A Nonparametric Quantile Analysis of Intergenerational Mobility in China*

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Abstract: Scientifically measuring intergenerational mobility (IGM) and comprehensively analyzing the effects of factors influencing IGM provide a theoretical basis to improve public policies. This paper measures the elasticity of IGM in China and investigates the interaction effects of macro and micro influencing factors using a nonparametric gradient boosting tree quantile regression model. The empirical results show that, first, the gradient boosting tree quantile regression model fits better than the linear quantile regression model, with particularly significant nonlinear characteristics among those with annual incomes between ¥30,000 and ¥150,000. The intergenerational income elasticity in China ranges from 0.1861 to 0.7026, indicating a clear "strong at both ends and weak in the middle" effect of parental income on offspring income. Second, intergenerational income mobility exhibits heterogeneity in both income and region, with significant differences in the income transmission process and degree of nonlinearity across different regions. Third, this paper specifically explores the IGM characteristics of the two income groups, revealing that the most significant influencing factors for achieving income stratification are economic growth, industrial optimization, intergenerational educational mobility, and wealth capital investment. Finally, this paper explores the poverty trap from the perspective of IGM, showing that in eastern regions, children from wealthy families may experience higher immobility or a wealth trap, while in other regions, children from impoverished families experience higher immobility or a poverty trap.

Keywords: Gradient boosting tree quantile regression; Heterogeneity analysis; Intergenerational income mobility; Partial dependence; Random forest.

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1 Introduction

Against the backdrop of China's increasingly open social structure, the issue of equal opportunity has become prominent. Intergenerational income mobility is not only closely related to people's sense of fairness, gain, and happiness, but also an important foundation for economic growth and social progress (Tang, 2006; Yang and Lian, 2015). Intergenerational income mobility refers to the change in income levels or relative positions in the overall income distribution between parents and children. It directly reflects whether children can break through the income constraints of their parents and achieve upward mobility, as well as the degree of transmission of income advantages or disadvantages between generations. It is an important indicator for measuring the fairness of social income distribution and equality of opportunity, and a key dimension in the process of common prosperity. A decline in intergenerational income mobility may cause a series of serious social problems. To address this issue, the Chinese Central Government recently pointed out that it is necessary to improve the institutional mechanisms for promoting equal opportunity and unblock social mobility channels, and also she reiterated the need to unblock social mobility channels and improve people's quality of life.

An important dimension of income inequality lies in intergenerational income distribution. More and more scholars are beginning to study how to improve intergenerational income mobility and achieve equal opportunity and income equity. The earlier result of intergenerational mobility (IGM) for US is very small, reflecting that mobility between different social classes is quite weak, and the problems of class solidification begin to attract attention (Atkinson et al., 1978; Solon, 1992; Zimmerman, 1992). The earlier result of IGM for China is also very small, and the gradual weakening of IGM is an important reason for the deterioration of income distribution (Fang and Ying, 2010; Wang, 2005; Xu, 2015; Zhou and Zhang, 2013). Some scholars have begun to construct more accurate indicators of intergenerational income mobility and explore its impact mechanism, such as the impact of public education, trade openness, resource endowment, digital economy, and social networks on IGM in China (Lang et al., 2026; Li, 2019; Liang and Li, 2019; Liu and Zhao, 2020; Lu et al., 2015).

In the literature, a common approach used to measure intergenerational income elasticity (IGE) is the log-linear model (Becker and Tomes, 1979), which can measure the intergenerational persistence of income. However, the calculation results of this method might not be robust and cannot accurately describe the mobility of the entire income distribution (Chetty et al., 2017). To overcome this problem, some scholars have used intergenerational income percentile ranking indicators to measure intergenerational income mobility (Yang and Wang, 2020). However, using percentile ranking cannot show information about the magnitude of intergenerational income changes and can also mask the absolute differences in income inequality at different locations in the income distribution (Chen et al., 2023). Recently, Maasoumi et al. (2025) propose a general construction of IGM measures that can incorporate any transparent economic preferences. They are interpreted as the marginal effect of parental normalized social welfare on children's normalized welfare. Conventional regressions are special cases with implicit economic preferences that fail inequality-aversion and the Pigou–Dalton principle of transfers. For more details, the reader is referred to the paper by Maasoumi et al. (2025) and references therein.

Existing literature on investigating the influencing factors of intergenerational mobility is fragmented, focusing on isolated aspects rather than the overall picture. Which influencing factors are significant, and which are insignificant? Without resolving these questions, it is impossible to propose more constructive public policy recommendations. Against this backdrop, a comprehensive understanding of the characteristics of IGM in China and the relationships between influencing factors provides a theoretical basis for proposing more scientific and targeted policy recommendations.

The main contributions of our paper can be synthesized into the following three dimensions. First, the research method of this paper, which is also the most important contribution, is that this paper first compares the fitting efficiency of the nonparametric model with that of linear quantile regression, and the results show that the former is better than the latter. This paper uses the nonparametric gradient boosting tree quantile regression (GBTQR) model to measure the nonlinear intergenerational income mobility elasticity, and introduces macro and micro influencing factors as interaction terms into the model to measure their impact on IGM. This nonlinear IGM elasticity measurement method cannot only comprehensively describe the mobility of the entire income distribution, but also comprehensively consider the interaction effects of other influencing factors. Furthermore, this paper uses nonlinear quantile percentile ranking and nonlinear random forest quantile regression (RFQR) to conduct robustness tests. Second, regarding the transmission mechanism of factors influencing intergenerational income mobility, this paper comprehensively considers both macroeconomic and microeconomic factors. Macroeconomic factors include economic growth, industrial optimization, and changes in social welfare, while microeconomic factors include human capital investment (education), social capital investment (social networks), and wealth capital investment. Empirical results are used to verify the intergenerational income transmission path in the basic theory, thus, refining and supplementing existing literature. Third, regarding the heterogeneity of IGM, this paper divides the population into middle-, high-, and low-income groups based on the income of the parents and children. It discusses whether all influencing factors have heterogeneous effects in different groups and analyzes the reasons for this heterogeneity in depth. Most importantly, this paper explores the IGM characteristics of two groups: those with low-income parents and middle- to high-income children, and those with high-income parents and middle- to low-income children. A special discussion on the poverty trap is also included, leading to more targeted policy recommendations for different groups.

The rest of the paper is organized as follows. Section 2 gives a brief literature review, and Section 3 introduces the econometric methodology, Section 4 provides the empirical results and robustness check, and Section 5 develops more analyses on heterogeneity issues and the discussion of the poverty trap in China. Finally, Section 6 concludes the paper.

2 Literature Review

Innovatively, Becker and Tomes (1979) propose the IGM model by using a linear regression framework, in which, offspring permanent income is set as the dependent variable, with parental income serving as the core independent variable. The regression coefficient is defined as the IGM elasticity. Subsequently, with the execution of micro-surveys and the expanding accessibility of micro-data, research on IGM in China has garnered escalating attention. Since 2010, studies on IGM elasticity in China have grown both in quantity and depth. Especially, some scholars have also employed linear regression to specifically quantify the linear IGM elasticity in the Chinese context.

Interestingly, Wang and Li (2012) use the China Health and Nutrition Survey (CHNS) database from 1989, 1991, 1993, and 1997 to measure the income shift from parent to child in four types of families: rural, urban, suburban, and peri-urban, which is one of the earliest studies on IGM by Chinese scholars. It considered the nonlinear characteristics of the data and examined the relationship between the Gini coefficient and IGM, indirectly verifying the validity of the Great Gatsby curve. However, its database at the time only covered 8 provinces in the China's Eastern, Central, and Western regions, failing to measure IGM elasticity specifically.The estimated results of IGM in China are closely related to the databases used and the estimation period. The result is 0.83 based on 8 waves of CHNS data from 1989 to 2009. Based the CHIP and CGSS database urban IGM for 1988, 1995, 2002, and 2006 are estimated as 0.447, 0.36, 0.207, and 0.045, respectively, while the corresponding rural results were 0.338, 0.258, 0.274, and 0.330. Based on four waves of CHNS database from 1989 to 2009, the results for 2000, 2004, 2006 and 2009 were 0.66, 0.49, 0.35, and 0.46, respectively. The results based on the CGSS and CLDS database ranging from 0.29 to 0.41.Using the CHIP and CHNS databases, the urban IGM for 2002, 2007 and 2012 are estimated as 0.4720, 0.708, and 0.3272 (Chen and Yuan, 2012; He and Huang, 2013; Wang and Li, 2012; Xu, 2015; Yang and Lian, 2015). Due to the different survey purposes and emphases of the above databases (for example, the questionnaire focus strength of the CHFS database lie in the financial dimensions of household assets and liabilities, while the CHIP database focuses on tracking changes in China's income distribution, labor market, and socio-economic status), there are significant differences in the designed questionnaires and collected data, leading to different covariates considered when measuring IGM. Furthermore, there is significant divergence in the judgment of the trend of IGM in China. Some scholars believe it is continuously declining, some believe it is rising, and some believe it follows a non-linear trend (Lü and Li, 2017; Yang and Wang, 2020).

