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The effects of foreign product demand-labor transfer nexus on human capital investment in China

Hui Hu [1,2]✉, Yuqi Zhu [2], Chien-Chiang Lee [3,4]✉ & Alastair M. Morrison [5]

Using about 73,000 individuals' data in China, this research, for the first time, analyzes the impact of labor transfer (LT) caused by foreign product demand (FPD) on human capital investment. Two-stage least squares estimation with the instrumental variable is applied and produced three findings. First, the FPD-LT model illustrates that with FPD increasing, more labor transfers from the agricultural sector to the non-agricultural sector. Second, working in the non-agricultural sector requires higher-level skills than in the agricultural sector. LT from agricultural sector to non-agricultural sector motivates people to invest more in human capital and promotes gender equality in human capital investment. Third, labor transferring from the agricultural sector to the non-agricultural sector enhances individuals' income, leading to the increase of children's human capital investments. The better-educated people make greater investment in their children's human capital, exacerbating intergenerational inequality.

[1] Economic Development Research Centre, Wuhan University, Wuhan, China. [2] School of Economics and Management, Wuhan University, Wuhan, China. [3] Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon. [4] School of Economics and Management, Nanchang University, Nanchang, China. [5] School of Management and Marketing, Greenwich Business School, University of Greenwich, Old Royal Naval College, Park Row, London, UK. ✉email: hui.hu@whu.edu.cn; cclee6101@gmail.com

Introduction

Over the past 20 years, a large amount of labor has transferred from the agricultural sector to the non-agricultural sector in China (Abbasi et al. 2023). According to data from the National Bureau of Statistics (2022), the proportion of employment in the agricultural sector to total employment has decreased from 50% in 2001 to 22.3% in 2021. The labor transfer (LT) from the agricultural sector to the non-agricultural sector increases human capital investment, despite the cost of human capital investment (Gershoni and Low 2021). The increase in human capital investment reflects in two aspects. First, the non-agricultural sector needs more highly-skilled labor than the agricultural sector. Idle labor in the agricultural sector is not equipped with the skills required in the non-agricultural sector (Wang and Lee 2023; Lu and Ng 2013), which promotes human capital investment (Moeis et al. 2020; Emerick 2018). Second, the income in the non-agricultural sector is higher than the agricultural sector. The increase of income enhances parents' payment abilities for children's human capital investment (Ziva 2017; Greenland and Lopresti 2016).

Foreign product demand (FPD) is the main driver of LT from the agricultural sector to the non-agricultural sector. FPD reflects domestic comparative advantage (Guo et al. 2023; Lectard and Rougier 2018; Liu et al. 2021; Luo and Zhi 2019). China's FPD is mainly non-agricultural products (Cui and Liu 2018). With FPD increasing, the non-agricultural sector needs more labor (Wu and Ding 2021; Pierce 2016), which leads LT from the agricultural sector to the non-agricultural sector. According to the data from the National Bureau of Statistics (2022), from 2001 to 2022, FPD has increased 8 times and about 53% employees in agricultural sector transfer to non-agricultural sector.

LT from the agricultural sector to the non-agricultural sector would influence workers' human capital investment (Li 2015; Raghutla 2020; Shastry 2012; Oster and Steinberg 2013; Darku and Yeboah 2018). First, labor working in non-agricultural sector is required higher skills than agricultural sector, which motivates workers in human capital investment (Li 2018; Anjali et al. 2020; Autor et al. 2013). Second, workers in non-agricultural sector have higher wage than agricultural sector, which enhances workers' payment ability for human capital investment (Ziva 2017). FPD does not directly influence workers' human capital investment but it influences workers' human capital investment via LT. Hence, FPD is an appropriate instrumental variable to research the impact of LT on human capital investment.

Previous researchers have studied the effects of income changes and skill premiums caused by FPD on human capital investment (Li 2015; Raghutla 2020; Shastry 2012; Darku and Yeboah 2018). First, the increase of income raises the opportunity cost of human capital investment (Li et al. 2019; Atkin 2016). Ma et al. (2019) have suggested that FPD grows the incomes of labor-intensive industries in China. The augmentation of opportunity costs hinders people's investment in human capital. Second, skill premiums effect human capital by influencing the benefits and costs of human capital investment (Blanchard and Olney 2017; Rong et al. 2020; Malik 2019; Dix-Carneiro and Kovak 2015; Hu et al. 2023; Bianchi et al. 2022).

However, the literature provides little evidence on the LT effects caused by FPD on human capital investment (Wang 2021; Xi et al. 2018; Hickman and Olney 2011). Decisions on human capital investment are subject to investment costs and benefits (Falvey et al. 2010; Attanasio and Kaufmann 2017). The impact of FPD on LT can be a significant factor influencing the costs and benefits of human capital investment (Alan and John 2017). Income differences also result in the inequality of human capital investment (Lu and Gao 2011). Gender and intergenerational differences and their effects on human capital investment is worthy of analysis in the process of LT (Shittu and Abdullah 2019).

To reveal the influence of LT on human capital investment from the perspective of FPD, an empirical analysis is conducted using the FPD-LT model and cost-benefit analysis. This research draws upon micro- and macro-data covering 31 provinces and municipalities in China from 2001–2021. A unique dataset is analyzed comprising genders, incomes, education year, and educational backgrounds of about 73,000 individuals. These individuals are uniformly distributed across China's 31 provinces and municipalities, addressing the potential bias caused by regional differences. Data from China Household Income Project Survey (CHIPS) 2002, 2007, 2008 and China Household Finance Project Survey (CFPS) 2010, 2012, 2013, 2014, 2016, 2018, 2020 provided adult and children human capital investment. Many studies have use CFPS and CHIPS data to explore China's issues (Li et al. 2022; Gustafsson et al. 2014). For example, Zhao et al. (2023) have employed CFPS 2016 and 2018 to analyze the economic impact of non-communicable chronic diseases.

There are three main findings. First, increases in FPD result in labor transferring from agricultural sector to non-agricultural sector. Second, the LT from the agricultural sector to the non-agricultural sector promotes human capital investment. Since the increase in the female educational years is greater than for males, LT promotes gender equality in human capital investment in China. Third, LT enhances people's incomes. Due to higher incomes, individuals with higher education levels are more willing to invest in their children's human capital than others, exacerbating the intergenerational inequality in human capital investment.

First, this study contributes to the theoretical advancement of the human capital investment literature by adding the research perspective of LT caused by changes in FPD. The increase of FPD not only increases the demand for labor, more importantly, it promotes idle labor in agricultural sector to transfer to non-agricultural sector. LT influences the benefits and costs of human capital investment, which is worthy be studied. Also, this research focuses on gender and intergenerational transmission of human capital investment. The findings will be of assistance to practitioners and policymakers in promoting human capital accumulation and gender and generation equality in human capital investment.

