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The effect of intergenerational mobility on family education investment: evidence from China

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The discussion of inequality has been an enduring topic in sociology and economics. With the intensification of inequality, an increasing amount of research has begun to focus on the impact of inequality on various aspects of the economy and society. However, research on how inequality affects families' education investment behavior currently remains relatively scarce. This study contributes to filling this gap by presenting one of the first analyses of the effect of intergenerational mobility-based opportunity inequality on family education investment. Specifically, based on a Chinese population sample survey conducted in 2015 and the China Family Panel Studies survey conducted in 2018, this paper measures the intergenerational mobility of regions using an index of intergenerational educational rank correlation, and it uses extracurricular tutoring expenses to measure families' investment in their children's education. The benchmark regression results show that intergenerational mobility significantly negatively impacts family education investment, with the average family education investment decreasing by 25.75 percent for every 0.1-unit increase in intergenerational mobility. This negative effect remains significant after robustness tests, such as replacing the explanatory variables and dependent variables, considering the influence of important omitted variables, evaluating the impact of unobservable factors, and introducing an instrumental variable for two-stage least squares regression analysis. In addition, this negative impact is more prevalent among families with high socioeconomic status, while it is not significant in families with low socioeconomic status. The reason is that families with low socioeconomic status face greater credit constraints and intergenerational mobility incentives. Furthermore, an examination of the mechanisms involved reveals that although the improvement in intergenerational mobility may increase people's confidence in investing, it ultimately reduces family education investment by lowering excessive anxiety and the extent of status-seeking behavior among families. According to the analysis, promoting equality of opportunity could mitigate China's negative educational competition and facilitate the realization of the "Double Reduction" policy.

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Introduction

Despite rapid economic growth since the reform and opening up of the Chinese economy in 1978, China's income disparity has also gradually widened. As a result, the percentage of income flowing to the top 10 percent of the population increased from 27 percent in 1978 to 41 percent in 2015, while the rate of income flowing to the bottom half of the population declined from 27 percent to 15 percent (Piketty et al., 2019). Inequality is becoming an important factor affecting Chinese social stability and economic development.

As inequality intensifies, the contribution of families to their children's education is becoming increasingly significant. Since China's implementation of nine years of compulsory education and because the government pays most of the tuition for primary and junior high school students, family involvement in children's education has gradually shifted from schools to extracurricular activities. Chi and Qian (2016) calculated household education expenditures in different categories using data from the 2007 and 2011 China Urban Household Education Surveys. They found that out-of-school education expenditure increased rapidly from 2007 to 2011 and largely explained the overall increase in educational costs. Specifically, the proportion of extracurricular education expenditure to total education expenditure increased from 44 percent in 2007 to 60 percent in 2011.

Although family education investment plays a crucial role in the accumulation of children's human capital, as an important source of education investment, when family education investment becomes a means of competing for high-quality educational resources, it can result in some adverse effects. Several studies have pointed out that the rapid development of extracurricular education has widened the gap between different social classes in terms of access to educational resources and outcomes, thus weakening the role of schools in promoting equity (Bergh and Fink, 2009; Dawson, 2010; Abdelbaki, 2012). China recently released a policy document entitled "Opinions on Further Reducing the Burden of Homework and Off-Campus Training for Compulsory Education Students" ("Double Reduction" policy), which establishes targets and requirements for upgrading school education and regulating private tutoring after school.

Many scholars have examined the factors that affect a family's education investment. However, most of them focus on the micro level and find that family background is the most important factor, such as the income of the family, the educational level of the parents, and whether there are siblings in the family (Huston, 1995; Taubman, 1996; Tilak, 2002; Chen, 2020), and there is little discussion at the macro level. As an important macro-level social factor, intergenerational mobility (IGM) is considered one of the best indicators for measuring a society's success in providing equal opportunities to all members (Ichino et al., 2011). In recent years, an increasing number of scholars have started to pay attention to the social impact of intergenerational mobility. For example, in 2006, Miles Corak proposed "The Great Gatsby Curve", which expounded on the relationship between intergenerational mobility and income inequality. Indeed, a society with insufficient intergenerational mobility and a solidified class structure will inevitably lead to polarization in which the rich get richer and the poor get poorer, resulting in a continual increase in the income gap and highlighting the phenomenon of income inequality.

At the same time, the level of inequality directly affects people's subjective feelings. Existing research has shown that people living in areas with higher intergenerational mobility often have higher levels of happiness, social trust, and fertility intentions (Nikolaev and Burns, 2014; Barone and Mocetti, 2016). In contrast, low levels of intergenerational mobility will have a negative impact on people's subjective feelings, which may affect their decision-making behaviors, such as fertility and investment decisions (Yum et al., 2015; Yang et al., 2020).