In recent years, scholars have further explored the influencing factors on effects of IGM. Research on the influencing factors of intergenerational income mobility is divided into macro and micro aspects. On the macro level, domestic scholars unanimously believe that China's economic growth and industrial restructuring in recent years have greatly affected intergenerational income mobility. Micro factors include human capital investment (education), social capital investment (transfer payments, education, population migration, social networks), and wealth capital (entrepreneurship). For instance, Li et al. (2018) find that the promoting effect of economic development on intergenerational income mobility is mainly reflected in the middle-income group, while the IGM of low-income and high-income groups has not improved with economic development. Wang et al. (2019) use intergenerational order correlation to measure the IGM characteristics of different regions and different social classes. The study found that there are significant differences in IGM between different regions and different social classes, and factors such as public education expenditure are important factors affecting regional IGM. Zheng et al. (2020) find that industrial structure significantly affects IGM characteristics. Fan (2020) shows that government transfer payments can improve IGM characteristics. Numerous studies have empirically demonstrated that education, i.e., human capital investment, has the most significant and important impact on intergenerational income mobility (Blanden and Macmillan, 2016; Chen et al., 2021; Gu et al., 2022; Luo and Liu, 2018; Mayer and Lopoo, 2008; Wang and Yuan, 2015; Yang and Wang, 2020). Sun et al. (2012) find that population migration can increase employment opportunities, thus escaping the intergenerational low-income trap. Liu and Zhao (2020) use the percentile ranking correlation coefficient of income between parents and children to measure intergenerational income mobility, demonstrating from a social network perspective that social networks significantly promote intergenerational income mobility. Yin et al. (2024) measure intergenerational income mobility based on CHFS data combined with an income transfer matrix, concluding that family entrepreneurship improves income mobility and enhances its quality. Fan et al. (2021) use the the China Family Panel Studies (CFPS) database to measure IGM and its influencing factors in China. The results showed that intergenerational income elasticity increases from 0.390 for the 1970-1980 birth cohort to 0.442 for the 1981-1988 birth cohort. This increase is more evident among urban and coastal residents than rural and inland residents, and changes in intergenerational income persistence are correlated with market reforms, economic development, and policy changes.

Chetty et al. (2014) argue that linear intergenerational income elasticity estimation has two problems. First, the estimation sample cannot include observations with zero income, while children of low-income families may have zero income. If the data from low-income families is excluded and only data from middle- and high-income families are used, the estimated IGM elasticity will be higher than the actual value. Second, since the relationship between the income of offspring and parents in real data is non-linear, the use of linear methods makes the estimation results very sensitive to the distribution of income in the sample. Based on this, Dahl and DeLeire (2008) propose the intergenerational income percentile ranking correlation coefficient to measure IGM characteristics. This measure can include observations with zero income, but like intergenerational income elasticity, it cannot compare the IGM characteristics of different income groups. Finally, Eide and Showalter (1999) estimate intergenerational earnings mobility models using quantile regressions with the Panel Study of Income Dynamics (PSID) dataset for the US. which is the first attempt to use quantile regression to estimate IGM characteristics. They found that the intergenerational earnings correlation is greater at the bottom of the son's conditional earnings distribution than at the top, and that controlling for son's education reduces the intergenerational earnings correlation. Currently, no literature has used quantile regression to estimate the IGM elasticity in China.

3 Econometric Methodology

3.1 Linear Quantile Regression Model

Koenker and Bassett (1978) propose the linear quantile regression model, which describes the linear relationship between the dependent variable and all its explanatory variables at different quantiles. Compared with the least squares regression model, its main advantage is that it does not require setting stringent assumptions, thus, having stronger robustness. Particularly, it can automatically capture heterogeneity and heavy-tailed behaviors. Assuming a training set $\{x_i, y_i\}_{i=1}^n$, where y_i is the response variable, such as offspring income, $x_i \in R^p$ is the explanatory variable, including parental income. Given x_i, at $\tau(0 < \tau < 1)$ quantile, y_i the conditional quantile is denoted as $q_\tau(x_i) = F^{-1}(\tau \mid x_i)$, where $F_y(y \mid x_i)$ is the conditional distribution function of y_i given x_i. Then, β_τ is the coefficient vector in the linear quantile regression model $q_\tau(x_i) = \beta_\tau^\top x_i$ can be estimated by the following equation,

$$\hat{\beta}_\tau = \arg\min_{\beta_\tau} \sum_{i=1}^{n} \rho_\tau(y_i - \beta_\tau^{\mathrm{T}} x_i), \tag{1}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the loss function, the so-called check function in the quantile literature.

3.2 Nonlinear Quantile Regression Model

Different from the linear quantile model as in (1), traditional nonlinear quantile regression often employs some parametric approximation methods such as series expansion or B-splines. These methods use additive operations to process the response variable, meaning they cannot characterize the interaction effects of explanatory variables. Factors influencing IGM elasticity include both macroscopic and microscopic factors, and these factors interact with each other. Therefore, we introduce a nonlinear GBTQR model. With the rapid development and application of machine learning methods in recent years, Zheng (2012) and Yuan (2015) propose a GBTQR model. This model combines quantile regression with machine learning methods, fitting quantile regression to a loss function and iterating continuously to generate multiple quantile regression trees. Finally, the results of all quantile regression trees are summed to obtain the GBTQR model. In this paper, $q_\tau(x)$ is the nonlinear function between the offspring income and x (including the parent income) that we want to fit. The specific steps of the algorithm for generating a GBTQR model are as follows:

Step 1: Given a training set $\{x_i, y_i\}_{i=1}^n$, set the initial value $q_\tau^{[0]}(x_i)$ either to 0 or $y_{(\tau n)}$, the τ sample quantile, where $y_{(1)} \leq \cdots \leq y_{(n)}$ is the ordinal statistic of $\{y_i\}_{i=1}^n$.

Step 2: For m from 1 to M,

(a) calculate the negative gradient

$$U_i^{[m]} = -\left.\frac{\partial \rho_\tau(y_i - q)}{\partial q}\right|_{q=q_\tau^{[m-1]}(x_i)} = I\big((y_i - q_\tau^{[m-1]}(x_i)) \geq 0\big) - (1-\tau) \tag{2}$$

where $i = 1, \dots, n$.

(b) Fit $U_i^{[m]}$ as the response variable, and obtain the fitting result x_i with the negative gradient $q_{\tau,1}^{[m]}(x_i)$.

(c) Update $q_\tau^{[m]}(\cdot) = q_\tau^{[m-1]}(\cdot) + \eta_m q_{\tau,1}^{[m]}(\cdot)$, where η_m is the shrinkage parameter.

Step 3: Repeat Step 2 for a total of M times. $q_\tau^{[M]}(x_i)$, which is the final estimate of the GBTQR model, is denoted by $\hat{q}_\tau(x_i)$. To reduce the impact of randomness, we calculate the mean of 100 runs as the importance measurement value of $\hat{q}_\tau(x_i)$. Thus, (2) finally fits the nonlinear quantile function between the dependent variable and all explanatory variables.

