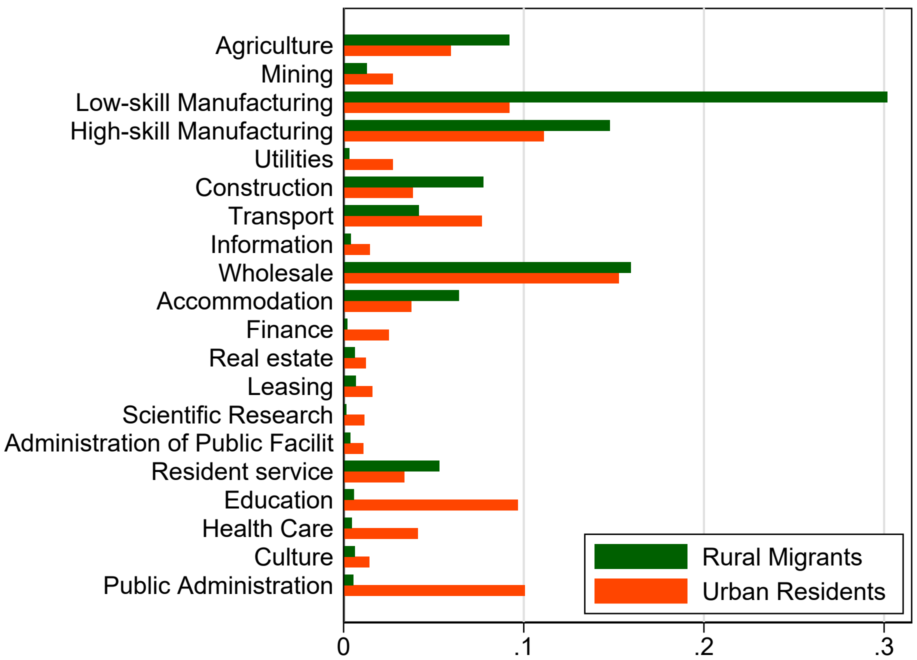


Figure A.5: Sectoral Distribution across Rural Migrants and Urban Residents



Notes: We disaggregate the manufacturing sector into high- and low-skill manufacturing. We define high–skilled workers as having a college degree or above, and low–skilled workers as the rest. High-skill manufacturing represents the manufacturing industries that have a higher share of high-skilled workers than the median manufacturing industry.

Table A.1: Origin-Based Hukou Index and Out-Migration

Dep. Var.:	(1) NonAgri	(2) NonAgri	(3) Out-of-Town Working Days	(4) Out-of-Town Working Days
Hukou Index	0.0286**	0.0219*	10.1739***	8.1416**
	(0.0128)	(0.0116)	(3.7702)	(3.3943)
Elder60×NRPS		0.0412***		10.6998***
		(0.0075)		(2.2201)
NRPS		0.0106		3.3031
		(0.0101)		(3.1011)
Elder60		0.0230***		7.1884***
		(0.0026)		(0.7687)
Individual controls	N	Y	N	Y
Province× Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	229,860	229,860	229,860	229,860
R-squared	0.1799	0.3608	0.1922	0.3847

Notes: Individual controls include age, age squared, years of education, a dummy for gender, a dummy for poor health, a dummy indicating whether there is an elderly aged 60 or above residing in the household, and the share of months in year t that the NRPS has been in effect. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Summary Statistics:
The NFP and the 2005 China 1% Population Sampling Survey

	NFP	Census,2005	
		Rural Hukou	Urban Hukou
Age	36.937	33.933	36.873
	(17.848)	(20.443)	(19.444)
Female	0.467	0.502	0.487
	(0.499)	(0.500)	(0.500)
Years of Schooling	6.779	6.509	9.728
	(3.080)	(3.559)	(4.251)
Poor Health Status	0.040	0.031	0.018
	(0.195)	(0.174)	(0.133)
Share of Workers	0.726	0.613	0.653
	(0.446)	(0.487)	(0.476)
Share of Elders	0.098	0.113	0.126
	(0.297)	(0.317)	(0.332)
Share of Workers Working in Non-agriculture	0.486	0.374	0.960
	(0.500)	(0.484)	(0.197)
Share of Workers to Migrate	0.166	0.123	0.198
	(0.373)	(0.329)	(0.399)
Rural Migrant/Urban Resident's Annual Earnings (log)	8.715	9.076	9.355
	(0.640)	(0.590)	(0.617)
Share of Migrants Working in:			
Agriculture	0.096	0.094	0.037
	(0.294)	(0.292)	(0.188)
Industry	0.256	0.463	0.266
	(0.436)	(0.499)	(0.442)
Construction	0.132	0.077	0.042
	(0.338)	(0.267)	(0.201)
Service	0.517	0.365	0.655
	(0.500)	(0.482)	(0.475)

Notes: Standard deviation in parentheses.

Table A.3: Summary Statistics:
Labor Allocation and Sector of Employment by Out-of-town Labor Supply

	Agri Sector		Non-Agri Sector
Sample: Number of working days out of town	0 day	$(0, 180]$ days	> 180 days
	(1)	(2)	(3)
Total working days	205.678	232.646	302.228
	(105.169)	(75.096)	(44.207)
Share of working days in:			
Within-town agri production	0.816	0.425	0.036
	(0.302)	(0.227)	(0.077)
Within-town non-agri production	0.184	0.066	0.005
	(0.302)	(0.143)	(0.028)
Out-of-town	0.000	0.509	0.959
	(0.000)	(0.235)	(0.084)
(Self-reported) Non-agricultural sector	0.174	0.389	0.918
	(0.379)	(0.488)	(0.275)
ln Daily wage in Non-agricultural sector	0.000	3.535	3.487
	(0.000)	(0.736)	(0.726)
ln Daily wage in agricultural sector	2.958	2.883	2.945
	(0.971)	(0.969)	(1.036)
Number of observations	145488	14788	69584

Notes: Standard deviation in parentheses.