Second, we construct FPD-LT Model to analyze the impact of the increase of FPD on LT. FPD not influences the demand of labor but also is the important factor that influencing LT. Then, we construct the benefits function and costs function of human capital investment to deduce how LT to influence individuals' human capital investment. Besides the theoretical analysis, we use 73,000 samples from CHIPS 2002, 2007, 2008 and CFPS 2010, 2012, 2014, 2016, 2018 and 2020 to empirically check the hypotheses concluded from theoretical analysis. Theoretical analysis and large sample make our conclusions are robust.

This article is organized as follows. The "Literature review" section reviews the exiting literature. The "Decisions on human capital investment" section presents the theoretical model. The "Data and empirical methods" section introduces the data and empirical methods, followed by the empirical results and robustness check in the "Results and discussions" section. The "Conclusions" section concludes and provides policy implications.

Literature review

Human capital is a driving force for the economic growth and has a profound impact on the individual's income (Lee et al. 2023; Wei and Sun 2023). The accumulation of human capital can upgrade technologies and industrial structure (Wang and Yang

2020; Long et al. 2020). Darku and Yoboah (2018) have concluded that trade openness has a positive effect on the growth of real GDP per capita due to the creation of an adequate stock of human capital. Hence, factors that influence human capital investment have received large attention in previous literature. Many studies have researched human capital investment from the perspective of trade openness.

First, some scholars have thought that trade openness would influence the demand of labor to influence individuals' human capital investment. The change of demand for labor with different skills can be regarded as skill premium effect (Yahya and Lee 2023; Dix-Carneiro and Kovak 2015). The change of skill premium motivates or restrains workers to invest in human capital (Li 2018; Anjali et al. 2020). When the demand for low-skilled workers increases, the skill premium between high-skilled workers and low-skilled workers narrows, hindering individuals' human capital investment. If the expansion of labor demand creates high-skilled jobs, the skill premium becomes large and people would increase their human capital investment to meet the demand of labor market and obtain a high wage.

Irum and Kausar (2016) have found that openness increases the demand of high-skilled workers and can promote the accumulation of human capital. Autor et al. (2013) have found that skill premium in American labor market rises on account of the increase in trade volume with China. It also increases high school attendance rate among American people. Atkin (2016) has found that Mexico's labor market needs more low-skilled workers after reforming and increasing its volume of exports. The increase in demand for low-skilled workers narrows skill premium, leading to higher school dropout rate among children aged over 16. In the long term, this study also argues that Mexico may be unable to accumulate its human capital. Li (2015) has found that workers reduced investment in human capital by dividing Chinese workers into urban group and rural group. That is because its trade becomes more open needs more low-skilled labor.

Second, some scholars have held the view that trade openness would influence individuals' human capital investment via income, which can be considered as expected return of human capital investment (Blanchard and Olney 2017; Rong et al. 2020; Malik 2019). Individual's human capital investment based on income effect is an ongoing debate. On the one hand, an increase in income means an increase in individual's payment ability, and thus stimulates more individuals to pursue higher education (Ziva 2017). Family income influences workers' investment decisions via intra-household resource allocation. Income is different from family to family, and credit facilities are difficult to meet people's expenditures. As a consequence, only some workers in families who have extra money after satisfying basic living needs will invest in human capital (Greenland and Lopresti 2016). On the other hand, the increase in income raises the opportunity cost of human capital investment (Li et al. 2019; Hu et al. 2023), which may hinder human capital investment.

Ma et al. (2019) have constructed theoretical framework to analyze the influence of employment on human capital. By the empirical analysis using provincial data in China during 1995–2015. They have suggested that trade openness increases the employment opportunity and income of labor-intensive industries, which is not beneficial to human capital investment. Shastry (2012) has indicated that people working in high-technology export industries tend to increase their human capital investment because trade openness increases the income of high-skilled workers (Shastry 2012; Jensen 2012; Oster and Steinberg 2013; Hu et al. 2018). It means that the expected return of human capital investment increases.

Third, some scholars have focused the effect of competition brought by trade openness on human capital investment. Pierce (2016) has pointed out that the trade between America and China could promote workers investing in human capital. It spurs American enterprises to improve themselves via competing with Chinese enterprises. Hence, these American enterprises need more high-skilled workers. Because American labor-intensive industries are at disadvantage compared with China while its skill-intensive industries are at advantage. Then American workers will be motivated to concentrate on investing in education, which will accumulate of human capital in America. Dix-Carneiro and Kovak (2015) and Hickman and Olney (2011) have found that American workers increase investment in human capital by an empirical study of panel data. For they want to enhance their own competitiveness, while America is constantly deepening the openness of its foreign trade.

The exiting literature has studied the skill-premium effect, income effect and competitiveness effect of trade openness and found that they have different effect on individuals' human capital investment. The literature provides little insights into the effect of LT on individuals' human capital investment. Different from literature, this study focuses on FPD rather than trade openness. The increase of FPD not only changes the demand for labor with different skills, but also it would attract labor to transfer from agricultural sector to non-agricultural sector.

After the Reform and Opening-up, China's FPD expanded rapidly, which increase the demand for labor. The large amount of idle labor in agricultural sector starts to transfer to non-agricultural sector. First, labor working in non-agricultural sector is required to have higher skill than in agricultural sector, which motivates individuals to invest in human capital. Second, working in non-agricultural sector makes individuals' have higher income, which would increase their payment ability for children's human capital investment. Furthermore, comparing with agricultural sector, working in non-agricultural sector enhances the social status of women, which would promote gender equality in human capital investment. Due to the difference in income, the intergenerational inequality of human capital investment is worthy being research. Hence, in this study, we research human capital investment from the perspective of LT brought by the increase of FPD.

Decisions on human capital investment

This research analyzes the relationship of labor transfer and people's human capital investment from the perspective of FPD. First, the FPD-LT Model is applied to explain the relationship of FPD and LT by using export/GDP to measure FPD (Fang et al. 2020; Gupta and Dutta 2019; Harris and Todaro 1970). Second, the decisions on human capital investment are investigated based on cost-benefit analysis (Orazio and Katja 2017; Falvey et al. 2010).

It is assumed that there are two sectors in the economy, the agricultural and the non-agricultural sector, indicated by A and NA, respectively. The labor force is the only input to production in both sectors, and the production functions are as follows:

$$Q_A = L_A^{\alpha_A}\left(0 \le \alpha_A \le 1\right) \tag{1}$$

$$Q_{NA} = L_{NA}^{\alpha_{NA}}\left(0 \le \alpha_{NA} \le 1\right) \tag{2}$$

$$L_A + L_{NA} = L \tag{3}$$

where Q_A and Q_{NA} are the outputs of the agricultural and the non-agricultural sectors, respectively. L_A and L_{NA} represent the labor force of the agricultural sector and the non-agricultural sector, respectively. It is assumed that there is no unemployed population. L is the total labor force. The parameters of α_A and α_{NA} represent the elasticity between labor and wage are bounded within 0 and 1.