3.3 Partial Dependence Plot

Another objective of this paper is to delve into the effects of parental income and macro- and micro-level factors on offspring income. Therefore, following Hastie et al. (2009) and Velthoen et al. (2023), we employ partial dependence values and partial dependence plots to reveal the effects of parental income on offspring income. We calculate the partial dependence values of parental income and offspring income, which are correlated with the linear regression β. This paper measures the IGM elasticity range at nonlinear quantile points, and then plots partial dependence relationships for all partial dependence values to more intuitively demonstrate the nonlinear characteristics of IGM, namely, the income of offspring and parents. Finally, it incorporates macro and micro variables affecting offspring income as interaction terms into the model to measure partial dependence values and test significance effects. The method for measuring the partial dependence relationship of the j-th variable $x_{i,j}$ (for example, parental income) in $x_i = (x_{i,1}, \dots, x_{i,j-1}, x_{i,j}, x_{i,j+1}, \dots, x_{i,p})$ is to eliminate $x_{i,j}$. The repeated values are sorted in ascending order and denoted as $\{x_j^{(L)}\}_{l=1}^{L}$, and substitute them into the following formula to calculate $x_j^{(l)}$ the partial dependency value under different values:

$$q_{\tau,j}(x_j^{(l)}) = \frac{1}{n} \sum_{i=1}^{n} \hat{q}_\tau(x_{i,1}, \dots, x_{i,j-1}, x_{i,j} = x_j^{(l)}, x_{i,j+1}, \dots, x_{i,p}).$$

Plotting $\{q_{\tau,j}(x_j^{(l)})\}_{l=1}^{L}$ against $\{x_j^{(l)}\}_{l=1}^{L}$ gives the partial dependence plot[1]. The reader is referred to the book by Hastie et al. (2009) and the paper by Velthoen et al. (2023) for details.

[1]It is worth noting that because the correlation between explanatory variables was not considered, the $q_{\tau,j}(x_j^{(l)})$ calculated in (1) is not used to estimate $E[\hat{q}_\tau(x_i)|x_{i,j} = x_j^{(l)}]$.

4 Empirical Analysis

4.1 Description of Data and Variables

This paper uses data from the China Household Income Project survey, termed as CHIP, which is a database regarded as the most comprehensive and rigorous publicly - available database regarding China's micro - level income at present. This survey questionnaire targets three groups of people: urban residents, rural residents, and migrants. The survey data mainly encompasses information on personal and household income, education, occupation, etc. This paper conducts research based on the two annually released CHIP survey datasets (for the years 2013 and 2018)[2]. Indeed, this CHIP dataset was used by Chen and Yuan (2012), Xu (2015), Luo and Liu (2018), and Chen et al. (2021), among others, to calculate the Chin's linear IGM.

Because the study focuses on IGM elasticity, it is necessary to pair offspring with parents based on the data. We used four methods to pair offspring with their parents: the head of household's father and the head of household; the head of household's father-in-law and the head of household's spouse; the male head of household and his children; and the female head of household's spouse and his children. Considering the impact of the life cycle, previous studies have found that children's income around age 30 is close to permanent income (Haider and Solon, 2006; He and Huang, 2013), and that the life cycle bias is smaller after the father's age exceeds 35 (Chetty et al., 2014; Mazumder, 2005; Yang and Zhang, 2015). Therefore, we selected samples where the children were 25-34 years old and not in school, and the parents were 40-65 years old and had not yet left the labor market. To ensure a similar age distribution across birth groups, i.e., to ensure a uniform distribution of data, we removed observations where the children were born after 1987 or before 1961. We also removed samples that violated this rule, considering that the father's age must be at least 15 years older than the children's age. Finally, we obtained 2271 valid paired observations.

Next, we present the detailed variable explanations.

(1) Explained Variable - Offspring Income

Based on the paired information, we obtained the offspring income data. To verify the robustness of the model, we used income percentile ranking for robustness testing. Following the ranking method of Chetty et al. (2014) , to avoid provincial heterogeneity, this paper ranked the income of parents and children in the same province and age group from low to high, that is, individuals with income greater than 0 were divided into 5 equal groups, and the ranking

[2] The questionnaires in the CHIP database for 2013 and 2018 are similar, resulting in consistent variables. However, the questionnaires prior to 2013 differ significantly. Therefore, this paper only uses the data from 2013 and 2018.

of the income of the parents and children among their peers (from 1 to 5) was obtained, where 1 indicates that the income level is in the lowest 20% of the income distribution among peers in the province, and 5 indicates that the income level is in the highest 20% of the income distribution among peers in the province. For individuals with income equal to 0, this study classified them into the lowest income level. Following the same method, this paper calculated the income level of the father and the income level of the mother, and took the maximum of the father's income level and the mother's income level as the parent's income level.

(2) Core Explanatory Variable

1. Parental Income. Based on the paired information, we obtain the parent income data. We also use the percentile ranking of parent income to test the robustness of the model.

According to the previous analysis, the factors affecting intergenerational income mobility include macroeconomic and microeconomic factors. Macroeconomic factors include economic growth, industrial optimization and social welfare changes, while microeconomic factors include population migration, education and marriage, social capital investment (social networks) and wealth capital investment. We will explain the above factors.

2. Economic Growth. We matched regional economic development with data based on the province where each sample is located; that is, we used the average GDP per capita of the region to measure the region's economic growth.

3. Industrial Optimization. Referring to Li et al. (2018), the proportion of regional tertiary industry GDP in overall GDP is used to measure regional industrial optimization.

4. Social Welfare Changes. Existing research shows that improved social welfare effectively narrows income inequality (Jin et al., 2020; Li et al., 2017; Yang et al., 2021), which may affect IGM characteristics. This paper includes social welfare changes in the influencing factors. The CHIP questionnaire asks whether the offspring have pension insurance, medical insurance, and social assistance. A value of 1 is assigned if yes, otherwise 0.

5. IGM through Education. We use the educational attainment of parents and children as variables of human capital investment. Restuccia and Urrutia (2004) analyse the impact of education (including early childhood education and university education) on IGM, and their research showed that about half of the income correlation between generations can be explained by parents' investment in their children's education. Following the approach of Restuccia and Urrutia (2004), this paper groups the educational attainment of parents and children (highlighting the difference between basic and higher education): 1 represents parents with a bachelor's degree or above, and children's educational attainment is not lower than or exceeds that of parents ($\geq$); 2 represents parents with a bachelor's degree or above, and children's educational attainment is lower than that of parents ($<$); 3 represents one parent with a bachelor's degree or above, the other not, and children with a bachelor's degree or above; 4 represents one parent with a bachelor's degree or above, the other not, and children with an educational attainment below a bachelor's degree; 5 represents both parents with an educational attainment below a bachelor's degree, and children with a bachelor's degree or above; 6 represents neither parent with a bachelor's degree, and both children with an educational attainment below a bachelor's degree.

6. Social Network. This paper uses "whether you received help from relatives and friends when looking for a job" to reflect the impact of social networks on intergenerational income mobility (Chen et al., 2009; Liu and Zhao, 2020; Peng and Yang, 2016).

7. Wealth Capital Investment. Based on CHIP data, this paper uses the amount of financial assets owned by parents as a variable for wealth capital investment.

8. Population Migration. Effective population migration is itself an important way for workers to improve their living standards and obtain equal opportunities. Especially for low-income groups, effective migration increases employment opportunities, access to better educational environments and a more equitable social environment, thereby improving IGM. Based on CHIP data, we use the consistency of the registered residence of the offspring and parents as a population migration variable.

(3) Control Variables

Control variables include: individual years of education, work status or industry type, household registration status, gender, whether they work in a public institution, and whether their parents are Party members. In addition, this paper also controls for age group dummy variables and province dummy variables. Data shows that in 2018, both parental and offspring incomes increased, and the regional per capita GDP also increased significantly, indicating a substantial and gradual improvement in economic growth and people's living standards. In 2018, the proportion of children with pension insurance, medical insurance, and social assistance was significantly higher than in 2013, indicating a substantial improvement in the social welfare system. The overall education level in 2018 was lower than in 2013. In 2013, the percentages for each group were 1.16%, 0.51%, 2.96%, 0.90%, 21.34%, and 73.14%, respectively, while in 2018, these percentages were 0.74%, 0.27%, 2.34%, 0.67%, 20.09%, and 75.89%. Groups 2 and 4 had the lowest percentages, indicating that the proportion of children with lower education levels than their parents (bachelor's degree or above) was very small. This also indirectly confirms that the higher the parents' education level, the greater their investment in and emphasis on education, leading to higher educational levels in their children. Group 6 (both parents had less than a bachelor's degree, and their children's education level was also below a bachelor's degree) had the highest percentage, indicating that the overall education level needs improvement, requiring attention not only to family education but also to public education. The proportion of people who received help from relatives and friends when looking for jobs in 2018 (33.96%) was significantly higher than in 2013 (25.32%). Factors influencing IGM mainly include genetic factors, human capital, wealth capital, and social capital. Social networks belong to social capital, and as people's awareness of IGM increases, the impact of social networks on IGM is also growing. The average parental wealth capital investment in 2013 was ¥128,000, higher than in 2013 (average ¥86,300). In recent years, with the improvement of people's financial literacy, more and more families are choosing wealth capital investment to promote family wealth accumulation. The proportion of offspring migrating their household registration in 2018 was higher than in 2013. Free migration can increase intergenerational income through increased employment opportunities. Under the premise of a more equitable social environment in the future, the impact of population migration on IGM will be more significant. Table 1 reports the main variables and their descriptive statistics; the values in parentheses are descriptive results for 2013 data.