Table A.4: Characteristics of Tracked and Untracked Individuals

	Tracked	Untracked	N	p-value
Age	37.462	37.222	874603	0.000
	(19.593)	(20.799)		
Female	0.474	0.496	874603	0.000
	(0.499)	(0.5)		
Poor Health	0.047	0.059	874603	0.000
	(0.211)	(0.235)		
At School	0.154	0.146	874603	0.002
	(0.361)	(0.353)		
In Labor Force	0.662	0.621	874603	0.000
	(0.473)	(0.485)		
Elder	0.126	0.155	874603	0.000
	(0.332)	(0.362)		
Among workers:				
Years of Schooling	7.120	7.575	561563	0.000
	(3.001)	(3.074)		
Working in Non-agriculture	0.515	0.578	561563	0.000
	(0.5)	(0.494)		
Migrant	0.231	0.257	561563	0.000
	(0.422)	(0.437)		
Working days in Agriculture	82.709	71.264	561563	0.000
	(105.67)	(104.681)		
Among migrants:				
Migrant's Working Days	292.499	294.64	119493	0.000
	(47.996)	(46.753)		
Migrant's Real Earning(log)	9.369	9.633	119493	0.000
	(0.784)	(0.794)		

Notes: Standard deviation in parentheses.

B Proof of Proposition 1 in Section 3

The LATE estimate captures the gains in daily wage of sectoral switchers whose migration decisions are marginally affected by the NRPS:

$$R_{\text{LATE}} = E\left[\ln\left(\frac{w_{na}h_{na}}{w_a h_a}\right) | \ln\left(\frac{w_{na}h_{na}}{w_a h_a}\right) + 2\ln\left(\frac{2-m}{2}\right) < 0 < \ln\left(\frac{w_{na}h_{na}}{w_a h_a}\right) + 2\ln\left(\frac{2+\frac{T}{w_a h_o}-m}{2+\frac{T}{w_a h_o}}\right)\right].$$

Note that

$$\ln\left(\frac{w_{na}h_{na}}{w_a h_a}\right) = \ln\left(\frac{w_{na}\exp\left(\boldsymbol{X}\beta + U_{na}\right)}{w_a \exp\left(\boldsymbol{X}\beta + U_a\right)}\right) = R + d,$$

where $d = U_{na} - U_a$. Then,

$$R_{\text{LATE}} = R + E\left[d| - 2\ln\left(\frac{2+\frac{T}{w_a h_o}-m}{2+\frac{T}{w_a h_o}}\right) - R < d < -2\ln\left(\frac{2-m}{2}\right) - R\right].$$

Consider the case when $\frac{T}{w_a h_o}$ is sufficiently small, and hence $\ln\left(\frac{2+\frac{T}{w_a h_o}-m}{2+\frac{T}{w_a h_o}}\right) \approx \ln\left(\frac{2-m}{2}\right) + \frac{2}{(2-m)h_o}\frac{T}{w_a}$. Then,

$$R_{\text{LATE}} = R + E\left[d| - 2\ln\left(\frac{2-m}{2}\right) - \frac{4}{(2-m)}\widetilde{T} - R < d < -2\ln\left(\frac{2-m}{2}\right) - R\right].$$

where $\widetilde{T} = \frac{T}{w_a h_o}$. Let $G(x) = \int_{-\infty}^{x} v f(v) dv$, $b_1 = 2\ln\left(\frac{2-m}{2}\right)$, $b_2 = \frac{4}{2-m}$, and $p(m)$ be the PDF of m. The LATE estimator can be rewritten as:

$$R_{\text{LATE}} = R + \frac{\int \left(G(-b_1 - R) - G(-b_1 - b_2\widetilde{T} - R)\right) p(m)dm}{\int \left(F(-b_1 - R) - F(-b_1 - b_2\widetilde{T} - R)\right) p(m)dm}.$$

Note that,

$$\lim_{\widetilde{T}\to 0} \frac{G(-b_1 - R) - G(-b_1 - R - b_2\widetilde{T})}{\widetilde{T}} = G'(-b_1 - R) = (-b_1 - R)f(-b_1 - R)$$

$$\lim_{\widetilde{T}\to 0} \frac{F(-b_1 - R) - F(-b_1 - R - b_2\widetilde{T})}{\widetilde{T}} = F'(-b_1 - R) = f(-b_1 - R).$$

By L'Hôpital's rule,

$$\begin{aligned}
\lim_{\widetilde{T}\to 0} R_{\text{LATE}} &= R - \frac{\int \left(2\ln\left(\frac{2-m}{2}\right) + R\right) f\left(-2\ln\left(\frac{2-m}{2}\right) - R\right) p(m)dm}{\int f\left(-2\ln\left(\frac{2-m}{2}\right) - R\right) p(m)dm} \\
&\approx \frac{\int mf\left(-2\ln\left(\frac{2-m}{2}\right) - R\right) p(m)dm}{\int f\left(-2\ln\left(\frac{2-m}{2}\right) - R\right) p(m)dm} \\
&= \frac{E\left[mf\left(M(\boldsymbol{X}, \boldsymbol{Z}) - R\right)\right]}{E\left[f\left(M(\boldsymbol{X}, \boldsymbol{Z}) - R\right)\right]}.
\end{aligned}$$

The approximation in the second line follows because $\ln\left(\frac{2-m}{2}\right) \approx -\frac{m}{2}$.

C Additional Empirical Results

C.1 Observational Migration Returns in Other Contexts

Hamory et al. (2021) show that, after controlling for individual fixed effects the estimated APG drops from 36 log points to 24 log points for Indonesia, and from 48 log points to 22 log points for Kenya.[23] Alvarez (2020) shows that controlling for individual fixed effects also leads to a large reduction in the estimated income gap between the manufacturing sector and the agricultural sector in Brazil, from 48 log points to 9 log points, as well as a large reduction in the estimated income gap between the service sector and the agricultural sector in Brazil, from 48 log points to 4 log points. Using the data from the US, Herrendorf and Schoellman (2018) find that the wage gains based on switchers is only 6%, much lower than the cross-sectional wage gap of 76%. These results suggest that the labor returns to migration are small in many countries.