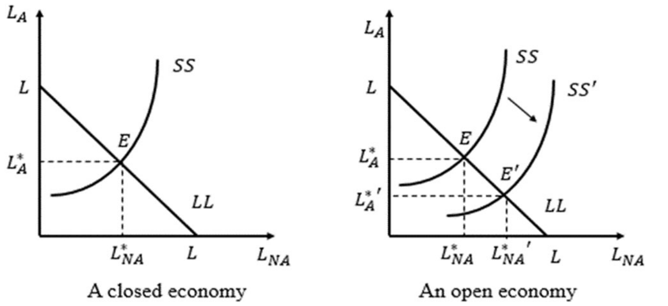

Fig. 1 The equilibrium in a closed and an open economy.

Supposing the price of the agricultural product P_A is 1, the nominal wage of the agricultural sector W_A is the following based on profit maximization. $\overline{W_A}$ is the real wage:

$$W_A = \alpha_A L_A^{\alpha_A - 1} \tag{4}$$

$$\overline{W_A} = W_A / P_A = \alpha_A L_A^{\alpha_A - 1} / P_A = \alpha_A L_A^{\alpha_A - 1} \tag{5}$$

Analogously, the nominal wage and real wage of the non-agricultural sector W_{NA}, $\overline{W_{NA}}$ are as follows:

$$W_{NA} = \alpha_{NA} L_{NA}^{\alpha_{NA} - 1} \tag{6}$$

$$\overline{W_{NA}} = W_{NA} / P_{NA} = \alpha_{NA} L_{NA}^{\alpha_{NA} - 1} / P_{NA} \tag{7}$$

In a closed economy, because the wages in the agricultural sector are lower than the wages in the non-agricultural sector, rational labor will transfer from the agricultural to the non-agricultural sector. Idle labor in the non-agricultural sector will find temporary employment or return to the agricultural sector. The equilibrium will not be achieved until the real wage in the non-agricultural sector equals that in the agricultural sector. The equilibrium condition is as follows:

$$\overline{W_{NA}} = \overline{W_A} \tag{8}$$

$$L_A = \alpha_A^{\frac{1}{1-\alpha_A}} \alpha_{NA}^{\frac{1}{\alpha_A - 1}} P_{NA}^{\frac{1}{1-\alpha_A}} L_{NA}^{\frac{\alpha_{NA}-1}{\alpha_A - 1}} \tag{9}$$

The left part of Fig. 1 shows the equilibrium. Line LL represents Eq. (3). Curve SS represents Eq. (9). Since the productivity in the non-agricultural sector is greater than the agricultural sector, line SS is steep. To achieve the same output as the non-agricultural sector, more labor force should be inputted into the agricultural sector.

In an open economy, comparative advantages influence the trade structure, which has an impact on comparative prices. China mainly exports non-agricultural products, so the comparative price of non-agricultural products rises. Curve SS goes down right to curve SS' and the new equilibrium is achieved. The right part of Fig. 2 shows the new equilibrium. The employed population in the non-agricultural sector increases and the employment population in the agricultural sector decreases. Also, the non-agricultural product is the main export product of China, and the proportion is more than 90% according to the export data in 2021. Meanwhile, labor can transfer between the agricultural and non-agricultural sectors freely with the necessary skills (Wang and Fu 2019; Fung et al. 2018).

Hypothesis 1 (H_1): An increase of FPD promotes labor transferring from the agricultural sector to the non-agricultural sector.

The second research question addresses the relationship of labor transfer and human capital investment. Decisions on human capital investment are co-determined by costs and benefits. When investing in human capital, people have to balance the incomes they can earn from entering the labor market in the current period (opportunity cost) with the return on investing in human capital in the future (return of investment). The costs of investing in human capital include direct and indirect costs. The direct costs are time, effort, and expenditures in human capital investment, and the indirect costs are jobs that are currently available in the labor market and wages that can be obtained. The benefits of investment are higher wages in the future because of human capital investment.

Compared with the agricultural sector, labor in the non-agricultural sector is required with higher-level skills. Individuals can obtain high wages (W_{NA}) in the non-agricultural sector. Working in the agricultural sector, individuals obtain low wages (W_A). When the cost of human capital investment exceeds the expected return, people choose to reduce their human capital investment and enter the sector requiring lower-level skills. Reducing human capital investment and earning the current wage can help increase household income in the short term but it undermines the long-term development of individuals. Based on the costs and benefits of human capital investment, this research structures benefit and cost functions. It is assumed that the net benefit of human capital investment is greater than 0:

$$R(t) = \int_{t+E}^{T} \left(\alpha W_{NA} - W_A\right) e^{-r(z-t)} dz \tag{10}$$

$$C(t) = \int_{t}^{t+E} \left(\beta W_{NA} + W_A\right) e^{-r(z-t)} dz \tag{11}$$

where the skill level of the highly-skilled labor is normalized to α. W_{NA} represents the wages of highly-skilled labor. The work of low-skilled labor is simple, repetitive, and not dependent on worker's skill level. W_A is the original wage (obtaining a wage even without human capital investment). Supposing the wage of highly-skilled labor is greater than the original wage. Increasing one unit of W_{NA}, individual should pay β. E is the education year.

The benefit of human capital investment $R(t)$ is the difference between total wage of highly-skilled labor (αW_{NA}) and total wage of low-skilled labor (W_A). The cost of human capital investment $C(t)$ is the low-skilled wage given up for human capital investment (W_A) and expenditure of human capital investment (βW_{NA}). The cumulative benefit and cost are discounted to initial value is for convenient comparison. When the benefit of human capital investment is greater than the cost of human capital investment, individuals will invest in human capital. When $R(t)$ is equal to $C(t)$, the quantity of human capital (α) can be obtained by:

$$\alpha = \frac{e^{-r(T-t-E)} - e^{rE}}{e^{-r(T-t-E)} - 1} \frac{W_A}{W_{NA}} + \frac{1 - e^{rE}}{e^{-r(T-t-E)} - 1} \beta \tag{12}$$

$\frac{W_A}{W_{NA}}$ and $\frac{L_A}{L_{NA}}$ are wage ratio and labor ratio between agricultural sector and non-agricultural sector. Recalling Eq. (4), the relationship between is $\frac{W_A}{W_{NA}}$ and $\frac{L_A}{L_{NA}}$ based on Eq. (4) and as follows:

$$\alpha = \frac{e^{-r(T-t-E)} - e^{rE}}{e^{-r(T-t-E)} - 1} \rho \left(\frac{L_A}{L_{NA}}\right)^{\rho - 1} + \frac{1 - e^{rE}}{e^{-r(T-t-E)} - 1} \beta \tag{13}$$

In Eq. (13), the parameter ρ with the same implication with parameter α_A and α_{NA} in Eqs. (4) and (6) is bounded within 0 and 1. The values of $\frac{e^{-r(T-t-E)} - e^{rE}}{e^{-r(T-t-E)} - 1}$ and ρ are more than zero. In China, the increase of FPD promotes labor to transfer from the agricultural sector to the non-agricultural sector. With $\frac{L_A}{L_{NA}}$ decreasing, the value of α rises. The increase of skill level of highly-skilled labor (α) means that individuals invest more in human capital investment. Hence, the decrease of $\frac{L_A}{L_{NA}}$ motivates individuals to invest in human capital.