Given this background, this paper aims to explore the following three issues: first, does opportunity inequality, as measured by intergenerational mobility, affect family education investment? Second, if there is an effect, what are the underlying mechanisms – will it encourage parents to invest more or instead reduce educational anxiety and result in less investment? Finally, given that there are differences in borrowing constraints and incentive levels, is this effect heterogeneous across households with different socioeconomic statuses?

To answer these questions, we use data from the China 1 percent Population Sample Survey conducted in 2015 to measure the degree of intergenerational mobility in various cities using the intergenerational rank correlation proposed by Dahl and DeLeire (2008). We apply multiple robustness tests in combination with China Family Panel Studies (CFPS) survey data on family education investment (FEI) and other family characteristics to empirically confirm that intergenerational mobility negatively affects family education investment and to explore the impact mechanism involved. Furthermore, the results of the heterogeneity analysis demonstrate that this difference is significant only in high socioeconomic families and not in low socioeconomic families due to the heterogeneity of credit constraints and the level of incentives among them. The negative effect of intergenerational mobility on family education investment is primarily attributable to the reduction in parents' excessive educational anxiety and the extent of parents' status-seeking behavior.

Our study makes several contributions to the literature. First, this paper provides one of the first estimates of the causal effect of intergenerational mobility on family education investment. Therefore, our research contributes to the literature concerning the impact of intergenerational mobility or inequality of opportunity on residents' micro behaviors. Second, our study enriches our understanding of the mechanism of how opportunity inequality affects family education investment. In addition to the incentive mechanism discussed in previous research, this paper discusses how intergenerational mobility affects education investment through its impact on excessive parental anxiety about education and parental status-seeking behavior. Third, compared to previous studies employing micro surveys to determine the degree of intergenerational mobility in China, our study uses census data, creating a larger sample size, and the measurement of intergenerational mobility is more accurate due to certain data advantages.

This paper proceeds as follows. Section 2 is the literature review. Section 3 presents the measures for intergenerational mobility used in this paper and introduces the dataset employed. Our empirical methodology and the results of the effect of intergenerational mobility on family education investment and several robustness tests are shown in Section 4, as well as heterogeneity and mechanism analyses. Finally, Section 5 concludes.

Literature review

Currently, research on the effect of regional intergenerational mobility on family education investment is very limited. However, studies on the impact of inequality on family education investment provide some relevant insights.

The literature suggests that increasing equality of opportunity may incentivize people to increase their education investment. Equality of opportunity can be defined as the degree to which individual achievement is determined by self-driven factors (Dworkin, 1981; Arneson, 1989). In other words, individuals residing in areas with a higher degree of equal opportunity are more likely to achieve success through their efforts. Since education has a significant impact on individuals' lives, a higher level of equality of opportunity could increase people's motivation to invest in education. This hypothesis has been proposed by several studies (Browman et al., 2019; Mae, 2019; Wen and Witteveen, 2021). Song and Zhou (2019) empirically confirmed the negative effect of the level of inequality of opportunity on household education expenditure using CFPS panel data.

In addition, some studies have examined the relationship between income inequality and family education investment, but the findings are inconsistent. Some studies have shown that income inequality causes the total consumption of the household and family to decrease, while the consumption of education in the household increases (Sun and Wang, 2013; Alvarez-Cuadrado and El-Attar Vilalta, 2018). This phenomenon is often explained through the status-seeking hypothesis, which posits that as income disparity widens, individuals are more likely to compare their income with that of others. Human capital is an important determinant of income, and investing in education can improve an individual's chances of attaining higher social status in the future (Du et al., 2022; Wang et al., 2022).

Conversely, some studies have found that family education investment can be negatively affected by income inequality as a result of credit restrictions (Aiyar and Ebeke, 2020). In the absence of credit constraints, both wealthy and poor families could make optimal investments in their children's human capital. However, with credit constraints, poor families are unable to make optimal investments, leading to further poverty among children and exacerbating overall inequality (Carneiro and Heckman, 2002; Lochner and Monge-Naranjo, 2011; Caucutt and Lochner, 2020; Mogstad and Torsvik, 2021).

Moreover, in recent years, some studies have begun to investigate the impact of inequality on family education investment from an anxiety perspective. According to Karen Horney (1936), anxiety extends to the field of culture because a competitive culture has a profound impact on anxiety levels. In this sense, "pathological competition" is viewed as a cultural model. Regarding family parenting, anxiety is highly contagious and spreads rapidly among groups, resulting in widespread social anxiety (Cai and Hu, 2022).