Lagakos et al. (2020) use the China Family Panel Study (CFPS) data to estimate the return from switching sectors in China and find that the cross-sectional OLS estimate is significantly higher than the FE estimate. Their outcome measure is different from ours in two aspects. First, the gains of migration in Lagakos et al. (2020) is based on consumption per capita, which is probably a lower bound for income gains, because income elasticity of consumption is generally less than 1. In fact, when we use the real earning data from the CFPS, we obtain an OLS estimate of 1.09 and FE estimate of 1.29. (The details are available upon request.) Second, their measure is on an annual basis. In Table C.1, we repeat the analysis

[23] Relatedly, using annual income as the outcome measure, Pulido and Święcki (2018) find that the estimated sectoral income gap reduces from 54 log points to 33 log points in Indonesia when individual fixed effects are controlled for.

in Table 3 but employ log annual earnings as the outcome variable. The OLS estimate is statistically similar to that of the FE estimate. Both estimates are more than twice as large as those based on daily wage, suggesting endogenous adjustment of labor supply associated with migration.

C.2 Heterogeneity: IV Estimation

With the heterogeneity of migration costs across different rural areas in China, the IV estimate captures the weighted average of baseline migration costs faced by the NRPS-induced switchers across the rural areas. To further shed light on this interpretation, we group villages into two groups depending on whether the average Hukou Index (which is negatively related to migration barriers) faced by out-migrants in 2009-2013 is above or below the median, and estimate the LATE specific to each group. Column (1) of Table C.2 reports the IV regression results. The IV estimates imply that, among the compliers, working in the non-agricultural sector increases daily wage by 104 log points in regions with high baseline migration cost (i.e., with Hukou Index below the median). The corresponding effect is 78 log points for regions with low baseline migration cost (i.e., with Hukou Index above the median).

C.3 Robustness: Control Function Estimation

In this appendix, we extend the control function model in several dimensions so that it depends less on functional form restrictions and demands a less stringent identification assumption. First, we estimate the first-stage selection equation by extending equation (8) with the interactions between the instrument and controls (except for the village and province-year fixed effects), which allows the NRPS to affect migration decisions in a more non-parametric way.[24] Using the residuals obtained from this augmented model ($\hat{\nu}_{ihjt}$), we estimate the following second-stage regression:

$$\ln y_{ihjt} = \gamma_1 NonAgri_{ihjt} + X_{ihjt}\gamma_2 + \eta NonAgri_{ihjt} \times \hat{\nu}_{ihjt} + \psi\hat{\nu}_{ihjt} + \varphi_j + \varphi_{pt} + u_{ihjt}.$$

[24] We use age group dummies and education group dummies to capture the effects of age and education on the migration decision non-parametrically.

Under the identification assumption that

$$E[U_{a,ihjt}|\nu_{ihjt}] = \psi\nu_{ihjt} \quad \text{and} \quad E[U_{na,ihjt} - U_{a,ihjt}|\nu_{ihjt}] = \eta\nu_{ihjt}, \tag{C.1}$$

the estimated coefficient γ_1 reflects the ATE. The regression result is reported in column (2) of Table C.2. Second, in column (3), we further include the quadratic term of the residual and its interaction with $NonAgri$. This specification relaxes the linearity assumption in (C.1). (Wooldridge, 2015) Third, as is pointed out in Card (2001), in a general setting, changes in the instrumental variable may affect the entire mapping between unobserved abilities and the outcome of interest, which leads to a violation of assumption (C.1).[25] Following Card (2001), to address the problem, column (4) extends the control function approach by adding an interaction term of the residual with $NonAgri$, and a three-way interaction with $NonAgri \times Z$. Across these extended models, the estimates of γ_1 remain stable and range from 0.28 to 0.29.

C.4 Mechanisms: Additional Results

C.4.1 Further Evidence

Table C.3 presents the heterogeneous effects of the NRPS on sector of employment by gender and by the presence of young children in a household, which provides indirect evidence for the mechanisms associated with the demand for home production in our model. Columns (1) and (2) find a more pronounced effect of $Elder60_{hjt} \times NRPS_{jt}$ for female workers. Columns (3) to (5) show that the responses of migration decision to $Elder60_{hjt} \times NRPS_{jt}$ is stronger for households with the presence of child aged 15 or below, but only for the female sample. These findings are consistent with the fact that female workers engage more in home production (such as child care) in the context of rural China. Therefore, we should expect its effect on migration be more pronounced for the female sample. They

[25] To be clear, in this case,

$$Cov(U_a, \nu|Z = 1) \neq Cov(U_a, \nu|Z = 0), \quad Cov(U_{na} - U_a, \nu|Z = 1) \neq Cov(U_{na} - U_a, \nu|Z = 0),$$

which violates assumption (C.1). Nevertheless, a simple extension of the control function is appropriate with the identification assumption being:

$$E[U_a|\nu] = \eta_0(1 - Z)\nu + \eta_1 Z\nu \quad \text{and} \quad E[U_{na} - U_a|\nu] = \psi_0(1 - Z)\nu + \psi_1 Z\nu.$$

also align with the proposed mechanisms that the introduction of the NRPS allows elders to reallocate time from farm work to non-farm home production such as taking care of their grandchildren.

Columns (1) to (3) of Table C.4 explore the effect of $Elder60_{hjt} \times NRPS_{jt}$ by location of non-agricultural employment. The effect only reveals when the non-agricultural employment is outside the county of the registered Hukou. We take these findings as another supportive evidence for the mechanisms emphasized by our model. Specifically, sector switching costs associated with home production increase with migration distance. Hence, if the NRPS alleviates the related costs, we should expect the non-agricultural employment in more distant locations be a more relevant margin of adjustment.

In column (4), we allow the effect of the NRPS to vary by the age of the elderly. Relative to households without an elderly, na employment probability increases by 2.1%, 5.3%, and 3.9% following the introduction of the NRPS, for workers from households with an elderly aged 55-59, 60-69, and 70 or above, respectively. Individuals aged 55-59 are not entitled to NRPS transfers, and hence the significantly positive estimate of Elder55-59×NRPS suggests anticipatory responses to the NRPS. More importantly, the effect is the most pronounced for the households with elderly aged 60-69 for whom the labor supply channel should be the most relevant. In line with these findings, Table C.5 reveals significant impacts of NRPS only among elderly individuals aged below 70 or those with a good health status.