Table 1. Main variables and their basic statistical summary

Variable Name	Specific Meaning	Sample Size	Mean	Standard Deviation
Parental Income	Annual income of parents in 2018 (2013) (in ten thousand yuan)	1493 (778)	5.34 (3.92)	6.767 (5.02)
Offspring Income	Annual income of offspring in 2018 (2013) (in ten thousand yuan)	1493 (778)	4.74 (3.17)	4.752 (3.55)
Economic Growth	Per capita gross domestic product of the region in 2018 (2013) (in ten thousand yuan)	1493 (778)	7.05 (4.97)	2.72 (1.99)
Industrial Optimization	Proportion of the GDP of the tertiary industry in the region in 2018 in the overall GDP in 2018 (2013)	1493 (778)	0.52 (0.45)	0.067 (0.10)
Changes in Social Welfare	Whether the offspring have endowment insurance in 2018 (2013)	1493 (778)	1.27 (0.75)	0.447 (0.43)
	Whether the offspring have medical insurance in 2018 (2013)	1493 (778)	1.03 (0.93)	0.173 (0.26)
	Did the offspring receive social assistance in 2018 (2013)	1493 (778)	1.98 (0.04)	0.103 (0.19)
IGM in education	IGM in education in 2018 (2013)	1493 (778)	5.67 (5.60)	0.75 (0.85)

Variable Name	Specific Meaning	Sample Size	Mean	Standard Deviation
Social Network	Did they receive help from relatives and friends when looking for a job in 2018 (2013)	1493 (778)	1.66 (0.26)	0.474 (0.44)
Wealth Capital Investment	Amount of financial assets owned by the parents in 2018 (2013) (ten thousand yuan)	1493 (778)	12.8 (8.63)	22.66 (15.99)
Population Migration	Are the registered residences of the offspring and parents the same in 2018 (2013)	1493 (778)	1.94(1.01)	0.223(0.11)

4.2 Testing Nonlinear Versus Linear Models

We use matched data from 2018 for baseline regression, with offspring income as the dependent variable and parent income as the independent variable. We fit the data using nonlinear quantile regression gradient boosting trees and linear quantile models, denoted as Model 1 and Model 2, respectively. The average loss ratio of the two models at five quantiles (0.05, 0.25, 0.50, 0.75, and 0.95 quantiles) is: $\mathrm{AL}_{Ratio} = \frac{\mathrm{AL}_1}{\mathrm{AL}_2}$, where $\mathrm{AL}_j = \sum_{i=1}^{n} \rho_\tau(y_i - \hat{y}_{i,j})/n$ for $j = 1$ and 2, and $\hat{y}_{i,j}$ is the fitted value of $y_{i,j}$ for the model j. If $\mathrm{AL}_{Ratio} = 1$, this indicates that the predictive ability of the two models is comparable; if $\mathrm{AL}_{Ratio} < 1$, this indicates that Model 1 has a better fit. This paper performs a Diebold-Mariano test as in Diebold and Mariano (1995) on the fit of the two models. Let $\hat{y}_{i,j}$ denote the fitted value for the model j, and the fitting error be expressed as $\varepsilon_{i,j} = \hat{y}_{i,j} - y_{i,j}$. Define $L(\cdot) = \rho_\tau(\cdot)$ to represent the loss function. To determine whether there is a statistically significant difference in the fit between Model 1 and Model 2, we test the null hypothesis: $H_0 : E[L(\varepsilon_{i,1})] = E[L(\varepsilon_{i,2})]$ versus the alternative hypothesis $H_1 : E[L(\varepsilon_{i,1})] \neq E[L(\varepsilon_{i,2})]$. To this end, we define the loss difference as: $d_i = L(\varepsilon_{i,2}) - L(\varepsilon_{i,1})$, then, the null hypothesis is equivalent to testing $H_0 : E[d_i] = 0$. The DM test statistic can be expressed as: DM= $\sqrt{n}\bar{d}/S_{\bar{d}}$, where $\bar{d}$ is the mean of the loss difference d_i and $S_{\bar{d}}^2$ is a consistent estimator of the asymptotic variance of $\sqrt{n}\bar{d}$. Diebold and Mariano (1995) proved that DM$\to_d N(0,1)$ as the sample size $n \to \infty$.

We calculate the average loss ratio and DM test statistic for the two models at 5 quantiles. A positive Diebold-Mariano statistic indicates that Model 1 is better than Model 2, and a negative value indicates the opposite. Table 2 reports the comparison results. The results shown by the average loss ratio and DM test statistic of the two models are summarized as follows: First, at all quantiles, the average squared loss ratio of the nonlinear quantile to the linear quantile is less than or equal to 1, indicating that the nonlinear regression model has a better fit. Furthermore, the DM statistic passes the significance test, indicating that the nonlinear GBTQR model significantly improves the estimation performance. Second, comparing the results, we can see that the goodness of fit of the two models differs significantly at low and high quantiles, and the difference is greater than at the middle quantile, indicating that the nonlinear GBTQR model fits the characteristics of both lower-income and higher-income populations better.

Table 2. The DM results for test the GBTQR model versus linear model

Quantile	AL_{Ratio}	DM Statistic	p-value
0.05	0.9660	7.7069	0.0000
0.25	0.9830	8.6789	0.0000
0.50	0.9894	3.3113	0.0000
0.75	0.9756	10.2277	0.0000
0.95	0.8595	4.0752	0.0000

4.3 Influencing Factor Analysis

Due to the superiority of the nonlinear GBTQR model, we will use this model to analyze the relative importance of all factors to offspring income. Offspring income is the dependent variable, parent income is the explanatory variable, other influencing factors are used as interaction terms, and the partial dependence value between parent income and offspring income is measured (where the estimation results of the three factors of social welfare change are combined). Table 3 reports the effects of parental income and other variables as interaction terms on offspring income.

Table 3. Partial dependence values for offspring income in 2018 based on the GBTQR model

Variables	Quantile level				
	0.05	0.25	0.50	0.75	0.95
Parental income	0.3942***	0.2954***	0.1861***	0.2684***	0.7026***
Parental income ×Economic growth	0.4729***	0.5647***	0.4274***	0.4135***	0.0370***
Parental income × Industrial optimization	0.0015***	0.0127***	0.0234***	0.0045***	0.0031***
Parental income × Population migration	0.0017***	0.0000	0.0003***	0.0000	0.0000
Parental income × IGM of education	0.0015***	0.0272***	0.0550***	0.1860***	0.0086***
Parental income × Social welfare	0.0901***	0.0323***	0.0075***	0.0000	0.0003***
Parental income × Social network	0.0053***	0.0005***	0.0000	0.0000	0.0000
Parental income × Wealth capital investment	0.0328***	0.0671***	0.3002***	0.1275***	0.2483***

Note: *, **, and *** indicate that the explanatory variables pass the significance test at the significance levels of 0.1, 0.05, and 0.01 respectively.