While family educational anxiety is not always negative, it can raise parents' awareness of their children's education and assist in improving their human capital (Gofen, 2009; Yang and Zhao, 2020). However, when it exceeds the normal range, parents may overemphasize their children's academic achievement, leading to unreasonable interference in their children's activities, such as school selection or excessive tutoring against their children's will (Liu, 2023), which may create excessive family educational anxiety. Excessive educational anxiety can significantly increase the psychological pressure on children and produce a toxic social environment with intense competition for educational resources. Studies have found that households with excessive educational anxiety tend to invest more in extracurricular tutoring (Bray, 2013; Lin, 2019). Furthermore, many theoretical studies have demonstrated that excessive parental anxiety about education leads to an intensification of social inequality (Irwin and Elley, 2011; Ying and Wright, 2021). Therefore, increasing intergenerational mobility may reduce excessive parental educational anxiety.

As previously mentioned, intergenerational mobility is one of the best measures of equality of opportunity. Higher intergenerational mobility means that individuals face a more level playing field, which may affect people's subjective feelings. At the same time, "The Great Gatsby Curve" illustrates that income inequality is positively correlated with intergenerational income elasticity. Given that income inequality can affect family investment in education by affecting status-seeking, it is reasonable to assume that intergenerational mobility operates through the same mechanism.

Nevertheless, to date, there have been few articles exploring and testing the effect of intergenerational mobility on family education investment. The article closest to our research is Wen and Witteveen (2021), which explores the impact of individuals' perceived intergenerational mobility on education investment and finds that high levels of equal opportunity can incentivize people to invest in education. However, their study does not consider the impact of other mechanisms such as status-seeking and educational anxiety, nor does it deal with potential endogeneity issues. Given that intergenerational mobility has different impacts on household education investment through different channels, the ultimate impact of intergenerational mobility is difficult to determine and requires more rigorous empirical analysis. Thus, our article is dedicated to addressing this deficit.

IGM measure and dataset

IGM measure. In the previous literature, there have mainly been two aspects of differences in measuring intergenerational mobility. First, scholars have mainly measured intergenerational mobility from three dimensions: income, education, and occupation (Corak Miles, 2013; Nikolaev and Burns, 2014; Alesina et al., 2021). Among them, income and education are the most common dimensions. Second, there have been three main methods of measurement, including intergenerational elasticity, intergenerational transition matrices, and intergenerational rank correlation (Hertz et al., 2008; Fan et al., 2021; Halliday et al., 2021). The intergenerational transition matrix is typically used to study the specific direction of intergenerational mobility among different population groups, but this issue is not the focus of our paper.

Since income is the dimension that can best represent an individual's socioeconomic status, early research mainly focused on intergenerational income mobility. The measurement of intergenerational income mobility originated from Becker and Tomes (1979), who conducted a linear regression of the logarithm of child income and parent income, as shown in Eq. (1):

$$logY_1 = \alpha + \beta logY_0 + \varepsilon \tag{1}$$

where the estimated coefficient β represents intergenerational income elasticity, which measures the statistical correlation between parent income and child income, while 1-β can be used to measure intergenerational mobility.

However, the logarithmic setting of intergenerational income elasticity makes the estimation of mobility highly unstable because the relationship between log child income and log parent income is nonlinear (Chetty et al., 2014). Therefore, Dahl and DeLeire (2008) developed the intergenerational rank correlation index, which measures the correlation between a father's permanent income ranking within his cohort and his child's ranking within his or her cohort, using only relative position information between individuals. Thus, it makes no distributional assumptions beyond monotonicity, making it more robust to measurement issues (Chetty et al., 2014). Currently, an increasing number of studies use intergenerational rank correlation to measure intergenerational mobility (Mazumder, 2016; Andersen, 2021; Halliday et al., 2021).

In addition, due to problems such as lifecycle bias and difficulties in obtaining simultaneous income information for both parents and their children (Fan et al., 2021), most research has turned to studying intergenerational education mobility. Intergenerational education mobility has several advantages: first,

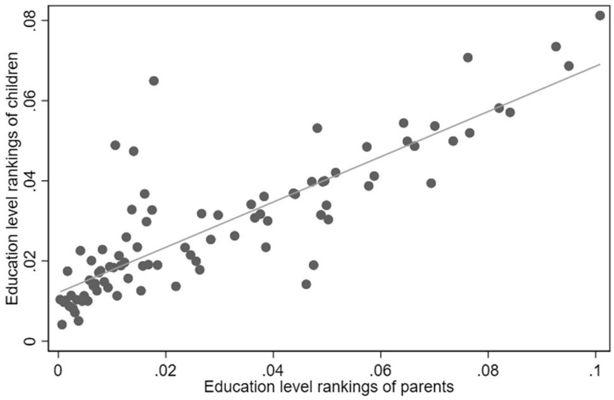

Fig. 1 The relationship between education level rankings of parents and children.

compared to income, the measurement of educational level is more explicit and has less measurement error when measured at any point in an individual's lifetime after completing education. Second, education has a significant impact on lifetime income and can be considered a proxy variable for lifetime income. Third, educational information for parent-child pairings is readily available, especially in developing countries (Alesina et al., 2021). Finally, since the main purpose of Chinese parents' provision of extracurricular tutoring is to help their children enter better universities and obtain higher degrees, using the intergenerational education mobility index is more suitable for our research.