C.4.2 Potential Omitted Channels

Due to an income effect, the introduction of the NRPS may have a direct impact on potential earnings which is mediated by the co-residence status with an elderly. For example, if the households with an elderly increase their investment in fixed capital for production with the NRPS transfers, the exclusion restriction is violated leading to a bias of our IV estimate. To alleviate such a concern, Table C.6 explores whether the introduction of the NRPS affects saving and investment behaviours differentially for households with different structure in year t. We find that the introduction of the NRPS does not have a differential effect on household with an elder or not for: (i) savings rate ($= \frac{\text{NetIncome-Consumption}}{\text{NetIncome}}$, where $NetIncome$ is the total income net of tax and production costs), (ii) investment on fixed capital for production, (iii) amount of loans borrowed, (iv) change in the amount of farmland under operation, and (v) the use of intermediate input per unit labor in agricultural production.

The cash transfers received from the NRPS may encourage out-migration for individuals that were previously constrained by limited access to credit. To investigate this alternative channel, we examine the heterogeneous impacts of the NRPS across households with varying levels of wealth in column (1) of Table C.7. Specifically, we divide households into two groups based on whether their deposits are above or below the median. Likewise, in column (3), households are categorized into two groups based on their levels of cash holdings. If the credit constraint serves as the primary channel through which the NRPS influences migration decisions, it is reasonable to anticipate a stronger impact among households with lower levels of wealth or cash holdings. However, there is no discernable heterogeneous impacts of Elder60×NRPS across different groups. Columns (2) and (4) replicate the analysis by dividing households into tertiles based on their deposits or cash holdings, respectively, and obtain consistent results.

C.5 Robustness: Human-Capital-Adjusted Daily Agricultural Earnings

In the baseline analysis, we impute the individual-level agricultural daily earnings by apportioning the household-level agricultural income to each household member based on their respective working days in the agricultural sector. A potential concern is that this imputation approach may underestimate the agricultural earnings of individuals with a stronger absolute advantage in agriculture within the household, which may result in an upward bias for the estimated sectoral income gap if these individuals have a higher propensity of migrating to the non-agricultural sector. To address this issue, we consider an alternative measure of nominal daily agricultural earnings that accounts for the observed differences in human capital across household members. In particular, we proceed as follows. Firstly, using the 2005 mini population census, we estimate a Mincer regression for workers in the agricultural sector, relating log agricultural monthly income to a dummy for female, years of education, age and age-squared. Secondly, using the Mincer estimates, we impute the individual-level human capital according to: $hc_i = \exp(-0.1212 \times Female + 0.0335 \times Educ + 0.0223 \times Age - 0.0002 \times Age^2)$. For an individual i in household h, her daily nominal earnings is given by: $\frac{hc_i \times i\text{'s working days in } a}{\sum_{j \in h} hc_j \times j\text{'s working days in } a} \frac{\text{Household } h\text{'s value-added from } a}{i\text{'s working days in } a}$. This nominal income is then converted to the real earnings based on the same procedure described in Appendix A.3.

Table C.8 employs the human-capital-adjusted measures and repeat the analysis in Section 4. It is reassuring to find that across different specifications (i.e., OLS, individual fixed effects, IV, and control function), the estimates resemble those in our baseline analysis.

Table C.1: Sector of Employment and Annual Earnings: OLS and Individual FE

Dep. Var.: ln Annual Earnings	(1)	(2)	(3)	(4)
Migration	0.7951***		0.8085***	
	(0.0120)		(0.0134)	
Rural to urban switchers		0.7271***		0.7429***
		(0.0145)		(0.0175)
Urban to rural switchers		-0.0291		0.0186
		(0.0180)		(0.0184)
Urban stayers		0.7850***		0.8152***
		(0.0143)		(0.0184)
Individual controls	Y	Y	Y	Y
Province× Year FE	Y	Y	Y	Y
Village FE	Y	Y	N	N
Individual FE	N	N	Y	Y
Observations	229,860	154,607	229,858	142,209
R-squared	0.3955	0.3901	0.6718	0.6835

Notes: Individual controls include age, age squared, years of education, a dummy for gender, a dummy for poor health, a dummy indicating whether there is an elderly aged 60 or above residing in the household, and the share of months in year t that the NRPS has been in effect. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: Sector of Employment and Daily Wage: Additional Results

Dep Var: ln Daily Wage	(1) IV	(2) CF	(3) CF	(4) CF
Hukou Index: below median × NonAgri	1.0384***			
	(0.3949)			
Hukou Index: above median × NonAgri	0.7756**			
	(0.3699)			
NonAgri		0.2916***	0.2873***	0.2801***
		(0.0379)	(0.0405)	(0.0405)
Residual		0.2954***	0.2762***	0.2776***
		(0.0371)	(0.0435)	(0.0438)
Residual × NonAgri		-0.4956***	-0.4417***	-0.4808***
		(0.0416)	(0.0819)	(0.0828)
Residual^2			-0.0340	-0.0035
			(0.0484)	(0.0482)
Residual^2 × NonAgri			-0.0035	0.0098
			(0.0950)	(0.0952)
Residual × Z				0.2355***
				(0.0556)
Residual × NonAgri × Z				0.0989
				(0.0702)
First-stage specification		Linear + interactions with Z	Linear + interactions with Z	Linear + interactions with Z
Individual controls	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	229,860	229,860	229,860	229,860
R-squared	–	0.4202	0.4202	0.4209
Kleibergen-Paap F-Stat	14.54	–	–	–

Notes: The first-stage specification in column (1) include the IV (NRPS×Elder60), and control variables in the vector X_{ihjt}: age, age squared, years of education, a dummy for gender, a dummy for poor health, a dummy indicating whether there is an elderly aged 60 or above residing in the household, and the share of months in year t that the NRPS has been in effect. The first stage specification in columns (2)-(4) additionally includes the interaction between the IV and X_{ihjt}. Individual controls include all variables in the vector X_{ihjt}. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1

Table C.3: NRPS and Sector of Employment:
By Gender and the Presence of Child Aged 15 or Below