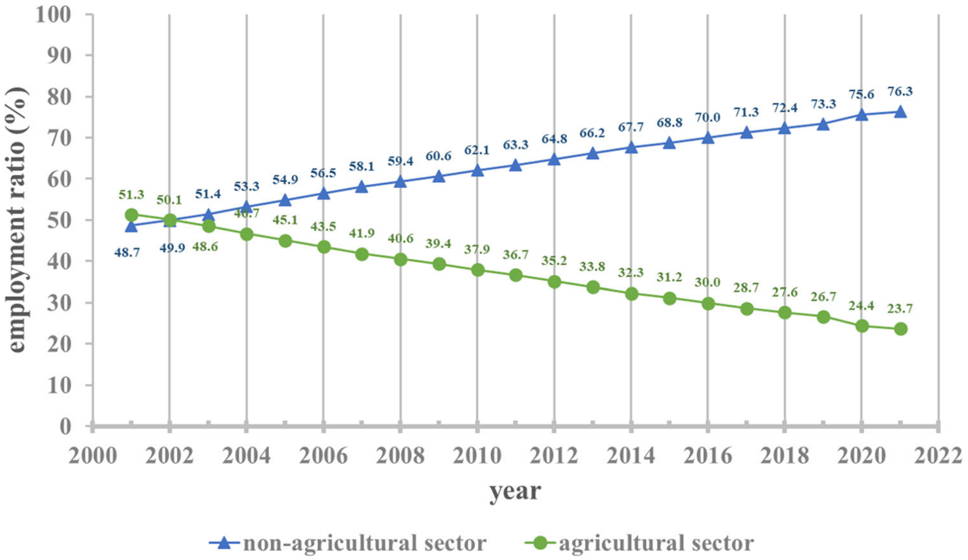

Fig. 2 Employed population rate in agricultural and non-agricultural sectors (2001–2021).

Hypothesis 2 (H_2): Labor transferring from the agricultural sector to the non-agricultural sector has a positive influence on individuals' human capital investment.

Based on the cost and benefit analysis, a model is constructed of individual's income and children's human capital investment. It assumes that individuals invest in their children's human capital (*CHCI*) as a proportion p of household income. The individual's income is $\alpha(W_{NA} - W_A) + W_A$. The individual with high skills can provide highly-skilled labor with skill level α and his/her income is $\alpha(W_{NA} - W_A) + W_A$. The individual without high skills ($\alpha = 0$) provide 0 highly-skilled labor and his/her income is W_A. $W_{NA} - W_A$ is the wage difference between highly-skilled and low-skilled labor:

$$\mathrm{CHCI}(t) = \int_t^{t+E} p\left[\alpha\left(W_{NA} - W_A\right) + W_A\right]e^{-r(z-t)}dz \tag{14}$$

$$\frac{d\mathrm{CHCI}(t)}{d[\alpha(W_{NA} - W_A) + W_A]} = \int_t^{t+E} pe^{-r(z-t)}dz = \frac{p}{r}\left(1 - e^{-rE}\right) > 0, \alpha \in [0, 1] \tag{15}$$

With wages increasing, the investment of child human capital rises, which is displayed in Eq. (15). Labor transferring from the agricultural sector to the non-agricultural sector leads to the increase in children's human capital investment due to the increase of income and hypothesis H3 is proposed:

Hypothesis 3 (H_3): Labor transferring from the agricultural sector to the non-agricultural sector promotes individuals to invest more in children's human capital due to increasing incomes.

This research also focuses on the gender equality of human capital investment and intergenerational transmission of human capital investment. The impacts of labor transfer on female and male human capital investment and children's human capital investment are tested for individuals with different educational levels.

Data and empirical methods

Empirical methods. The FPD is a key factor causing labor transfer; then labor transfer influences individuals' decisions on human capital investment. To estimate the impact of labor transfer on human capital investment, this research draws from the research method of Dong et al. (2019) and Eq. (13) to establish the regression model (1):

$$\mathrm{humancapital}_{ict} = \beta_0 + \beta_1 LT_{ct-1} + \lambda_c + \eta_t + \varepsilon_{ict} \tag{16}$$

The subscript i represents the individual, the subscript c represents the province, and the subscript t represents the year. $\mathrm{humancapital}_{ict}$ represents the human capital investment; LT_{ct-1} is the labor transfer of a province; η_t is the time fixed effects; λ_c is the province fixed effects; ε_{ict} represents the random error term.

According to the cost-benefit analysis, an individual's human capital investment dependents on the costs and benefits of that investment. The costs and benefits of human capital investment vary across different people. However, labor transfer can reflect the changes in costs and benefits of human capital investment in general. For example, working in the agricultural sector discourages people from investing in human capital because of human capital investment with costs without benefits. Working in the non-agricultural sector, the expected return on human capital investment increases, which motivates individuals to invest in human capital. Especially when people transfer to the non-agricultural sector, they attach more importance to their children's human capital investment. Hence, labor transfer influences the costs and benefits of human capital investment, which influence individuals' decisions on human capital investment.

However, there is a possibility that the increase of average educational level results in labor transfer. With educational level increasing, individuals would transfer from the agricultural sector to the non-agricultural sector. The model (16) is estimated by ordinary least square (OLS), followed by a two-stage least square (2SLS) estimation using the instrumental variable (IV) to address the endogenous problem raised by reverse causation. To address endogenous problems and maintain the consistency of control variables, more control variables are not added to the empirical model. The data used in this study is multiple period cross-sectional data. Compared with autocorrelation problems, we pay more attention to heteroscedasticity problem. First, we use Breusch–Pagan test to check whether there is heteroscedasticity problem. Second, we use weighted least square (WLS) to amend heteroscedasticity problem. Based on the basic regression, a heterogeneity analysis is done on the number of years of education in human capital investment. The heterogeneity analysis researches gender differences in human capital investment.

To control for missing variables and other potential endogenous problems that may exist in this model, one phase lag of FPD is selected as the instrumental variable for labor transfer. FPD is measured by the proportion of export volume in GDP. FPD has direct impacts on the demand for the labor force, but may not directly affect the supply of labor and the length of people's education. A change in FPD could lead to a change in labor demand. Specifically, changes in FPD influence the labor demands of secondary and tertiary industries. FPD is exogenous to the supply decisions of the labor force, so it does not influence the decisions on human capital investment. Specifically, the one-stage estimation of IV itself has important economic implications. It can represent the effect of a shift in FPD on labor transfer, which helps in understanding the interrelationship among FPD, labor transfer, and human capital investment.