Therefore, we characterize IGM based on the slope of this ranking and rank relationship:

$$Rank_{1ic} = \alpha_c + \beta_c Rank_{0ic} + \varepsilon_{ic} \quad (2)$$

In the equation above, subscripts i. and c. denote the family and city, respectively, and subscripts 1 and 0 represent the child and parent, respectively. Therefore, $Rank_{1ic}$. is the educational level ranking of children of the i_{th}. family in region c., and $Rank_{0ic}$. denotes the educational level ranking of children of the i_{th}. family in region c. Coefficient β_c. describes the correlation of educational attainment between parents and children in city c. Then, IGM_c is $1 - \beta_c$; the higher its value is, the stronger the degree of intergenerational mobility in the city.

As educational attainment is highly concentrated at specific discrete levels (12 years for high school graduates, 9 years for senior school graduates, etc.), we determine an individual's educational level ranking by calculating the number of individuals within the same cohort in their region who have received more years of education than they have. For example, if an individual has completed 9 ars of education and 1000 individuals within their cohort in the region have completed more than 9 years of education, their education ranking would be 1001. The rankings of both samples with the same educational level will differ if they are in different cities due to the differences in educational structure and sample size in each municipality. Using Beijing as an example, Fig. 1 illustrates the relationship between the educational level of Beijing parents and their offspring. It is evident that the two are highly linearly related, which is also an important prerequisite for the construction of intergenerational mobility indicators.

Dataset. Our data are derived from three main sources: the China 1 Percent Population Sample Survey of 2015, the China Family Panel Studies (CFPS) survey, and several city-level databases.

Table 1 IGM in some cities.

Rank (percent)	IGM
1	0.826
10	0.741
20	0.712
30	0.675
40	0.636
50	0.617
60	0.592
70	0.576
80	0.509
90	0.452
100	0.321

Population sample survey data. The measurement of cities' IGM in our study is based on sample survey data collected in 2015 from Chinese citizens. The survey evaluated China as a whole and prefecture-level cities as a subpopulation by employing stratified, two-stage, probabilistic, and proportional sampling methods, as well as cluster sampling methods, to select 99,147 survey communities from 2977 counties, 33,671 townships, and 85,365 village committees across 31 provinces in China. A total of 21.31 million registered permanent residents were surveyed, accounting for 1.55 percent of China's total population. The dataset provides information about an individual's age, level of education, relationship to the head of household, and domicile location, enabling us to calculate IGM across cities.

Compared with earlier studies that used micro survey databases to measure intergenerational mobility in China (Chen, 2013; Yuan and Zhang, 2015), our measure of cities' IGM is more precise, as we employ a larger and more representative population sample. Specifically, the processing of data to measure IGM proceeded as follows: Initially, we removed samples with missing variables such as domicile location and educational level, individuals younger than 16 years, and those still in school. We specifically excluded floating populations to obtain a more accurate local IGM measurement. Second, we kept heads of household, their children, and parents in the sample and then ranked each individual's educational level based on his or her relationship to the head of household and domicile location. Finally, we regressed the rankings based on Eq. (2) by city to obtain coefficient β_c. and to calculate IGM_c, which serves as our core independent variable.

Table 1 displays the IGM values for several cities. Eleven cities are included, varying in percentiles from 1 percent to 100 percent, with one city in each of the 10 percentiles. The table illustrates that intergenerational mobility levels vary greatly across Chinese cities, with the most and least severe class consolidation having IGM levels of 0.321 and 0.826, respectively, indicating a difference of 0.505 between them. These findings suggest notable differences inequality of opportunity among different Chinese cities and provide a premise for the empirical analysis of this paper.

CFPS data. The 2018 China Family Panel Studies (CFPS) survey provides information about investments in children's education and other family characteristics. The CFPS is an ongoing project of Peking University's Institute of Social Science Survey (ISSS), and its sample represents 95 percent of the Chinese population from 25 provinces/municipalities/autonomous regions (excluding Hong Kong, Macao, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan) and contains rich information on communities, families, and individuals. The dataset provides data on the demographic and social factors of both households and individuals, including family background. The CFPS also

Table 2 Summary statistics of the variables.