Dep. Var.:	(1) NonAgri Female	(2) NonAgri Male	(3) NonAgri All	(4) NonAgri Female	(5) NonAgri Male
Elder60 × NRPS × Child15			0.0144	0.0287*	0.0008
			(0.0115)	(0.0153)	(0.0140)
Elder60 × NRPS	0.0686***	0.0200**	0.0309***	0.0483***	0.0187
	(0.0094)	(0.0086)	(0.0094)	(0.0125)	(0.0115)
NRPS × Child15			-0.0004	-0.0005	0.0002
			(0.0068)	(0.0080)	(0.0087)
Elder60 × Child15			0.0252***	0.0254***	0.0248***
			(0.0049)	(0.0057)	(0.0063)
NRPS	-0.0062	0.0219*	0.0107	-0.0064	0.0222*
	(0.0118)	(0.0103)	(0.0106)	(0.0107)	(0.0126)
Elder60	0.0231***	0.0182***	0.0102***	0.0127***	0.0044
	(0.0031)	(0.0033)	(0.0035)	(0.0042)	(0.0047)
Child15			-0.0487***	-0.0693***	-0.0322***
			(0.0025)	(0.0028)	(0.0033)
Individual controls	Y	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y	Y
Village FE	Y	Y	Y	Y	Y
Observations	108,057	121,802	229,860	108,057	121,802
R-squared	0.3616	0.3536	0.3626	0.3667	0.3543

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. *** p<0.01, ** p<0.05, * p<0.1

Table C.4: NRPS and Sector of Employment:
By Locations and Age Groups of the Elderly

Dep. Var.:	(1) NonAgri within County	(2) NonAgri outside County within Province	(3) NonAgri outside Province	(4)) NonAgri All
Elder60 × NRPS	0.0020	0.0159***	0.0230***	
	(0.0044)	(0.0050)	(0.0068)	
NRPS	0.0116*	0.0044	-0.0059	0.0055
	(0.0069)	(0.0063)	(0.0068)	(0.0111)
Elder60	0.0024	0.0086***	0.0121***	
	(0.0016)	(0.0018)	(0.0022)	
Elder55-59×NRPS				0.0206**
				(0.0093)
Elder60-69×NRPS				0.0524***
				(0.0106)
Elder≥70×NRPS				0.0413***
				(0.0092)
Elder55-59				0.0788***
				(0.0036)
Elder60-69				0.1252***
				(0.0043)
Elder≥70				0.0287***
				(0.0034)
Individual controls	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	229,860	229,860	229,860	229,860
R-squared	0.1471	0.1643	0.2891	0.1911

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. *** p<0.01, ** p<0.05, * p<0.1

Table C.5: NRPS and Elderly Labor Supply

Dep. Var.: Working days Sample:	(1) All Poisson	(2) Age<70 Poisson	(3) Age*geq*70 Poisson	(4) Good Health Poisson	(5) Poor Health Poisson
NRPS	-0.0812**	-0.0895**	0.1210	-0.1247***	0.0768
	(0.0382)	(0.0378)	(0.0837)	(0.0430)	(0.0677)
Individual controls	Y	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y	Y
Village FE	Y	Y	Y	Y	Y
Observations	47,131	29,420	17,107	23,769	23,145

Notes: Individual controls include years of education, a dummy for gender, and dummies of health status. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1

Table C.6: NRPS and Other Household Level Outcomes

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	Savings Rate	ln(1+Fixed Investment)	ln(1+Loan)	ΔArable Land	Immediate Input per Labor Input
	OLS	OLS	OLS	OLS	OLS
Elder60×NRPS	0.0067	-0.0203	0.0341	-0.0013	0.0178
	(0.0080)	(0.0360)	(0.0452)	(0.0042)	(0.0209)
NRPS	0.0010	-0.0410	-0.0621	-0.0153*	-0.0307
	(0.0134)	(0.0651)	(0.0869)	(0.0079)	(0.0389)
Elder60	-0.0036	0.0072	-0.1288***	-0.0079***	-0.0084
	(0.0035)	(0.0153)	(0.0202)	(0.0016)	(0.0068)
Individual controls	Y	Y	Y	Y	Y
Province×Year FE	Y	Y	Y	Y	Y
Village FE	Y	Y	Y	Y	Y
Observations	107,802	110,632	110,632	102,975	101,403
R-squared	0.1199	0.0891	0.1318	0.0848	0.4475

Notes: Household controls include average age, average years of education, share of male, share of poor health status among the working-age household members, and start-of-period arable land per capita. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: NRPS, Migration, and Household Wealth

Dep. Var.: NonAgri	(1)	(2)	(3)	(4)
Wealth Measure:	Deposits	Deposits	Cash	Cash
Wealth: Below Median×Elder60×NRPS (β_1)	0.0497***		0.0177***	
	(0.0169)		(0.0040)	
Wealth: Above Median×Elder60×NRPS (β_2)	0.0671***		0.0276***	
	(0.0144)		(0.0043)	
Bottom Tercile×Elder60×NRPS (π_1)		0.0431*		0.0249***
		(0.0229)		(0.0047)
Middle Tercile×Elder60×NRPS (π_2)		0.0821***		0.0129***
		(0.0164)		(0.0050)
Top Tercile×Elder60×NRPS (π_3)		0.0532***		0.0290***
		(0.0167)		(0.0052)
Individual and household controls	Y	Y	Y	Y
Province×Year FE	Y	Y	Y	Y
Village FE	Y	Y	Y	Y
Observations	114,724	114,724	174,626	174,626
R-squared	0.3732	0.3736	0.3468	0.3468
F test	$\beta_1 = \beta_2$	$\pi_1 = \pi_2 = \pi_3$	$\beta_1 = \beta_2$	$\pi_1 = \pi_2 = \pi_3$
p-value	0.426	0.238	0.929	0.967

Notes: All regressions control for wealth group dummies, the interaction terms of wealth group dummies and Elder60, and the interaction terms of wealth group dummies and NRPS. 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. *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: Sector of Employment and Daily Wage: OLS and Individual FE (Human Capital Adjusted Measure)