On the basis of analyzing years of education, the investment in children's education is studied. To analyze the impact of labor transfer on education expenditure, the regression model (17) is created as follows:

$$\text{lneduexp}_{ict} = \alpha_2 + \beta_2 * LT_{ct-1} + \lambda_c + \eta_t + \varepsilon_{ict} \quad (17)$$

Labor transfer brings about increases in children's human capital investment mainly due to the increase of income. The regression model is established (18) to analyze the impact of labor transfer on people's income:

$$\text{income}_{ict} = \alpha_1 + \beta_1 * LT_{ct-1} + \lambda_c + \eta_t + \varepsilon_{ict} \quad (18)$$

Equations (17) and (18) are used to study the influence of labor transfer on children's human capital investment. In the equation, lneduexp_{ict} is children's education expenditure, representing children's human capital investment; income_{ict} represents income; LT_{ct-1} is the labor transfer of the province; η_t is the time fixed effects; λ_c is the province fixed effects; ε_{ict} represents the random error term. The one phase lag of FPD is used as the instrumental variable of labor transfer in Eq. (16).

People with different educational background have dissimilar tendencies toward their children's education expenditures. The heterogeneity of the individuals' educational levels is analyzed by the model (17), which investigates the differences in investment in children's education among people with diverse educational backgrounds.

Data and variables. The impact of FPD on labor transfer is examined after China's accession to the World Trade Organization by using macro data from 31 provinces and municipalities from 2001 to 2021. The labor force is the number of people aged from 16 to 59. Provincial panel data from 2001 to 2021, including 31 provinces and municipalities are used to check the robustness of conclusions. FPD is the proportion of exports to GDP in province c, reflecting the product demand from foreign countries. The logarithmic form is applied to the influence of the relative changes of FPD on labor transfer. To reflect the orientation of labor transfer, it is measured by the ratio of the difference between the increment of the employment population and the increment of the employment population in the agricultural sector to the total employment population. Being more than 0 means transfer from the agricultural sector to the non-agricultural sector and being less than 0 means transfer from the non-agricultural sector to agricultural sector. Also, it can be called the non-agricultural employed rate:

$$\text{FPD}_{ct} = \ln\left(\frac{\text{export}_{ct}}{\text{GDP}_{ct}}\right) \quad (19)$$

$$\text{LT}_{ct} = \frac{\left(\text{EP}_{ct} - \text{EP}_{ct-1}\right) - \left(\text{EP}_{Act} - \text{EP}_{Act-1}\right)}{\text{EP}_{ct}} \quad (20)$$

where EP_{ct} represents the total employment population of province c in t year. EP_{ct-1} represents the total employment population of province c in $t-1$ year. EP_{Act} represents the employment population of the agricultural sector of province c in t year. EP_{Act-1} represents the employment population of the agricultural sector of province c in $t-1$ year.

According to the analysis in the "Decisions on human capital investment" section, the cost of education can be divided into two categories. One is the direct cost of education. The other indirect cost of education is the income that people give up because they access education. Family members are divided into working people and children. For the employed people, length of education in years (edyr) is used as the variable to measure human capital investment. For children, the educational expenditures for them paid by parents is selected as the proxy variable, and it is formed by taking logarithms: (lneduexp). To mitigate the effects of outliers on parameter estimation, the Winsorization at both the upper and lower 1% is applied to all continuous variables. Table 1 reports the definitions and the statistical descriptions of each variable.

The macro data at the provincial level is from the National Bureau of Statistics of China. The data at the provinces and municipalities level is derived from the China Urban Statistics Yearbook 2002–2022. The data also included the annual statistical yearbooks and statistics bulletins (2002, 2007, 2008, 2010, 2012, 2014, 2016, 2018 and 2020) of 31 provinces and municipalities. Data on individuals, including income, education year, education expenditure, gender, education background, are from CHIPS 2002, 2007, 2008 and CFPS 2010, 2012, 2013, 2014, 2016, 2018, 2020. We use CFPs in 2002, 2007, 2008, 2010, 2012, 2014, 2016, 2018 and 2020. Due to the missing data of some key variables, after pretreatment, we obtain 72,915 observations finally.

Results and discussions

FPD and labor transfer. Figure 2 shows labor transfer in China from 2001 to 2021. FPD has grown at a rapid pace driven by the reform and opening-up policy, especially after joining the World Trade Organization in 2001. With the expansion of FPD, the employed population in the non-agricultural sector has expanded and the employed population in the agricultural sector has declined. In 2001, the employed population in the non-agricultural sector accounted for less than 50% of total employed population. However, in 2021 the employed population in the non-agricultural sector accounted for nearly 77%. By contrast, agriculture's share of total employed population fell from about 50 to 23%.

FPD has a profound impact on China's labor transfer to the non-agricultural sector. China mainly exports non-agricultural products, which creates many jobs in the non-agricultural sector. Some of the idle labor in the agricultural sector has transferred to the non-agricultural sector. In the meantime, advances in labor tools and production techniques increase the productivity in the agricultural sector and free up part of its labor force, prompting a shift of more labor to the non-agricultural sector. Furthermore, the wages in the non-agricultural sector are higher than that in the agricultural sector, which also attract a shift of the labor to the non-agricultural sector.

Figure 3 shows the relationship of FPD and the non-agricultural employment rate. The non-agricultural employment rate reflects labor transfer. As reported in Fig. 3, the non-agricultural employment rate is positively related to FPD. When the FPD increases, the non-agricultural employment rate increases, which means more labor transferred to the non-agricultural sector. To explain the positive relationship more specifically, Table 2 reports the empirical results. Robust standard error and control *year* and *province* fixed effect are used in the regression models for providing robust results.

Table 1 Definitions of variables and summary statistics.