Variable	Definition	N	mean	sd	min	max
lnFEI	log of the family education investment	1226	6.783	2.852	0	11.51
IGM	intergenerational mobility	1226	0.615	0.114	0.321	0.826
Curban	urban household registration permit of the child	1226	0.542	1.028	0	1
Cgender	gender of the child(male = 1)	1226	0.475	0.500	0	1
Cage	age of the child	1226	9.374	3.350	0	16
Cstage	learning stage of the child	1226	2.727	1.780	0	5
Cschool	type of the child's school (key/model school = 1)	1226	0.307	0.462	0	1
edum	education degree of the child's mother	1068	4.470	1.663	0	8
eduexp	parental education expectation for the child	1223	7.034	0.832	4	9
fsize	family population size	1226	5.083	1.840	2	14
fbooks	number of family books	1226	69.37	146.6	0	2100
Hgender	gender of the head of the household(male = 1)	1226	0.423	0.494	0	1
Hage	age of the head of the household	1226	44.49	11.99	17	79
childsize	number of children in the family	1226	1.763	0.737	1	7
lnfinc	log of the family's annual income	1201	11.13	0.999	0	13.82
ave_fund	financial allocation level per student in the compulsory education stage (unit: yuan)	1226	12,984	5699	5846	39,087
GDP	gross domestic product of the city (unit: 100 million yuan)	1226	6112.17	8773.76	289.58	32679.87
Gini	Gini coefficient of the city	1226	0.1611	0.0373	0.0508	0.2766
DIM	degree of incentive of the mother	1168	4.333	1.123	1	5
DIF	degree of incentive of the father	983	4.208	1.183	1	5
EEA	excessive education anxiety(yes = 1)	1180	0.0398	0.196	0	1
SSM	degree of statue seeking of the mother	1171	2.204	1.744	0.2	10
SSF	degree of statue seeking of the father	985	2.243	1.674	0.2	10

involves a longitudinal survey and includes six updates: 2010, 2012, 2014, 2016, 2018, and 2020. Our paper makes use of the most recently available complete data (2018 CFPS 2018). The 2018 CFPS includes 4 questionnaires, i.e., family roster, family economic, individual self-report, and child proxy questionnaires, covering approximately 15,000 households and 44,000 individuals in total.

The data for the dependent variable, family education investment, come from a question included in the 2018 CFPS child proxy questionnaire for children aged 0–16. The question asks, "In the past 12 months, how much did your family pay for this child to attend extracurricular/home tutoring?" The concept of "extracurricular tutoring" refers to the training that a child receives after school to enhance his or her academic performance or to develop specific skills, such as painting and piano playing. While some private schools provide extracurricular tutoring, not all schools do so. Given China's nine-year compulsory school system, there is almost no difference in the amount of money that parents spend on their children's primary and secondary school education. Therefore, spending on extracurricular activities serves as a better measure of FEI than other 2018 CFPS data pertaining to families' education expenditures, such as school education expenses. Using the identifiers of children and their parents, we can match different databases and obtain data on individual and family control variables. In addition, we use city identifiers to match IGM and other city data with the 2018 CFPS.

City data. To account for potential missing variables, such as investments in public education and economic development levels, we require data on education expenditures and the GDP of each city. We collected this information from sources including the *China City Statistic Yearbook*, the *Educational Finance Statistical Yearbook*, and the official website of the statistical bureau of each city. Additionally, to mitigate the impact of income inequality, we calculated the Gini coefficient using CFPS data for robustness testing; the specific method for this calculation is outlined in a later section. Table 2 presents the summary statistics for the key variables used in our research.

Empirical analysis

Methodology. To test the influence of IGM on FEI, we constructed the following benchmark model:

$$ln(FEI_{ijcp} + 1) = \beta_0 + \beta_1 IGM_c + \delta X_i + \varphi X_j + \gamma X_c + v_p + \varepsilon_{ijcp} \quad (3)$$

where FEI_{ijcp} denotes the education investment in child i in family j in city c in province p; IGM_c denotes the intergenerational education mobility of city c; and X_i, X_j and X_c are control variables that may be associated with FEI. Specifically, X_i represents data on the individual characteristics of each child such as age, gender, current learning stage, household registration status, the mother's highest degree attained, and attendance at a key/model school. The vector X_j contains information on the family, including annual income, the number of children and household members, the gender and age of the head of household, education expectations, and the number of books owned. X_c denotes the financial allocation level per student in compulsory education at the city level. We also include provincial fixed effects v_p, and error terms ε_{ijcp} are clustered at the city level. Finally, we take the natural logarithm of FEI to simplify the interpretation of our results and to mitigate potential concerns over heteroscedasticity.