Dep. Var.: ln Daily Wage	(1) OLS	(2) FE	(3) IV	(4) CF
Migration	0.3008***	0.3529***	0.8827**	0.3290***
	(0.0141)	(0.0156)	(0.3626)	(0.0283)
Individual controls	Y	Y	Y	Y
Province× Year FE	Y	Y	Y	Y
Village FE	Y	Y	N	Y
Individual FE	N	N	Y	N
Observations	229,860	229,823	229,860	229,860
R-squared	0.4208	0.7117	–	0.4224
Kleibergen-Paap F-Stat	–	–	29.97	–

Notes: Columns (1) to (4) respectively re-estimate the specifications from column (1) Table 3, column (3) Table 3, column (3) Table 4 and column (4) Table 4. Individual controls include age, age squared, years of education, a dummy for gender, a dummy for poor health, a dummy indicating whether there is an elderly aged 60 or above residing in the household, and the share of months in year t that the NRPS has been in effect. Robust standard errors are clustered at the village×year level. *** p<0.01, ** p<0.05, * p<0.1

D Model Appendix

D.1 Household Production Income

This section derives the formula for household production income. Given the total labor supply of old and young agents in the rural area, l_o and l_y, and the output prices p_a and p_{na}, the household allocates labor between agriculture and non-agriculture to maximize total household income:

$$\max_{l_{oa},l_{or},l_{ya},l_{yr}} \{p_a A_a (h_o l_{oa} + h_y l_{ya})^\alpha + p_{na} A_r (h_o l_{or} + h_y l_{yr})^\alpha\}$$

subject to

$$l_{ij} \geq 0, i = o, y, j = a, r;$$

$$l_{ia} + l_{ir} = l_i, i = o, y.$$

The F.O.Cs are

$$\alpha p_a A_a (h_o l_{oa} + h_y l_{ya})^{\alpha-1} h_o = \alpha p_{na} A_r (h_o l_{or} + h_y l_{yr})^{\alpha-1} h_o = \lambda_o$$

$$\alpha p_a A_a \left(h_o l_{oa} + h_y l_{ya}\right)^{\alpha-1} h_y = \alpha p_{na} A_r \left(h_o l_{or} + h_y l_{yr}\right)^{\alpha-1} h_y = \lambda_y$$

Thus, we have

$$h_o l_{oa} + h_y l_{ya} = \left(\frac{p_a A_a}{p_{na} A_r}\right)^{\frac{1}{1-\alpha}} \left(h_o l_{or} + h_y l_{yr}\right)$$

From the budget constraints, we have

$$h_o l_o + h_y l_y = \left[1 + \left(\frac{p_a A_a}{p_{na} A_r}\right)^{\frac{1}{1-\alpha}}\right] \left(h_o l_{or} + h_y l_{yr}\right),$$

which implies

$$h_o l_{or} + h_y l_{yr} = \frac{\left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}}{\left(p_a A_a\right)^{\frac{1}{1-\alpha}} + \left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}} \left(h_o l_o + h_y l_y\right),$$

$$h_o l_{oa} + h_y l_{ya} = \frac{\left(p_a A_a\right)^{\frac{1}{1-\alpha}}}{\left(p_a A_a\right)^{\frac{1}{1-\alpha}} + \left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}} \left(h_o l_o + h_y l_y\right).$$

Therefore, the agricultural and non-agricultural output of the household are

$$y_a = A_a \left(h_o l_{oa} + h_y l_{ya}\right)^{\alpha} = \frac{A_a \left(p_a A_a\right)^{\frac{\alpha}{1-\alpha}}}{\left[\left(p_a A_a\right)^{\frac{1}{1-\alpha}} + \left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}\right]^{\alpha}} \left(h_o l_o + h_y l_y\right)^{\alpha}$$

$$y_r = A_r \left(h_o l_{or} + h_y l_{yr}\right)^{\alpha} = \frac{A_r \left(p_{na} A_r\right)^{\frac{\alpha}{1-\alpha}}}{\left[\left(p_a A_a\right)^{\frac{1}{1-\alpha}} + \left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}\right]^{\alpha}} \left(h_o l_o + h_y l_y\right)^{\alpha}$$

And the household production income is

$$y_f = \left[\left(p_a A_a\right)^{\frac{1}{1-\alpha}} + \left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}\right]^{1-\alpha} \left(h_o l_o + h_y l_y\right)^{\alpha} = A_f h_f^{\alpha},$$

where

$$A_f = \left[\left(p_a A_a\right)^{\frac{1}{1-\alpha}} + \left(p_{na} A_r\right)^{\frac{1}{1-\alpha}}\right]^{1-\alpha}, \quad \text{and} \quad h_f = h_o l_o + h_y l_y.$$

D.2 Labor Supply Decisions of Rural Households

D.2.1 The Case of No Migration

This section derives the first-order conditions for parents' and adult children's optimization problems when adult children choose to migrate.

The parent's optimization problem is

$$\max_{l_o\in[0,n_o]} n_o\left\{\frac{1}{1-\gamma}c\left(e_o\right)^{1-\gamma}-\frac{\eta}{1+\frac{1}{\phi}}\frac{\left(\xi l_o+l_y\right)^{1+\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}}\right\}.$$

Note that

$$\frac{h_o l_o}{h_f}y_f=h_o l_o A_f\left(h_o l_o+h_y l_y\right)^{\alpha-1}.$$

So,

$$\begin{aligned}\frac{\partial}{\partial l_o}\left(\frac{h_o l_o}{h_f}y_f\right) &= h_o A_f\left[\left(h_o l_o+h_y l_y\right)^{\alpha-1}-(1-\alpha)h_o l_o\left(h_o l_o+h_y l_y\right)^{\alpha-2}\right]\\ &= h_o A_f\left(h_o l_o+h_y l_y\right)^{\alpha-2}\left(\alpha h_o l_o+h_y l_y\right).\end{aligned}$$

Thus, the F.O.C. for l_o is

$$c^{-\gamma}c'\left(e_o\right)\frac{h_o A_f}{n_o}\left(h_o l_o+h_y l_y\right)^{\alpha-2}\left(\alpha h_o l_o+h_y l_y\right)/\kappa_r=\eta\xi\frac{\left(\xi l_o+l_y\right)^{\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}}. \tag{D.1}$$

Similarly, the child's optimization problem is

$$V_a=\max_{l_y\in[0,n_y]} n_y\left\{\frac{1}{1-\gamma}c\left(e_y\right)^{1-\gamma}-\frac{\eta}{1+\frac{1}{\phi}}\frac{\left(\xi l_o+l_y\right)^{1+\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}}\right\},$$

and the corresponding F.O.C. for l_y is

$$c^{-\gamma}c'\left(e_y\right)\frac{h_y A_f}{n_y}\left(h_o l_o+h_y l_y\right)^{\alpha-2}\left(\alpha h_y l_y+h_o l_o\right)/\kappa_r=\eta\frac{\left(\xi l_o+l_y\right)^{\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}}. \tag{D.2}$$

The equations (D.1) and (D.2) can be used to jointly solve for l_o and l_y when the child does not migrate.