First, as interaction variables, the variables that passed the significance test at all quantiles were economic growth (macroeconomic factor), industrial optimization (macroeconomic factor), IGM through education (microeconomic factor), and wealth capital investment (microeconomic factor). Population migration had a significant effect at the 0.05 quantile, social welfare had a significant effect except at the 0.75 quantile, and social networks were significant at the 0.05 and 0.50 quantiles. Second, economic growth significantly affects IGM. Existing literature on how economic growth promotes intergenerational income mobility suggests that, on the one hand, industrialization and marketization generally enhance IGM (Blalock et al., 1967). Owen and Weil (1998) argue that economic growth leads to increased overall social income, thereby increasing household spending on education, and rising education levels enhance IGM. On the other hand, economic growth demands greater individual skills, leading to more efficient market-based income distribution. Erikson and Goldthorpe (1993) compare IGM characteristics in developed countries, finding that countries with high levels of economic development (Sweden, Japan, the US, Australia) exhibit significantly higher IGM than those with relatively lower levels of development (Netherlands, France, Italy, Germany, the United Kingdom). Here, we verify that economic growth can effectively promote IGM. Third, economic growth promotes the optimization of industrial structure, and this optimization, by influencing employment choices, promotes intergenerational income mobility.By comparing the partial dependence values of each quantile of the explanatory variables, first, the IGM elasticity is in the range of 0.1861 to 0.7026. Since this paper uses a nonlinear quantile estimation method, the result obtained is an interval rather than a point estimate. Existing literature uses linear IGM elasticity and gives point estimates. The point estimates of all literature are within the interval of the estimation results in this paper (Chen and Yuan, 2012; Fan et al., 2021; He and Huang, 2013; Lü and Li, 2017; Wang and Li, 2012; Xu, 2015; Yang and Wang, 2020; Yang and Lian, 2015). However, the quantile method used in this paper can describe the mobility across the entire income distribution. Second, the 0.05 and 0.95 quantiles show higher values than other quantiles, indicating poor IGM between low-income and high-income groups, while IGM is slightly stronger among middle-income groups. This suggests a clear "strong at both ends, weak in the middle" characteristic in the impact of parental income on offspring income. The middle class is the most stable social stratum. In recent years, the government has consistently advocated a policy of "raising the high, expanding the middle, and increasing the low", meaning "increasing the income of low-income earners, expanding the middle-income group, and ultimately achieving common prosperity". For low-income groups, efforts should be made to improve their intergenerational upward mobility channels, creating favorable conditions for them to escape the "intergenerational inheritance trap." Third, the interaction effect of economic growth on promoting IGM is strongest at the 0.25 quantile (0.5647), followed by the 0.05 quantile (0.4729). However, as the quantile increases, the effect gradually weakens, decreasing to 0.0370 at the 0.95 quantile. The economic development model dominated by economic growth since China's reform and opening up has promoted the equitable development of individuals. However, economic growth has not had a strong effect on the equitable development of high-income groups, indicating that economic development is necessary for the next generation to have the opportunity to move up the social ladder, especially for low-income groups, whose future upward mobility will benefit more from the prosperity of the country. Fourth, the interaction effect of wealth capital investment on offspring income gradually strengthens at all five quantiles. For low-income groups, there is no surplus capital for wealth capital investment, meaning they are easily constrained by financing limitations, preventing it from reaching its full potential. For middle- and high-income groups, wealth capital investment can significantly promote IGM. Existing theories related to intergenerational income mobility (Becker et al., 2018; Becker and Tomes, 1979; Solon, 2004) consistently agree that the factors influencing offspring income from the parent generation mainly include human capital investment, social capital investment, and wealth capital investment. The conclusions of this paper are consistent with those of existing literature. Fifth, the interaction effect of education on IGM is significant at all quantiles. Since the 1990s, China's overall education level has been continuously improving. This improvement in education level increases parental income and, conversely, enhances children's identification with education, further promoting higher education levels and increased income for the next generation. Our analysis shows that the partial dependence values of the interaction of intergenerational educational mobility at the five quantiles are 0.0015, 0.0272, 0.0550, 0.1860, and 0.0086, respectively. The effect gradually strengthens from the 0.05 to 0.75 quantiles, decreasing slightly at the 0.95 quantile, but still remaining higher than the effect at the 0.05 quantile. This indicates that the middle-income group has the strongest perception of the impact of intergenerational educational mobility, and most high-achieving students from small towns come from middle-income families. For low-income groups, higher education may present financial constraints. The research by Luo and Liu (2018) shows that the expansion of education at the primary and secondary levels makes children of parents with lower levels of education more likely to benefit, while the expansion at the higher education level benefits children from families with higher levels of education more. This study demonstrates that improvements in compulsory education levels benefit children from low-income families more, while improvements in higher education levels benefit children from middle- and high-income families more.

This research enriches the understanding of the impact of education on IGM. Finally, social welfare has a significant effect at low quantiles but not at high quantiles, indicating that social welfare systems have a greater impact on the income of low- and middle-income groups than on high-income groups. According to the precautionary savings theory, social insurance helps reduce the uncertainty faced by families in the future, thus reducing precautionary savings and releasing consumption, thereby promoting human capital investment in future generations. Furthermore, for poor and low-income families, the use of welfare policies can promote family asset accumulation, helping to escape the intergenerational transmission of poverty.

4.4 Partial Dependence Analysis

This article uses a partial dependence diagram to further examine the impact of parental income on offspring income. image1It demonstrates the impact of parental income on offspring income at different quantiles, where the horizontal axis represents parental income and the vertical axis represents offspring income. Figure 1 shows that the impact of parental income on offspring income exhibits significant nonlinear characteristics. First, as the income of the parent gradually increases, the income growth of the offspring is slower in the early stage (parent income of 0 - ¥30,000), faster in the middle stage (parent income of ¥30,000 - ¥150,000), and gradually stabilizes in the later stage (parent income of over ¥150,000). Secondly, the impact of parental income on offspring income varies at different quantiles. At the mid high score locus, the influence of parental income on offspring income is stronger; At the low percentile, the impact of parental income on offspring income is relatively weak. Thirdly, from the partial dependence diagram, we can conclude that the two inflection points where the income of offspring is affected by the income of their parents are ¥30,000 and ¥150,000 (annual income). This means that the non-linear characteristics of the income of offspring and parents are very strong for those with monthly income between ¥2,500 and ¥12,500, which is consistent with the income characteristics of middle-income groups.

4.5 Dynamic Trends of Intergenerational Income Mobility

This paper uses matched data from 2013 for regression analysis, with offspring income as the dependent variable and parental income as the independent variable. The same macroeconomic and microeconomic factors are used as interaction terms. Table 4 reports the partial dependence values of the impact of the independent variables on offspring income in 2013. First, economic growth (macroeconomic factor), industrial optimization (macroeconomic factor), IGM through education (microeconomic factor), and wealth capital investment (microeconomic factor) still

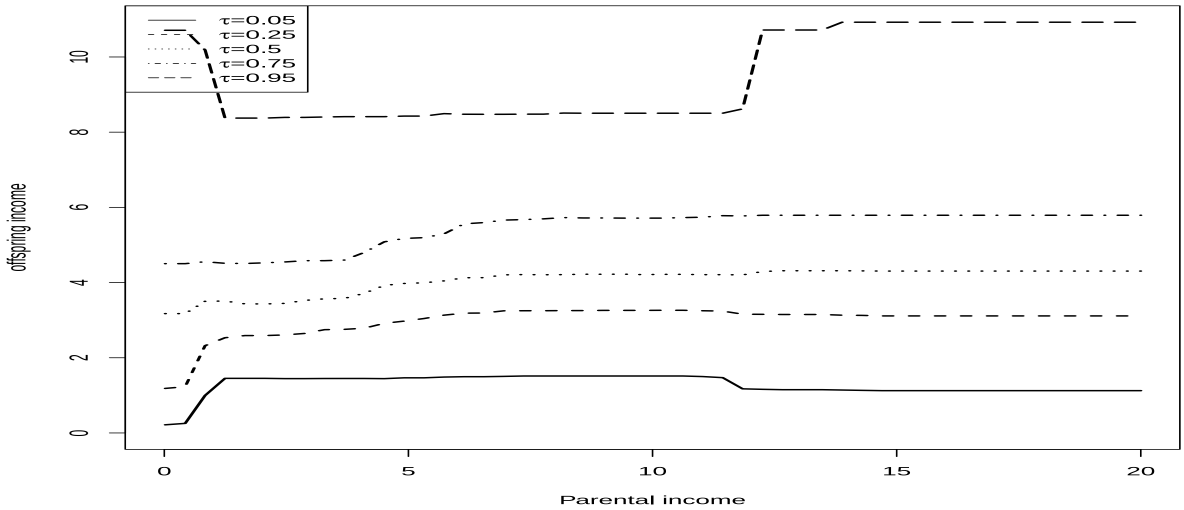

Figure 1. Partial dependence diagram between offspring income and parental income in 2018

have significant interaction terms at all quantiles. Social networks (microeconomic factor) also had a significant interaction term effect at all quantiles in 2013. Second, according to the estimation results, IGM was better in 2013 than in 2018, while IGM was poor in 2018, especially at quantiles 0.05 and 0.95, i.e., low-income and high-income groups. Third, social networks promote intergenerational income mobility through enhanced information sharing, reduced credit constraints, and improved employment for children, with a particularly strong effect on low-income families. Fourth, regarding wealth capital investment, the impact on high-income groups in 2013 was significantly higher than in 2018, indicating that as wealth accumulates, people are increasingly aware of the importance of wealth capital investment, and its proportion in household wealth is also increasing. According to the annual China Household Wealth Distribution and High Net Worth Household Wealth Report released by the China Household Finance Survey and Research Center of Southwestern University of Finance and Economics, the proportion of financial assets in high-income households is increasing, and their participation in the financial market is also increasing. The results of this analysis are consistent with this. In the future, on the one hand, the country should maintain the financial market environment and reduce credit constraints; on the other hand, it should improve the financial literacy of the entire population so that financial capital investment can also greatly promote the wealth accumulation of low-income and middle-income groups. To model the dynamic change of IGM, one might use the idea as in Cai et al. (2025), which is very challenging and left as a future research area.