Variable	Definition	Mean	Std. Dev.	Min	Max	Type
Panel A: macro data						
Labor transfer (non-agricultural employed rate)	The ratio of the difference between the increment of the employment population and the increment of the employment population in the agricultural sector to the total employment population	0.018	0.034	−0.146	0.168	Macro data
Foreign products demand (FPD)	The ratio of the export volume of a city to its GDP, reflecting the product demand from foreign countries. Logarithmic form	−2.305	1.201	−5.498	−0.113	Macro data
Employment rate	The proportion of employed population in the labor force	0.750	0.078	0.538	0.894	Macro data
Labor	The number of labor force (million)	4293.336	2073.7	162.3629	8759.36	Macro data
Total employed population	The number of employed population (million)	3320.747	1729.909	117.22	7039	Macro data
High school ratio	The proportion of population with high school degree in total population (%)	14.171	4.577	5.7	27.8	Macro data
College ratio	The proportion of population with college degree and above in total population (%)	11.601	7.375	2.7	56.1	Macro data
Average education year	The average length of each province's populations' education	8.715	0.906	6.12	12.56	Micro data
Panel B: micro data						
Education year	The length of people's education	8.386	4.889	0	23	Micro data
Sex	1 is male and 0 is female	0.492	0.499	0	1	Micro data
Edudy	Junior college degree or above is 1; other is 0	0.131	0.337	0	1	Micro data
Education expenditure	The total education expenses for children for one year	7.306	2.145	−0.511	14.376	Micro data
Income	Family income (yuan RMB)	28,669.2	38,771.82	0	17,800	Micro data
Observation	72,915					

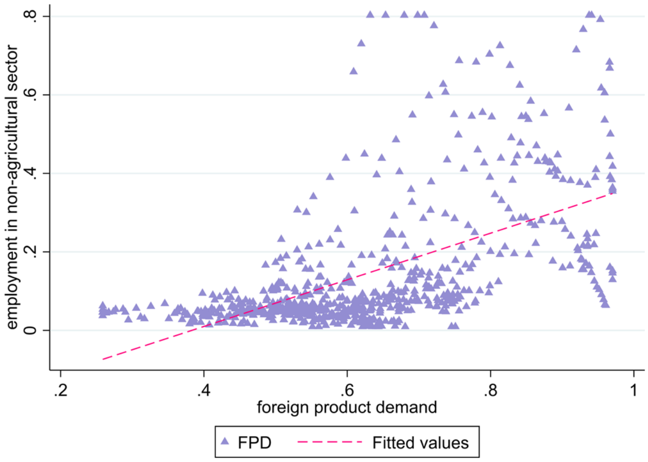

Fig. 3 Relationship of non-agricultural employment rate and FPD.

Table 2 Regression results of relationship between FPD and labor transfer.

	Labor transfer (1)	Edudy (Edudy = 1, junior college) (2)
FPD	0.007*** (0.001)	0.009*** (0.001)
Year	Y	Y
City	Y	Y
Constant	0.045*** (0.001)	0.259*** (0.000)
Observations	72,915	72,915
R-squared	0.461	0.320

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

Column (1) of Table 2 shows the OLS regression results of the influence of FPD on labor transfer, which is the estimated results for Eq. (16). The increase in FPD motivates labor transfer to the non-agricultural sector and supported the first hypothesis. For every 1% increase in FPD, labor transfer to non-agricultural sector increased by 0.7% with a significance level of 1%. The results indicates that FPD produces a demand for labor in the non-agricultural sector. The increase in FPD created jobs in the secondary and tertiary industries, so FPD is positively related to labor transfer from the agricultural sector to the non-agricultural sector, supporting H_1.

This research also estimates whether the employed population has junior college qualifications or higher. Column (2) of Table 2 shows the results, which are similar to the results in column (1). The increase in FPD enhances the proportion of the employed population with junior college qualifications or higher. For every 1% increase in FPD, probability of the employed population with junior college qualifications or higher increases 0.009 with a significance level of 1%. Hence, FPD expands the demand for highly-skilled labor, which provides a potential explanation for the relationship of labor transfer and years of education in Table 3.

Figure 4 shows the employed population in the non-agricultural sector in East, Middle and West of China from 2001 to 2021. The largest amount of non-agricultural employment is in the East and the least in the West. The East, with a high level of openness, is greatly impacted by FPD. On the contrary, the West, with a lower degree of openness, is less influenced by FPD compared with the East and Middle. In conclusion, the greater the impact of FPD is, the greater the employed population and new employment are in the non-agricultural sector.

Table 3 Regression results of relationship between labor transfer and length of education.

	Education year		
	OLS	**WLS**	**2SLS-IV**
Labor transfer	4.720*** (0.506)	2.271*** (0.712)	5.902* (3.293)
Year	Y	Y	Y
City	Y	Y	Y
Constant	11.155*** (0.033)	12.635*** (0.107)	2.372*** (0.057)
Observations	72,915	72,915	72,915
R-squared	0.192	0.201	0.122
Breusch–Pagan test	5425.34		
p vlaue	0.00		

Robust standard errors are in parenthesis.
* and *** indicates 10% and 1% level of significance, respectively.

Labor transfer, individuals' human capital investment and gender differences. Table 3 reports the regression results of the impacts of labor transfer on the years of education. Column (1) shows the OLS regression results. For every 1% increase in labor transfer to the non-agricultural sector, years of education increases by 4.720% with 1% significance level. According to the results of BP test, there is heteroscedasticity problem. We use WLS to amend heteroscedasticity problem, and the results are shown in Column (2). For every 1% increase in labor transfer to the non-agricultural sector, years of education increases by 2.271% with 1% significance level. Column (3) reports the 2SLS regression results. Labor transfer to the non-agricultural sector has a positive impact on years of education. Specifically, for every 1% increase in labor transfer to the non-agricultural sector, years of education year grows by 5.902% with a significance of 10%, supporting H_2. As concluded before, with higher FPD, more individuals chose to extend their length of education.

Gender inequality in education always is a controversial theme (Shittu and Abdullah 2019). To study differences in length of education between males and females, the sample is divided into males and females. Table 4 reports the results for the heterogeneity of educational years by gender. Labor transfer to the non-agricultural sector has positive impacts on the educational years for both males and females. For every 1% increase in the non-agricultural employment rate, the educational years for males increase by 3.890%. For every 1% increase in the non-agricultural employment rate, the length of education for females increases by 5.453%. The increase in the female educational years is greater than for males. Since the average years of education for men are longer than for women in China (Li and Cheng 2019), the increase in FPD appears to promote greater gender equality in human capital investment.

Labor transfer, income and children's human capital investment. The results reveal that FPD acts as a catalyst influencing the labor market and then influencing people's human capital investment. Furthermore, children's human capital investment is worthy of analysis. The relationships of labor transfer and children's human capital investment need to be analyzed. This section discusses the direct impact of labor transfer on human capital investment. The one phase lag of FPD is used as the instrumental variable of labor transfer, studying changes in children's human capital investment with FPD increasing.