D.2.2 The Case of Migration

In this section, we derive the first-order conditions for parents' and adult children's optimization problems when adult children choose to migrate.

The parent's optimization problem in this case is

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

and the F.O.C. for l_o is

$$c^{-\gamma}c'\left(e_o\right)\frac{h_o}{n_o}A_f\left(h_ol_o+h_yl_y\right)^{\alpha-2}\left(\alpha h_ol_o+h_yl_y\right)/\kappa_r=\eta\xi\frac{\left(\xi l_o+l_y+l_{na}\right)^{\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}} \tag{D.3}$$

The child's optimization problem is

$$V_{na}=\max_{l_y+l_{na}\leq n_y}n_y\left\{\frac{1}{1-\gamma}c\left(e_y\right)^{1-\gamma}-\frac{\eta}{1+\frac{1}{\phi}}\frac{\left(\xi l_o+l_y+l_{na}\right)^{1+\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}}\right\},$$

and the corresponding F.O.C.s for l_y and l_{na} are

$$c^{-\gamma}c'(e_y)\frac{h_yA_f}{n_y}\left(h_ol_o+h_yl_y\right)^{\alpha-2}\left(\alpha h_yl_y+h_ol_o\right)/\kappa_r=\eta\frac{\left(\xi l_o+l_y+l_{na}\right)^{\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}} \tag{D.4}$$

and

$$c^{-\gamma}c'(e_y)\frac{w_{na}h_{na}}{n_y}(1-m_1)/\kappa_u=\eta\frac{\left(\xi l_o+l_y+l_{na}\right)^{\frac{1}{\phi}}}{\left(n_o+n_y\right)^{1+\frac{1}{\phi}}} \tag{D.5}$$

The Equations (D.3), (D.4), and (D.5) can be used to jointly solve for l_o, l_y, and l_{na} when the child migrates. Comparing (D.4) and (D.5), if $\max_{l_y\in[0,n_y]}\{h_yA_f\left(h_ol_o+h_yl_y\right)^{\alpha-2}\left(\alpha h_yl_y+h_ol_o\right)/\kappa_r\}<w_{na}h_{na}(1-m_1)/\kappa_u$, then $l_y=0$.

D.3 General Equilibrium Conditions

The total demand for agricultural goods is

$$D_a=N_r\int p_ac_a(\boldsymbol{X},\boldsymbol{U},\boldsymbol{\lambda},\boldsymbol{n},\boldsymbol{Z})dF(\boldsymbol{X},\boldsymbol{U},\boldsymbol{\lambda},\boldsymbol{n},\boldsymbol{Z})+p_ac_a^uN_u$$

Similarly, the total demand for non-agricultural goods is

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

The goods market clearing conditions are

$$D_a=Y_a,D_{na}=Y_{na}.$$

where Y_a and Y_{na} are the total effective outputs of agricultural and non-agricultural goods.

The government's budget constraint is

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

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

E Calibration Appendix

E.1 Sector Prices and Distributional Costs

This subsection outlines the procedure of calibration for $p_{a,t}$ and $p_{na,t}$. Firstly, we construct prices for the benchmark year 2005 using the data from the GGDC productivity level database. Specifically, the GGDC provides sector-specific price data, denoted as $p_{i,2005}^{GGDC}$, for 10 sectors. These prices are defined as follows:

$$p_{i,2005}^{GGDC} = \frac{\text{National Price Value-added of Sector i and Year 2005}/E_{2005}}{\text{2005 International Price Value-added of Sector i and Year 2005}}, i = 1, ..., 10.$$

Here, E_{2005} is the China-US nominal exchange rate (price of US dollar in RMB) in 2005. For agriculture, we simply have

$$p_{a,2005}^{GGDC} = p_{1,2005}^{GGDC}.$$

For the non-agricultural sector, we have

$$p_{na,2005}^{GGDC} = \frac{\text{National Price Non-ag Value-added in Year 2005}}{\sum_{i=2}^{10} \left(\text{National Price Value-added of Sector i and Year 2005}/p_{i,2005}^{GGDC}\right)}.$$

These measures are equivalent to the prices relative to the price of US GDP in 2005:

$$p_{j,2005}^{GGDC} = \frac{\text{Price of sector } j \text{ output in 2005 US dollar}}{\text{Price of US GDP in 2005}}, \ j = a, na.$$

Secondly, since our expenditure data is indexed to the price level of urban Beijing in 2003, we need to convert $p_{j,2005}^{GGDC}$ accordingly.

Denote $\kappa_t^{BJ} = \frac{p_{c,t}}{p_{c,2003}^{BJ}}$ be the price of a reference consumption basket in year t relative to the 2003 price of a consumption basket in urban Beijing, where $p_{c,t}$ is in current RMB.[26]

Let $\Omega_{j,2005} = p^{GGDC}_{j,2005} \times$ Price of US GDP in 2005 $\times\, E_{2005}$, where $\Omega_{j,2005}$ is the price of sector j output in 2005 RMB. Using the sector-specific GDP deflator from the NBS with 2005 normalized to one, we define $\Omega_{j,t} = \Omega_{j,2005} \times \text{deflator}_{j,t}$ as the price of sector j output in current RMB. Finally, we convert the prices into 2003 Beijing RMB as follows:

$$p_{j,t} = \Omega_{j,t}/\kappa^{BJ}_t,\ j = a, na.$$

Thus, our sector prices are

$$p_{j,t} = \frac{p^{GGDC}_{j,2005} \times \text{ Price of US GDP in 2005} \times E_{2005} \times \text{deflator}_{j,t}}{\kappa^{BJ}_t}.$$

Since we don't know $\bar{p}$ = Price of US GDP in 2005 x E_{2005}, we infer it from the data, and we will discuss how we calibrate $\bar{p}$ in the next section. Hence,

$$p_{j,t} = P_{j,t}\bar{p},$$

where $P_{j,t} = \frac{P^{GGDC}_{j,2005} \times \text{deflator}_{j,t}}{\kappa^{BJ}_t}$. The calibrated $P_{j,t}$ are shown in Table C.9.