Table 4. Partial dependence values between various variables and offspring income for 2013

Variable	Quantile level				
	0.05	0.25	0.5	0.75	0.95
Parental income	0.2570***	0.1369***	0.1892***	0.2274***	0.3857***
Parental income × Economic growth	0.0850***	0.3815***	0.2809***	0.1556***	0.0183***
Parental income × Industrial optimization	0.0460***	0.0041***	0.0004***	0.0005***	0.0007***
Parental income × Population migration	0.0000	0.0000	0.0000	0.0000	0.0000
Parental income × IGM of education	0.0001***	0.0301***	0.0383***	0.0276***	0.0301***
Parental income × Social welfare	0.0000	0.0000	0.0000	0.0000	0.0000
Parental income × Social network	0.0219***	0.0496***	0.0028***	0.0003***	0.0099***
Parental income × Wealth capital investment	0.5900***	0.3978***	0.4883***	0.5886***	0.5552***

4.6 Robustness Tests

First, we assess the parental-offspring income association using intergenerational income percentile ranking as a robustness check. With 2013 matched data as the sample, we again use partial dependence plots to examine how parental income affects offspring income. Figure 2 shows the impact of parent income percentile ranking on offspring income percentile ranking at different quantiles, where the horizontal axis represents parent income percentile ranking and the vertical axis represents offspring income percentile ranking.The results show that the impact of parental income on offspring income has a non-linear characteristic. However, because the percentile ranking is smaller than the difference in the original income data, the non-linear characteristic of the data is relatively weakened, and its non-linear characteristic is less significant than the level values. First, as parental income gradually increases, offspring income grows faster in the early stage (parental income percentile ranking of 0-20%), and gradually stabilizes in the middle and later stages (parental income percentile ranking of above 20%). Second, the impact of parental income on offspring income varies at different percentiles. At the middle and high percentiles, the impact of parental income on offspring income is stronger; at the low percentiles, the impact of parental income on offspring income is weaker. The above analysis shows that the model in this paper is robust.

Next, we further do a robust check for a different quantile modeling approach, such as RFQR[3], which is also a commonly used machine learning method for nonlinear quantile regression. The detailed computing algorithm for the RFQR model can be found in the paper by Meinshausen (2006) or the R package **quantregForest**. However, there are some differences

[3]We sincerely appreciate the Editor and the anonymous referee who brought our attention to this issue.

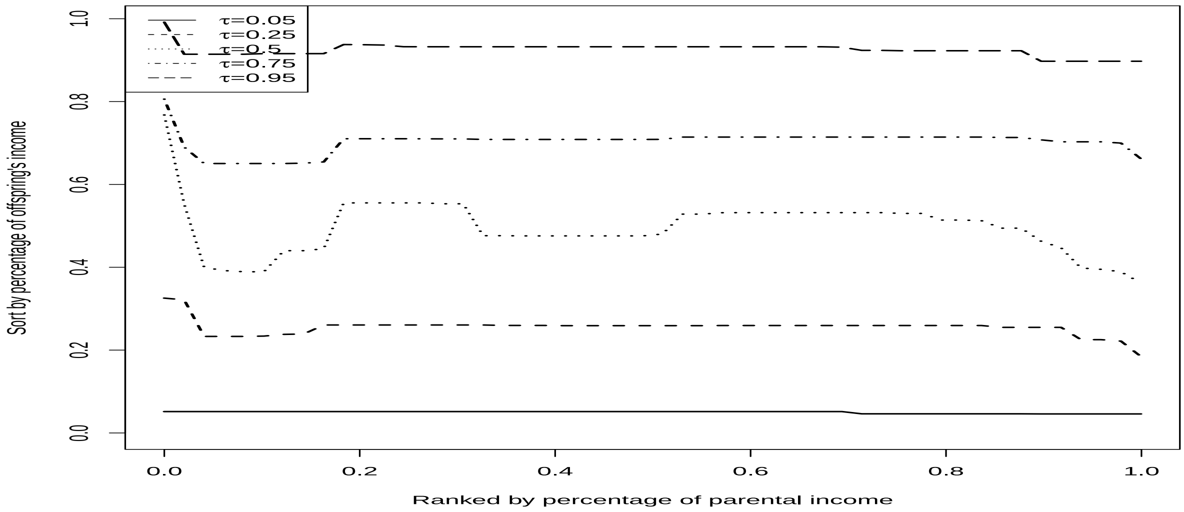

Figure 2. Partial dependence diagram of the percentile ranking of offspring income and the percentile ranking of parental income in 2013

in suitability between RFQR and GBTQR models when analyzing income inequality. Income data often contains a large number of outliers, such as extreme values in a small number of high-income groups or statistical errors in low-income groups. Random forests' low sensitivity to outliers allows them to retain tail information while avoiding model bias caused by extreme values. For example, when analyzing the income determinants of the 10th and 90th percentiles, it can effectively reduce the interference of extreme incomes in the wealthy class or statistical errors in low-income groups on quantile coefficient estimation. The combination of gradient boosting trees and quantile regression is better at capturing the fine heterogeneity and complex driving mechanisms in income distribution, showing a significant advantage, especially when pursuing high-precision analysis. Income data contains a large number of nonlinear relationships and feature interaction effects (such as the interaction between education and industry having a much greater impact on high-income groups than low-income groups). The serial iterative optimization characteristic of gradient boosting trees can accurately fit this complex pattern specific to quantiles. This precision advantage makes it a core tool for analyzing income inequality heterogeneity. Furthermore, the flexible adaptability of gradient boosting trees to loss functions allows them to customize optimization objectives for the heteroscedasticity of income data. For example, stricter loss penalties can be applied to higher income quantiles (with greater variance) to improve tail estimation accuracy. This is crucial for analyzing the income inequality drivers of high-income groups (such as the interaction between financial assets and occupational status). The difference in application also lies in the focus of policy analysis:

random forests require scenarios that quickly validate the universality of policies, such as assessing the overall impact of minimum wage adjustments on different income quantiles, quickly outputting the approximate distribution range of policy effects. Gradient boosting trees, on the other hand, require scenarios that precisely pinpoint the policy's impact, such as designing differentiated education poverty alleviation policies. Their quantile regression models can accurately identify the marginal benefits of educational resource investment at different income quantiles, providing a precise basis for allocating resources to low-income groups.

This paper then uses the RFQR model to analyze the data. Table 5 reports the average loss ratio and DM test statistic of the RFQR model and the linear quantile model. Comparing

Table 5. The DM results for testing the RFQR model versus and linear model

quantile	AL_{Ratio}	DM statistic	p-value
0.05	1.0053	4.2689	0.0000
0.25	0.9976	4.3256	0.0000
0.50	0.9894	4.8086	0.0000
0.75	0.9425	8.0805	0.0000
0.95	0.8423	3.0203	0.0026

the fitting effects of the nonlinear GBTQR model in Table 2, it can be seen that the RFQR also outperforms the linear quantile regression model. However, compared with the nonlinear GBTQR model, the difference is not significant. The RFQR model performs worse at the 0.05 and 0.25 quantiles, but outperforms the GBTQR model at the 0.75 and 0.95 quantiles. Both models perform similarly at the 0.5 quantile. Next, this paper uses random forest quantile regression to calculate the IGM and influencing factors effects on the 2018 data. Table 6 reports the calculation results. Compared with the results in Table 3, the results in Table 6 show that the IGM elasticity range calculated by random forest quantile regression is wider, and the variable influence effect is more significant. This further demonstrates the robustness of the analysis results and shows that the GBTQR model is more accurate than the RFQR model.