Table 5 shows the impacts of labor transfer on expenditures for children's education. To provide robust results, the robust standard error is used and *year* and *province* are controlled. The higher incomes people have, the more they spend on their children's education. For every 1% increase in people's incomes,

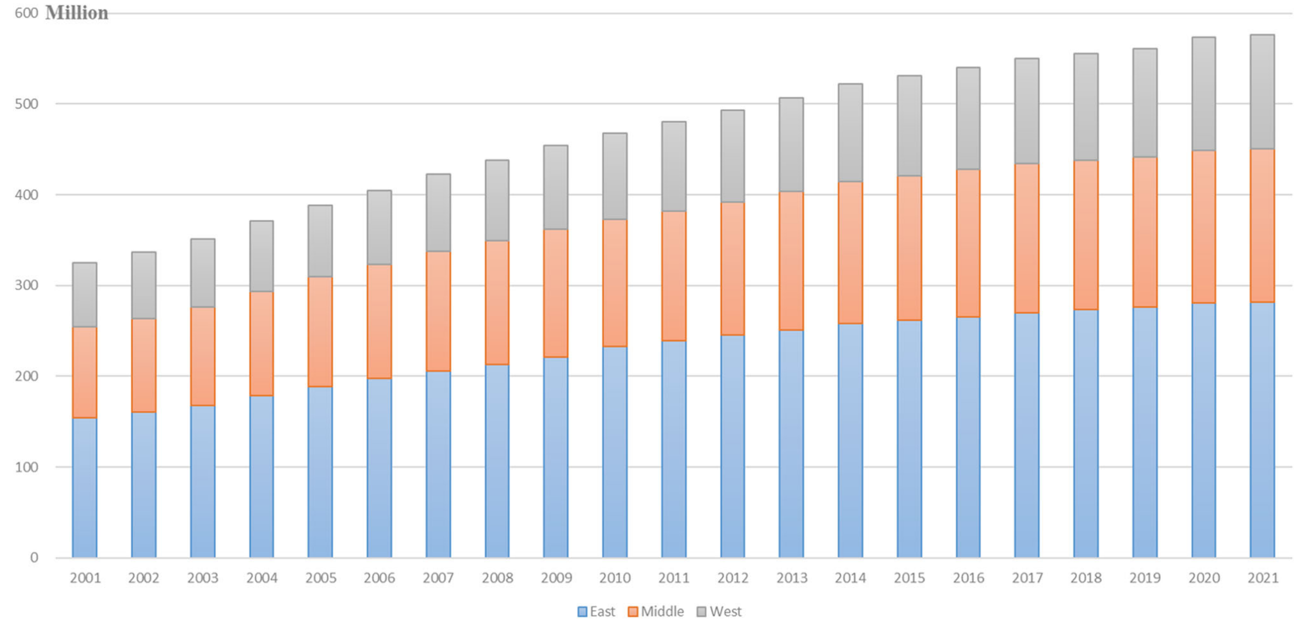

Fig. 4 Non-agricultural employed population in East, Middle and West of China.

Table 4 Analysis of heterogeneity: male and female.

	Education year	
	Male	Female
Labor transfer	3.890*** (0.664)	5.453*** (0.705)
Year	Y	Y
City	Y	Y
Constant	10.952*** (0.063)	11.360*** (0.069)
Observation	35,897	37,018
R-squared	0.147	0.240
Difference test	826.8	
p value	0.000	

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

Table 5 Regression results for the relationship between income and expenditure on children's education.

	Education expenditure		
	Overall	2002–2008	2010–2020
Labor transfer	5.313*** (0.190)	5.415*** (0.442)	6.980*** (0.207)
Year	Y	Y	Y
City	Y	Y	Y
Constant	7.096*** (0.026)	6.802*** (0.016)	9.083*** (0.019)
Observation	72,915	19,051	53,864
R-squared	0.382	0.410	0.117

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

the expenditure on children's education increased 5.313% with a significance level of 1%.

Based on the results of the step-wise regression, for every 1% increase in income, the expenditure on children's education increased 5.415% with a significance level of 1%, between 2002 and 2008. For every 1% increase in income, the expenditure on children's education increased 6.980% with a significance level of 1%, between 2010 and 2020. This implies that people could pay more for children's education over time, denoting that they are increasingly attaching more importance to children's human capital investment.

Table 6 reports the relationship of individuals' educational levels on children's educational expenditures. To analyze the impacts of parents' educational levels on children's education expenditures, the sample is divided into highly-educated (people with junior college qualifications and higher) and lower-educated (less than junior college qualifications). The result is that whether people are highly-educated or lower-educated, labor transfer enhances expenditures on children's education, which is consistent with the conclusion reported in Table 5. For every 1% increase in labor transfer, the children's educational expenditures of highly-educated people increase by 5.698% with a significance level of 1%. For every 1% increase in labor transfer, the children's educational expenditures by lower-educated people increase by 3.310% with a significance level of 1%. Highly-educated people attach greater significance to children's human capital investment than the lower-educated parents. Children whose parents have higher qualifications are more likely to receive more education than other children, which could further widen the gaps between different families. Guo and Qu (2022) have studied the competition of human capital investment. They hold the view that money, time, and parenting styles are the important factors influencing children's human capital investment.

Income is the main factor influencing children's human capital investment by individuals. Table 7 shows the relationship of labor transfer and income by OLS, WLS and 2SLS-IV. The instrumental variable (one phase lag of FPD) of labor transfer not only alleviates the endogenous problem, but also explains the relationship of FPD, labor transfer and income.

According to the OLS regression results, the impact of labor transfer to the non-agricultural sector on income is positive. Meng et al. (2023) have found workers from agricultural sector to non-agricultural sector may increases their wages mainly by improving their ability to search for information and negotiate wages. In order to solve heteroscedasticity problem, we use WLS to estimate, which supports the OLS results. According to the 2SLS-IV regression results, the result of the second stage supports

Table 6 Heterogeneity analysis: education level.

	Education expenditure	
	Junior college and above	Under junior college
Labor transfer	5.698*** (0.197)	3.310*** (0.020)
Year	Y	Y
City	Y	Y
Constant	7.013*** (0.027)	7.441*** (0.070)
Observation	9517	63,398
R-squared	0.365	0.449
Difference test	14.8	
p value	0.000	

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

Table 7 Regression results of relationship between labor transfer and incomes.

	Income		
	OLS	WLS	2SLS-IV
Labor transfer	5.814*** (0.389)	6.729*** (0.410)	21.264*** (5.901)
Year	Y	Y	Y
city	Y	Y	Y
Constant	10.150*** (0.050)	10.150*** (0.055)	9.496*** (0.253)
Observation	72,915	72,915	72,915
R-squared	0.311	0.313	0.297
Breusch–Pagan test	15,905.62		
p vlaue	0.000		

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

the results of OLS. The increase in labor transfer from the agricultural sector to the non-agricultural sector enhances income. For every 1% increase in labor transfer to the non-agricultural sector, income increases 21.264% with a significance level of 1%. FPD led to the transfer of labor from the primary to the secondary and tertiary industries, raising incomes. According results in Tables 5 and 6, H_3 was supported.

Robustness check. To check the robustness of the results, a robustness check is conducted by using provincial panel data from 2001 to 2021. The sample includes 31 provinces and municipalities in China. First, the relationship of FPD and labor transfer is analyzed, and then estimates of the impact of labor transfer on human capital investment are made. Primary and junior high school belong to compulsory education, which means that being educated in these stages is compulsory and the cost is low. Hence, this research uses the proportion of people with high school qualifications and junior college and higher qualifications in the total population to measure human capital investment. Also, we use the average educational year to measure human capital investment. If the proportion is larger and average educational year is longer, individuals pay more attention to human capital investment.