Baseline results. Table 3 presents the baseline regression results. The first two columns show the outcomes of ordinary least squares regression, where Column (1) controls for city-level variables and provincial fixed effects, and Column (2) adds individual- and family-level variables to Column (1). Due to the partial zero value of family education investment, where in some families, children do not attend extracurricular training, we also employ the Tobit model to make the result more reliable. Columns (3) and (4) present the corresponding regression results. The results indicate that an increase in IGM leads to a significant reduction in FEI when adopting different methodologies and controlling for various variables. According to the regression results shown in Column (2), the coefficient of the influence of IGM on FEI is −2.575, implying that there is approximately a 25.75 percent reduction in FEI when IGM increases by 0.1 units.

Table 3 Baseline results.

	(1) OLS	(2) OLS	(3) Tobit	(4) Tobit
VARIABLES	lnFEI	lnFEI	lnFEI	lnFEI
IGM	−2.682**	−2.575**	−2.980**	−2.795**
	(1.319)	(1.041)	(1.405)	(1.122)
Individual vars	No	Yes	No	Yes
Family vars	No	Yes	No	Yes
City vars	Yes	Yes	Yes	Yes
Province fe	Yes	Yes	Yes	Yes
Observations	1226	1044	1226	1044
R-squared/ Pseudo R-squared	0.113	0.234	0.0227	0.0513

Significance levels ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors clustered at the city level appeared in parentheses. The outputs of the Tobit and Probit models in this paper are all mean marginal effects.

Table 4 Robustness checks by replacing independent and dependent variables.

	(1) OLS	(2) Probit	(3) OLS	(4) Tobit
VARIABLES	dFEI	dFEI	lnFEI	lnFEI
IGM	−0.295**	−0.413***		
	(0.124)	(0.142)		
ImIGM			−2.574**	−2.798**
			(1.060)	(1.157)
Individual vars	Yes	Yes	Yes	Yes
Family vars	Yes	Yes	Yes	Yes
City vars	Yes	Yes	Yes	Yes
Province fe	Yes	Yes	Yes	Yes
Observations	1044	992	1044	1044
R-squared/ Pseudo R-squared	0.110	0.130	0.234	0.0513

Significance levels ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors clustered at the city level appeared in parentheses.

These results indicate that the influence of intergenerational mobility on family education investment is also significantly meaningful from an economic perspective.

Robustness. The main problem with the baseline regression is endogeneity. There are two possible causes of the endogeneity problem. The first is measurement error, which is primarily caused by the inaccuracy of the IGM measurement. In addition, omitted variables could have a simultaneous impact on both IGM and FEI, despite incorporating control variables across various dimensions in the baseline regression. The objective of this part of the article is to conduct robustness tests to address these concerns. This testing involves replacing the independent and dependent variables, including crucial variables that are initially omitted from the analysis, assessing the influence of unobservable factors, and finally utilizing an instrumental variable for two-stage least squares (2SLS) regression to verify the validity of our conclusions. These rigorous tests aim to mitigate the endogeneity issues and strengthen the reliability of our findings.

Replacement of the independent and dependent variables. For the independent variable, we create a dummy variable (dFEI) that is dependent on whether a child has extracurricular training. In this case, the independent variable takes the value of zero when FEI is zero, and it takes the value of one when FEI exceeds zero. To estimate the replaced data, we utilize OLS regression and the probit model for binary variables. The results are shown in Columns (1) and (2) of Table 4. Based on the findings, the conclusion drawn from the baseline regression remains valid: there is still a significant negative effect of IGM on FEI. Regarding the dependent variable, to further reduce lifecycle bias and to enhance measurement accuracy, we introduce the ages of parents and children, as well as their squared terms, following Eq. (2) (Gong et al., 2012), to recalculate the IGM of each city. Columns (3) and (4) of Table 4 present the results of the re-regression of the improved IGM (ImIGM) using OLS regression and Tobit models, respectively. After implementing the improved measurement method, the regression coefficient for IGM remains significantly negative. The results do not differ significantly from those obtained by the baseline regression, thereby further supporting our initial conclusions.

Consideration of important omitted variables. According to Maoz and Moav (1999) and Corak (2013), the degree of IGM can be affected by the level of economic development and income inequality in a region. Additionally, the price of educational resources varies between regions with varying economic development levels, and income inequality also influences people's subjective feelings, such as their confidence in the future, which has an adverse impact on FEI. Since both variables simultaneously affect IGM and FEI, we introduce city GDP and the Gini coefficient to control for economic development and income inequality, respectively. The Gini coefficient is calculated using the following formula:

$$Gini_c = 1 - \sum_{i=1}^{n_c} p_{ic}\left(2\mathrm{Q}_{ic} - \mathrm{w}_{ic}\right) \tag{4}$$

where p_{ic} and w_{ic} denote the population frequency and annual income share of family i in city c, respectively, and Q_{ic} represents the proportion of income accumulated from family 1 to family i after ranking the families in city c by per capita annual household income.