5 Heterogeneity Analyses

In the benchmark regression, this paper uses the full sample to analyze the nonlinear characteristics and trends of IGM. However, we are more concerned with the elasticity of IGM in China to achieve income class transitions. That is, what is the elasticity of IGM when parents have low income and their offspring have high income? Correspondingly, what is the elasticity of IGM when parents have high income and their offspring have low income? What

Table 6. Partial dependence values for offspring income in 2018 based on the RFQR model

	Quantile level				
Variables	0.05	0.25	0.50	0.75	0.95
Parental Income	0.2240***	0.2606***	0.0258***	0.2540***	0.2701***
Parental Income * Economic Growth	0.2177***	0.2347***	0.2013***	0.1649***	0.0329***
Parental Income * Industrial Optimization	0.1153***	0.1037***	0.1014***	0.1698***	0.1162***
Parental Income * Population Migration	0.0107***	0.0109***	0.0134***	0.0027	0.0030
Parental Income * IGM in Education	0.0865***	0.0820***	0.1194***	0.0526***	0.0742***
Parental Income * Social Welfare	0.0546***	0.0518***	0.0374***	0.0418***	0.0257***
Parental Income * Social Networks	0.0902***	0.0538***	0.0512***	0.0804***	0.1341***
Parental Income * Wealth Capital Investment	0.2010***	0.2026***	0.2175***	0.2339***	0.2734***

is the effect of the factors that cause income class rise and fall? Currently, no literature has answered the above two questions, and these two questions are precisely the most concerning issues for groups at both ends of the income spectrum. Existing literature on heterogeneity analysis of IGM characteristics mostly focuses on urban-rural heterogeneity, with fewer studies analyzing regional heterogeneity. This paper further divides the sample into Northeast, West, Central, and East regions for regional heterogeneity analysis.

Finally, the family characteristics of the poverty trap are mainly manifested in intergenerational transmission of poverty, which refers to the transmission of poverty and its related conditions and factors within the family from parents to children, causing children to repeat their parents' situation in adulthood - inheriting their parents' poverty and adverse factors and passing them on to their offspring - a vicious genetic chain. Knight et al. (2009) construct a poverty trap equilibrium equation based on family income, education, and credit constraints, and conducted an empirical analysis of school enrollment and dropout rates using sample data from rural Chinese families in 2002. The results showed that low family income levels negatively impact children's education, leading to a poverty trap. Gu and Zhang (2001), using a neoclassical growth model and studying the monotonicity of the average savings curve, find that many provinces in central and western China are likely to fall into a poverty trap. They argued that increasing investment, reducing the birth rate, and increasing technological investment could help these regions escape the poverty trap and maintain sustained economic growth. Breaking the poverty trap is an urgent concern for the Chinese government and low-income groups. This article analyzes innovatively the key factors influencing China's poverty trap from the perspective of IGM and provides policy recommendations.

5.1 Heterogeneity Analysis of Income Dividing Groups

To analyze the heterogeneity of different income groups, we categorize parental income into low-income, middle-income, and high-income groups in 2018 and match the offspring income accordingly. Data from families with low-income parents and high-income children, and families with high-income parents and low-income children, were selected and estimated using a nonlinear GBTQR model. Table 7 reports the estimation results for the two subsamples. The results show that the IGM elasticity of families with low-income parents and high-income children ranges from 0.1790 to 0.7852. Among the influencing factors, economic growth, industrial optimization, IGM through education, and wealth capital investment are significant at all quantiles. This result indicates that, first, the mobility of families with low-income parents and high-income children is relatively strong. The saying "knowledge changes destiny" is most concretely demonstrated here. Education, as an investment in human capital, is a significant factor influencing intergenerational upward mobility for middle- and low-income groups, especially for low-income groups, where education is a key factor in achieving upward mobility. For low-income groups, in addition to the state creating more equitable educational opportunities, raising individual awareness of education is also crucial. Local governments, especially in impoverished areas, need to continue educational promotion to solidify the public's understanding that knowledge changes destiny. Secondly, parents also need to make effective wealth capital investments for their children to achieve income stratification. Meanwhile, the IGM elasticity for high-income parents and low-income children ranges from 0.0050 to 0.4212, with the most significant influencing factors being economic growth, industrial optimization, and wealth capital investment. The primary reason for the decline in income levels of children from high-income parents is poor wealth capital investment, indicating that wealth capital investment is a double-edged sword; it can enable low-income parents to move to high-income children, but it can also significantly cause high-income parents to fall to low-income children.

Table 7. Partial dependence values of two subsamples of income - dividing groups

Low income of parents, High income of offspring					
	Quantile level				
Variable	0.05	0.25	0.5	0.75	0.95
Parental income	0.7852***	0.7166***	0.4312***	0.2590***	0.1790***
Parental income × Economic growth	0.0075***	0.0345***	0.0351***	0.0601***	0.0001***
Parental income × Industrial optimization	0.1902***	0.0325***	0.0426***	0.0125***	0.0274***

Parental income × Population migration	0.0007***	0.0006***	0.0878***	0.0086***	0.0000
Parental income × IGM of education	0.0015***	0.0182***	0.0004***	0.0179***	0.1054***
Parental income × Social welfare	0.0000	0.0000	0.0000	0.0003***	0.0000
Parental income × Social network	0.0011***	0.0003***	0.0000	0.0059***	0.0000
Parental income × Wealth capital investment	0.0137***	0.1973***	0.4027***	0.6357***	0.6881***

High income of parents, Medium and low income of offspring

	Quantile level				
Variable	0.05	0.25	0.5	0.75	0.95
Parental income	0.0530***	0.0118***	0.0050***	0.0313***	0.4312***
Parental income × Economic growth	0.4268***	0.5991***	0.2640***	0.1746***	0.0063***
Parental income × Industrial optimization	0.1968***	0.0063***	0.0765***	0.3784***	0.3607***
Parental income × Population migration	0.0000	0.0000	0.0002***	0.0066***	0.0000
Parental income × IGM of education	0.0000	0.0000	0.0047***	0.0012***	0.0025***
Parental income × Social welfare	0.0000	0.0000	0.0000	0.0003***	0.0000
Parental income × Social network	0.0000	0.0000	0.0112***	0.0037***	0.0000
Parental income ×Wealth capital investment	0.3235***	0.3828***	0.6382***	0.3838***	0.2091***

5.2 Regional Heterogeneity Analysis

This paper divides the 2018 full sample into eastern, central, and western regions based on the regions where the parents and children reside. Table 8 reports the estimation results for each regional subsample. The IGM elasticity in the eastern region ranges from 0.1661 to 0.4448, in the central region from 0.3660 to 0.9900, and in the western region from 0.0151 to 0.7008. IGM in the eastern region is superior to the other two regions. The eastern region has a stronger economic foundation and a higher level of development than the other two regions. Therefore, IGM in the eastern region is less dependent on economic growth and industrial optimization. Conversely, the effects of IGM through education and wealth capital investment are stronger. In the central and western regions, industrial development and expansion have led to economic growth and industrial optimization, which have played a crucial role in improving IGM. Regional heterogeneity analysis shows that there are significant differences in income transmission processes and the degree of nonlinearity across different regions. In the eastern region, children from wealthy families may have higher immobility or a wealth trap, while in other regions, children from poor families have higher immobility or a poverty trap.

Table 8. Values of partial dependence for subsamples in three regions

Central Region					
	Quantile level				
Variable	0.05	0.25	0.5	0.75	0.95
Parental income	0.7188***	0.3060***	0.6347***	0.3911***	0.9900***
Parental income × Economic growth	0.0038***	0.1500***	0.2626***	0.2482***	0.0000
Parental income × Industrial optimization	0.0055***	0.0097***	0.0256***	0.0569***	0.0000
Parental income × Population migration	0.0000	0.0000	0.0000	0.0020***	0.0000
Parental income × IGM of education	0.0163***	0.0331***	0.0151***	0.0985***	0.0000
Parental income × Social welfare	0.0000	0.0000	0.0000	0.0000	0.0000
Parental income × Social network	0.0005***	0.1542***	0.0012***	0.0236***	0.0000
Parental income ×Wealth capital investment	0.2549***	0.3470***	0.0608***	0.1797***	0.0001***
Western Region					
	Quantile level				
Variable	0.05	0.25	0.5	0.75	0.95
Parental income	0.2104***	0.0741***	0.0151***	0.1204***	0.7008***
Parental income × Economic growth	0.0000	0.0041***	0.3719***	0.0035***	0.0000
Parental income × Industrial optimization	0.3342***	0.0002***	0.0226***	0.0000	0.0000
Parental income × Population migration	0.0000	0.0000	0.0000	0.0000	0.0000
Parental income × IGM of education	0.0000	0.0003***	0.0138***	0.1579***	0.0004***
Parental income × Social welfare	0.0000	0.0000	0.0125***	0.0006***	0.0000
Parental income × Social network	0.0023***	0.0000	0.0002***	0.0051***	0.0003***
Parental income ×Wealth capital investment	0.4529***	0.9212***	0.5639***	0.7122***	0.2984***
Eastern Region					
	Quantile level				
Variable	0.05	0.25	0.5	0.75	0.95
Parental income	0.2706***	0.4448***	0.1661***	0.1967***	0.2678***
Parental income × Economic growth	0.0397***	0.1630***	0.1736***	0.0383***	0.0127***
Parental income × Industrial optimization	0.0075***	0.0026***	0.0101***	0.0510***	0.0046***
Parental income × Population migration	0.0000	0.0000	0.0000	0.0000	0.0000
Parental income × IGM of education	0.0154***	0.0245***	0.0527***	0.1539***	0.0002***
Parental income × Social welfare	0.1158***	0.0000	0.0000	0.0004***	0.0000
Parental income × Social network	0.0040***	0.0000	0.0000	0.0006***	0.0185***
Parental income ×Wealth capital investment	0.5470***	0.3650***	0.5974***	0.5591***	0.6962***