Table C.9: Calibration Results: Sector Prices

year	P_a	P_{na}
2003	0.341	0.319
2004	0.392	0.335
2005	0.384	0.346
2006	0.388	0.359
2007	0.435	0.377
2008	0.461	0.386
2009	0.466	0.392
2010	0.499	0.409
2011	0.529	0.418
2012	0.537	0.414
2013	0.541	0.409

The iceberg distributional costs, κ, in the urban and rural areas are measured by the consumption prices data posted by Carsten Holz on his webpage, which

[26]The effective expenditure is then $e = \frac{\text{Income in year } t \text{ RMB}}{\kappa_t}$.

update the original series reported in Brandt and Holz (2006) to more recent years. These prices vary across rural/urban regions, provinces, and years.

E.2 Calibrating Consumption Preference Parameters

Since the non-homothetic CES utility does not have the aggregation property, we need to use household expenditure data to calibrate the preference parameters. Consider the households with young agents and no migration. Then, all their income can be deflated by rural distribution cost κ_r. For each household in the group, the measured agricultural expenditure share in the model is

$$\frac{e_a}{e} = \frac{\kappa_r p_a c_a}{\kappa_r e} = \frac{p_a c_a}{e} = \frac{\varphi_a p_a^{1-\varepsilon} c^{1-\varepsilon} (e)^{\varepsilon}}{e} = \varphi_a p_a^{1-\varepsilon} c^{1-\varepsilon} (e)^{\varepsilon-1}$$

where $c = c(e)$ as defined before in Equation (10) of Section 5.1.5. We use non-linear least square to estimate $\varphi_a, \varepsilon, \mu$ and $\bar{p}$ to minimize the following objective function:

$$\sum_{\text{families with no elderly nor migrants}} \left[\frac{e_a}{e} - \frac{\widetilde{e_a}}{e}\right]^2.$$

where $\frac{\widetilde{e_a}}{e}$ is the agricultural expenditure share observed in the data. We choose to match the agricultural expenditure share for families without elderly or migrants because their expenditures are in rural areas and are more homogeneous.

The calibration results are shown in Table 6. The elasticity of substitution between agricultural and non-agricultural consumption (ϵ) is 0.349 and the income elasticity of non-agricultural goods (μ) is 2.475. This suggests that the income elasticity is smaller for agricultural goods than for non-agricultural goods, and therefore relative demand for agricultural goods declines with income. The calibrated $\bar{p} = 20.031$.

F Collective Decision Model

In this section, we develop a simple collective decision model. Given the sector choice, the household's collective decision problem is

$$\max_{c_{o,j}, c_{y,j}, l_{o,j}, l_{y,j}} \mu \ln (c_{o,j}) + (1-\mu) \ln (c_{y,j}) + \ln (b (1 - l_{o,j}) + 1 - l_{y,j})$$

subject to

$$c_{o,j} + c_{y,j} = w_o h_o l_{o,j} + w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T$$

Note that given the household income, the consumption allocation is determined by equalizing marginal utilities:

$$\frac{\mu}{c_{o,j}} = \frac{1-\mu}{c_{y,j}}$$

which implies that

$$c_{o,j} = \mu \left[w_o h_o l_{o,j} + w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T \right]$$

and

$$c_{y,j} = (1-\mu) \left[w_o h_o l_{o,j} + w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T \right]$$

And the household's problem becomes

$$\max_{l_{o,j}, l_{y,j}} \ln \left(w_o h_o l_{o,j} + w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T \right) + \ln \left(b \left(1 - l_{o,j} \right) + 1 - l_{y,j} \right)$$

We consider the case that $b > (w_o h_o) / (w_{y,j} h_{y,j})$. That is, old agents have a comparative advantage in home production. In this case, it is optimal for the family to set $l_{o,j} = 0$ and the labor supply decision for the young agent is

$$\max_{l_{o,j}, l_{y,j}} \ln \left(w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T \right) + \ln \left(b + 1 - l_{y,j} \right)$$

which implies

$$\frac{w_{y,j} h_{y,j}}{w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T} = \frac{1}{b + 1 - l_{y,j}}$$

$$w_{y,j} h_{y,j} (b+1) - w_{y,j} h_{y,j} l_{y,j} = w_{y,j} h_{y,j} \left(l_{y,j} - m\mathbf{1}_{[j=na]} \right) + T$$

$$l_{y,j} = \frac{b + 1 + m\mathbf{1}_{[j=na]} - \frac{T}{w_{y,j} h_{y,j}}}{2}$$

The above equation suggests that when pension transfer T increases, the labor supply of young agents $l_{y,j}$ declines. This is inconsistent with our empirical finding that NRPS leads to an increase in the labor supply of young agents.

Implementing Collective Decision Allocation with Transfers Now, consider the optimal collective labor supply without transfer:

$$l^c_{y,j} = \frac{b+1+m\mathbf{1}_{[j=na]}}{2}, l^c_{o,j} = 0$$

In the Nash equilibrium, if we set

$$\frac{T}{w_o h_o} = \frac{1+b-m\mathbf{1}_{[j=na]}}{2b}$$

Then,

$$l_{o.j} = \frac{2}{3}\left(\frac{1+b-m\mathbf{1}_{[j=na]}}{2b} - \frac{T}{w_o h_o}\right) = 0$$

and

$$l_{y,j} = \frac{1}{3}\left(b+1+2m\mathbf{1}_{[j=na]} + \frac{Tb}{w_o h_o}\right) = l^c_{y,j}$$

That is, the government can choose a tranfer level so that the labor supply of the non-cooperative equilibrium is the same as the optimal collective choice.