As displayed in Table 5, Columns (1) and (2) present the regression results obtained after introducing GDP using the benchmark model; Columns (3) and (4) represent the regression results obtained after introducing the Gini coefficient, and Columns (5) and (6) reflect regression results obtained after including both GDP and the Gini coefficient. After considering the influence of important omitted variables, the value of the estimated coefficient of intergenerational mobility is still significantly negative, although it has increased in most cases.

Evaluating the impact of unobservable factors. Altonji et al. (2005) proposed a strategy for addressing the bias caused by missing variables, and their strategy was later applied by Bellows and Miguel (2009) to examine the effects of war on collective behavior in linear models. Similarly, Nunn and Wantchekon (2011) utilized this approach to assess the impact of unobservable factors on identifying the causal relationship between the slave trade and trust. In general, the set of control variables (Q) can be divided into observable components ($x'\beta$) and unobservable ($\sim Q$) components. Bellows and Miguel (2009) derived the following equation based on Altonji et al. (2005):

$$\frac{\hat{\alpha}_{OLS,C}}{\hat{\alpha}_{OLS,NC} - \hat{\alpha}_{OLS,C}} = \frac{Cov\left(a,\tilde{q}\right)}{Cov\left(a,x'\beta\right)} \tag{5}$$

where $\hat{\alpha}_{OLS,C}$ and $\hat{\alpha}_{OLS,NC}$ on the left side of the equation represent the estimated coefficient of the core explanatory variable (IGM) with the control variables (usually the complete control set) and without the control variables (also called the limited control set),

Table 5 Robustness checks by considering important omitted variables.

	(1) OLS	(2) Tobit	(3) OLS	(4) Tobit	(5) OLS	(6) Tobit
VARIABLES	lnFEI	lnFEI	lnFEI	lnFEI	lnFEI	lnexp1
IGM	−1.871*	−2.019*	−2.720**	−2.945***	−1.994*	−2.143*
	(1.021)	(1.131)	(1.054)	(1.137)	(1.021)	(1.130)
GDP	0.643**	0.706**			0.670**	0.735**
	(0.313)	(0.351)			(0.330)	(0.368)
Gini			5.068*	5.364*	5.297*	5.622*
			(2.915)	(3.239)	(2.765)	(3.084)
Individual vars	Yes	Yes	Yes	Yes	Yes	Yes
Family vars	Yes	Yes	Yes	Yes	Yes	Yes
City vars	Yes	Yes	Yes	Yes	Yes	Yes
Province fe	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1044	1044	1044	1044	1044	1044
R-squared /Pseudo R-squared	0.238	0.0522	0.238	0.0521	0.242	0.0531

Significance levels ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors clustered at the city level appeared in parentheses.

Table 6 Robustness checks by evaluating the impact of unobtainable factors.

Controls in the restricted set	Controls in the full set	Ratio
None	Full	30.55
province fe	Full	4.03
Individual vars+family vars+province fe	Full	10.81
None	Full+GDP+Gini	4.02
province fe	Full+ GDP+Gini	1.63
Individual vars+family vars+province fe	Full+ GDP+Gini	5.82
		9.48

Table 7 Robustness checks by introducing instrumental variable.

	(1) 2SLS	(2) 2SLS	(3) IVTobit	(4) IVTobit
VARIABLES	IGM	lnFEI	IGM	lnFEI
IGM		−2.563**		−2.842**
		(0.901)		(1.225)
IV	−11.894***		−11.910***	
	(0.797)		(0.786)	
Individual vars	Yes	Yes	Yes	Yes
Family vars	Yes	Yes	Yes	Yes
City vars	Yes	Yes	Yes	Yes
Province fe	Yes	Yes	Yes	Yes
F statistic in the first stage		222.672		702.220
Observations	1044	1044	1044	1044
R-squared	0.965	0.234		

Significance levels ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors clustered at the city level appeared in parentheses. Besides, we used the partial option when stata ivreg2 was used for 2SLS estimation to solve the problem that the number of clusters was not enough to calculate the robust covariance matrix, and the constant is automatically partialled out in this situation, so the output does not report the coefficient estimates for the constant. Last, stata also does not report R square or Pseudo R-squared when using IV probit or IV tobit models. Tables 8 and 9 are the same as above issue.