Tables 8 and 9 show the relationships of FPD, labor transfer, and human capital investment at the provincial level. Table 8 reports the OLS regression results of the influence of FPD on labor transfer at the provincial level. To provide robust results, the robust standard error is used and *year* and *province* were controlled. Column (1) shows the impacts of FPD on the overall employment rate. FPD has positive impacts on the overall employment rate, which increases by 0.025% for every 1% increase in FPD with a significance of level 1%. Column (2) shows

Table 8 Regression results for the relationship between FPD and labor transfer.

	Labor transfer	
	Employment rate	Non-agricultural employment rate
	(1)	(2)
FPD	0.025*** (0.008)	0.032*** (0.009)
Year	Y	Y
Province	Y	Y
Constant	4.257*** (0.038)	4.204*** (0.048)
Observations	651	651
R-squared	0.818	0.916

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

Table 9 Regression results of relationship between labor transfer and average educational levels.

	Average educational level		
	High school	Junior college	education year
A: Employment rate			
Labor transfer	−1.056*** (0.138)	−1.645*** (0.237)	−0.064*** (0.020)
Year	Y	Y	Y
Province	Y	Y	Y
Constant	7.402*** (0.572)	9.575*** (0.982)	2.503*** (0.082)
Observation	651	651	651
R-squared	0.865	0.915	0.955
B: Non-agricultural employment rate			
Labor transfer	0.958*** (0.091)	0.684*** (0.158)	0.097*** (0.017)
Year	Y	Y	Y
Province	Y	Y	Y
Constant	−1.111*** (0.406)	−0.188*** (0.694)	1.819*** (0.073)
R-squared	0.869	0.897	0.958
Observation	651	651	651

Robust standard errors are in parenthesis.
*** indicates 1% level of significance.

the influence of FPD on the non-agriculture employment rate. Increasing FPD promotes the non-agriculture employment rate, which increases by 0.032% for every 1% increase in FPD with a significance level of 1%. The results indicate that FPD creates jobs, especially non-agriculture ones. FPD expands the demand for non-agricultural products, which motivates more labor transfer from the agricultural sector to non-agricultural sector.

Table 9 reports the OLS regression results for the influence of labor transfer on the average educational level. Part A is the regression results of the impacts of employment rate on the average educational level. Part B is the regression results of the impacts of the non-agricultural employment rate on the average educational level. To provide robust results, the robust standard error is used and *year* and *province* are controlled. The employment rate has negative impacts on average educational levels. For every 1% increase in the employment rate, the employed population with high school qualifications falls by 1.056% with a significance level of 1%. For every 1% increase in the employment rate, the employed population with junior college qualifications is down 1.645% with a significance level of 1%. When employment rate increases by 1%, the average educational year decreases by 0.064%. The results shows that with employment rates rising, less individuals chose to study more.

The non-agricultural employment rate has positive impacts on the average educational level. For every 1% increase in the ratio of the non-agricultural employment population to the overall employment population, the employed population with high school qualifications increases by 0.958% with a significance level of 1%. For every 1% increase in the non-agricultural employment rate, the employed population with junior college qualifications and higher increases by 0.684% with a significance level of 1%. When non-agricultural employment rate increases by 1%, the average educational year increases by 0.097%. The results indicates that increasingly individuals continued their education after the compulsory education. In summary, labor transfer from the agricultural sector to the non-agricultural sector has positive impacts on enhancing the average educational level.

People's decisions on human capital investment are related to investment costs and income. Increases in jobs make more individuals abandon investment in human capital due to added opportunity costs (Ziva 2017; Li et al. 2019). This is the likely reason for the increase of the employment rate having a negative impact on educational levels. However, the increase of the non-agricultural employment rate is positively related to educational levels. Workers are required a longer education than the agricultural sector if they want work in non-agricultural sector. Hence, the results suggests that an increase in employment rate has no positive impact on educational levels. Relative to the agricultural employment rate, only the increase of the non-agricultural employment rate (more labor transfer to the non-agricultural sector) promotes the improvement in educational levels.

Conclusions

This research investigates the link between LT and human capital investment from the perspective of FPD. Increases of FPD could make labor transfer from agricultural sector to the non-agricultural sector, which has far-reaching impacts on the decisions about human capital investment. The relationship of FPD and labor transfer is analyzed via the FPD-LT model and individuals' and children's human capital investment are investigated. The empirical analysis checks the relationship of FPD and labor transfer by using the data from 31 provinces and municipalities in China. Based on CHIPS and CFPS data, about 73,000 observations, the direct and indirect impacts of labor transfer on human capital investment are examined.

This research has four major findings. First, FPD has positive impacts on LT from the agricultural sector to the non-agricultural sector. In a region, the greater the impact of FPD is, the greater is the volume of employed population and new employment in the non-agricultural sector. Second, LT from agricultural sector to non-agricultural sector has a positive impact on years of education. As LT from agricultural sector to the non-agricultural sector rises, the increases in female educational years are greater than for males. Thus, the increase in FPD promotes gender equality in education. Third, in terms of children's human capital investment, the results show that LT enhances individuals' income and then results in the increase of children's educational expenditures. Those with junior college qualifications and higher spent more for their children's education than people with lesser education. This indicates that differences in people's educational levels will be widened by their children, which may exacerbate inequality for future generations.

Based on these findings, we have some recommendations. First, comparative advantages should be enhanced to increase FPD, especially the technology-intensity FPD. The increase of FPD, especially the technology-intensive FPD would need more labor with high-skills. Hence, many labor from agricultural sector would invest in human capital to meet skill requirement in non-agricultural sector. Second, governments should improve medical care, children's education and other social welfare for workers from agricultural sector. Third, governments should pay attention to individual's and children's human capital investment in agricultural sector.

However, this study has some limitations. First, this paper just focuses on the total volume of FPD and does not pay attention to the kinds of FPD. If the FPD is technology-intensive, the labor market would need more high-skilled workers. Second, we study individuals' human capital investment from the perspective of LT from agricultural sector to non-agricultural sector. In non-agricultural sector, there are some sub-sectors, which have various requirements on labor's skill. LT from agricultural sector to sub-sectors, requiring relatively low skills in non-agricultural sector, even doesn't promote individuals' human capital investment.

In the future study, we would explore the effect of LT from agricultural sector to sub-sectors in non-agricultural sector and within non-agricultural sector on individuals' human capital investment. Especially, it is worth noting that with the applications of artificial intelligence in various sectors (Ahmad et al. 2023), how human capital investment and gender inequality in human capital investment change.

Data availability

Data used during the study are available from the corresponding author by request.

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Additional information
Correspondence and requests for materials should be addressed to Hui Hu or Chien-Chiang Lee.