5.3 Discussion of the Poverty Trap

The level of intergenerational income elasticity represents the absolute degree of social income mobility, and through transfer matrix analysis, we can further understand the direction of IGM between parents and children in different income groups, thus gaining a deeper understanding of the possibility of the poverty trap for low-income groups. This article first regresses the samples with both parental and child income below 25% in 2018, and Table 9 reports the results. Then, the annual income of parents and children was classified into five levels based on quantiles, with income ranging from level 1 to level 5 from low to high, denoted by PC 1 to PC 5 for parents and OC 1 to OC5 for children, respectively. Table 10 shows the results of the income flow transition matrix analysis, with the income level of the behavioral father listed as the income level of the children. The units in the table represent the probability of the children transitioning from their father's income level to their own income level. First, the IGM elasticity of the sub sample with both parental and child incomes below 25% ranges from 0.4874 to 0.9900, far exceeding the estimated results of the entire sample. This indicates that the IGM of low-income populations is very poor, and the impact of education is limited. Low income levels have a negative impact on children's education, which in turn affects their upward mobility. Table 10 shows that in

Table 9. Partial dependence for offspring income for samples with parental and offspring income below 25% in 2018

Variables	Quantile levels				
	0.05	0.25	0.50	0.75	0.95
Parental Income	0.4874***	0.3187***	0.3476***	0.3271***	0.9900***
Parental Income * Economic Growth	0.0708***	0.4778***	0.5799***	0.0396***	0.0001
Parental Income * Industrial Optimization	0.2126***	0.0049***	0.0202***	0.0600***	0.0001
Parental Income * Population Migration	0.0000	0.0000	0.0001	0.0000	0.0001
Parental Income * IGM in Education	0.0000	0.0178***	0.0026***	0.3149***	0.0001
Parental Income * Social Welfare	0.014***	0.0168***	0.0005***	0.0001	0.0001
Parental Income * Social Networks	0.0243***	0.0106***	0.0021***	0.0120***	0.0001
Parental Income * Wealth Capital Investment	0.1906***	0.1533***	0.0469***	0.2461***	0.0001

2013 and 2018, the probability of offspring staying in the parent's class was the highest. When the parent's economic income was at level 1, the probability of their children's economic income staying at level 1 as adults was the highest. In 2013, it was 24.16%, and in 2018 it was 33.46%. China's poverty trap in 2018 was more severe than in 2013, and the probability of them flowing to high-level income groups was lower. In 2018, the probability of them flowing to level 5 was only 11.36%; When the father's economic income is at levels 2, 3, and 4, the distribution probability of their children's economic income flowing into the five income groups is relatively even, showing significant IGM. When the father's economic income is at level 5, the probability of their children's economic income staying at level 5 as adults is the highest, which was 31.36% in 2018, and the probability of maintaining a high income level (level 4 and level 5) is more than half.

Table 10. Income transfer matrix (%)

	2018				
	OC 1	OC 2	OC 3	OC 4	OC 5
PC 1	33.46	24.16	12.27	17.10	13.01
PC 2	18.06	34.03	13.89	20.14	13.89
PC 3	20.63	25.17	18.18	22.73	13.29
PC 4	14.08	22.64	16.90	24.88	21.60
PC 5	11.36	19.55	13.18	24.55	31.36
	2013				
	OC 1	OC 2	OC 3	OC 4	OC 5
PC 1	24.16	24.16	24.16	18.12	9.40
PC 2	19.54	26.44	18.39	18.39	17.24
PC 3	18.18	24.68	18.18	23.38	15.58
PC 4	16.79	24.82	21.17	19.71	17.52
PC 5	22.48	20.16	23.26	10.85	23.26

Table 11 reports the estimated results of the income flow transition matrix for sub samples by region. The results show that in the eastern region, the probability of the parent's income being at level 5 and the child's income remaining at level 5 is 37.63%, which is the highest value in the region; In the western region, the probability of parents having income at level 1 and children maintaining income at level 1 is 25.35%, which is also the highest value in the region. This is consistent with the results of regional heterogeneity analysis mentioned earlier. In the eastern region, children from wealthy families may have higher levels of immobility or wealth trap, while in other regions, children from poor families may have higher levels of immobility or poverty trap.

6 Conclusions

This paper uses the China Household Income Survey data and a nonlinear GBTQR model to conduct an empirical study on the nonlinear influence effects of macro and micro influencing factors on IGM. The research results show that: First, the nonlinear GBTQR model fits better than the linear quantile regression model, with particularly significant nonlinear characteristics among people with annual incomes between ¥30,000 and ¥150,000. The intergenerational income elasticity in China ranges from 0.1861 to 0.7026, and the impact of parental income on

Table 11. Regional income transfer matrix (%)

	OC 1	OC 2	OC 3	OC 4	OC 5
			East		
PC 1	25.38	25.38	20.77	15.38	13.08
PC 2	20.00	35.79	11.58	16.84	15.79
PC 3	23.60	21.35	29.21	14.61	11.24
PC 4	22.41	18.10	17.24	20.69	21.55
PC 5	9.68	16.13	16.13	20.43	37.63
			Central		
	OC 1	OC 2	OC 3	OC 4	OC 5
PC 1	23.58	25.20	23.58	8.31	19.51
PC 2	18.92	27.03	19.82	23.42	10.81
PC 3	18.95	23.16	28.42	14.74	14.74
PC 4	21.82	10.91	17.27	25.45	24.55
PC 5	16.36	16.36	20.91	16.36	30.00
			West		
	OC 1	OC 2	OC 3	OC 4	OC 5
PC 1	25.45	23.64	12.73	21.82	16.36
PC 2	26.23	26.23	19.67	16.39	11.48
PC 3	24.44	15.56	31.11	17.78	11.11
PC 4	14.75	16.39	18.03	31.15	19.67
PC 5	13.64	11.36	20.45	20.45	34.09

offspring income exhibits a clear "strong at both ends and weak in the middle" characteristic. Second, intergenerational income mobility characteristics show heterogeneity in income and region, with significant differences in the income transmission process and degree of nonlinearity across different regions. Third, this paper specifically explores the IGM characteristics of the two income groups, indicating that the most important influencing factors for achieving income class mobility are economic growth, industrial optimization, intergenerational educational mobility, and wealth capital investment. Finally, this paper explores the poverty trap from the perspective of IGM, showing that in the eastern region, children from wealthy families may have higher immobility or a wealth trap, while in other regions, children from poor families have higher immobility or a poverty trap.

Based on the research findings, this article further proposes the following policy recommendations: First, education remains a significant factor in promoting upward IGM within families, so the government needs to further favor education policies for low- and middle-income groups. Second, since wealth capital investment can either enable parents from low-income to middle- and high-income families, or significantly reduce parents from high-income to middle- and low-income families. In response, the government should broaden channels for popularizing capital market investment knowledge, increase investment in capital market investment education, continue to vigorously develop fintech. Third, promoting coordinated regional development is also an inevitable way to promote intergenerational income mobility throughout society. Policy inclination should be given to the Northeast and Western regions, and efforts should be made to optimize the industrial structure, expand employment, and improve income levels. Greater support should be given to talent introduction policies in the Northeast and Western regions, and talent mobility should be further promoted under the environment of equal opportunity, especially the return of lost talents.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that they do not use any generative AI and AI-assisted technologies in the writing process.

Declaration of competing interest

The authors claim that there are no relevant financial or non-financial competing interests to report for this article.

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Data availability

Data will be made available on request

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