respectively. On the right side of the equation, $Cov(a, \tilde{q})$ refers to the correlation between the core explanatory variable and the unobservable factor ($\tilde{q}$), and $Cov(a, x', \beta)$ refers to the correlation between the core explanatory variable and the observable factor. The smaller the difference between $\hat{\alpha}_{OLS,NC}$ and $\hat{\alpha}_{OLS,C}$ is, the stronger the explanatory ability of observable factors. The estimated coefficient of IGM can be interpreted as denoting causal effects if the adjustment of the control variable sets has little effect on the estimate. The larger the value of $\hat{\alpha}_{OLS,C}$ is, the greater the unobservable influence needed to change it. Since the main concern is the absolute coefficient difference, we apply the following:

$$Ratio = \left| \frac{\hat{\alpha}_{OLS,C}}{\left(\hat{\alpha}_{OLS,NC} - \hat{\alpha}_{OLS,C}\right)} \right| \tag{6}$$

It becomes apparent that as *Ratio* increases, unobservable factors will need to have more influence over observable factors to alter the consistency of the estimation results. In turn, this implies unobservable factors to have less impact on the research conclusion. First, we examine three types of limited sets: no control variables (none); only provincial fixed effects (provincial fe) as control variables; and the further inclusion of individual and family control variables (individual vars + family vars + provincial fe) as control variables. Subsequently, we consider two complete sets: the control variables in the benchmark model (Full) and a further control of GDP and the Gini coefficient (Full + GDP + Gini).

Ratio calculated under various circumstances is presented in Table 6. *Ratio* values range from 1.63 to 30.55, and the average value is approximately 9.48. These results indicate that omitting unobservable factors will not cause serious bias in the estimation results, as their influence is at least 1.63 times that of observable factors, with a mean of 9.48. Therefore, unobservable factors are unlikely to completely neutralize the effect of IGM on FEI.

Introducing an instrumental variable. We select the average of IGM in all other cities within the same province as the instrumental variable for IGM in a specific city. The feasibility of this instrumental variable is as follows. First, cities within the same province share similar cultural traditions, have close economic and social interactions, and implement similar policies in finance, education, and health care. As a result, there is likely to be a strong correlation between the levels of IGM among different cities. Second, the IGM in other cities can be considered relatively exogenous to the FEI in a specific city since IGM is a relatively abstract concept. Comparisons with residents may reveal the extent of IGM in education or the degree of equality of educational opportunities in a city. Moreover, FEI often has a neighborhood effect, which is greatly influenced by other families in the same community. Distance is associated with a lesser influence

Table 8 Heterogeneity analysis.

	(1) rural	(2) urban	(3) low cultural capital	(4) high cultural capital	(5) low economic capital	(6) high economic capital
VARIABLES	lnFEI	lnFEI	lnFEI	lnFEI	lnFEI	lnFEI
IGM	−1.268	−2.789***	−2.064	−3.863***	−2.335	−2.471*
	(2.027)	(1.027)	(1.284)	(0.979)	(1.618)	(1.387)
Individual vars	Yes	Yes	Yes	Yes	Yes	Yes
Family vars	Yes	Yes	Yes	Yes	Yes	Yes
City vars	Yes	Yes	Yes	Yes	Yes	Yes
Province fe	Yes	Yes	Yes	Yes	Yes	Yes
F statistic in the first stage	210.210	203.223	422.333	125.410	328.445	149.211
Observations	369	665	503	541	466	578
R-squared	0.143	0.086	0.096	0.201	0.120	0.108

Significance levels ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors clustered at the city level appeared in parentheses.

(Litian and Yubo, 2018). Therefore, the level of intergenerational mobility within a given city is unlikely to have a significant effect on investment in family education in that city.

Estimation is performed with both two-stage least squares (2SLS) and instrumental variable Tobit (IV Tobit) models. The estimation results are presented in Table 7. The results from the first stage indicate a negative correlation between the mean IGM of other cities within the same province, and the statistical value of F in the first stage is considerably higher than 10, demonstrating no weak instrumental variable problem. The negative correlation between IGM and the instrumental variables can be attributed to the disparities in the distribution of educational resources among different cities. The level of IGM in each city is influenced by the availability of educational resources within that city. As educational resources are competitive across cities, there exists an inverse relationship between the IGM in each city and the average IGM in other cities within the same province.

According to the overall regression results, the influence of IGM on FEI remains significant at the 5 percent level after the inclusion of the instrumental variables. According to the 2SLS model, the coefficient estimate value is −2.563, which is very similar to the OLS estimate value, and the coefficient estimate value for the IV Tobit model is also significantly negative. The results further demonstrate the robustness of the conclusions of this paper.

Heterogeneity. Several studies have consistently shown that family socioeconomic status (SES), which encompasses factors such as family economic capital, social capital, and cultural capital, plays a crucial role in shaping FEI. Higher SES families tend to invest more in family education (Slates et al., 2012). To capture these dimensions, this study uses two indicators, annual household income and the number of books owned by a family, categorizing the sample into high- and low-capital families based on the median values. Furthermore, China's unique urban-rural dual economic structure leads to disparities in educational development between urban and rural areas. Generally, urban areas have more educational resources, and families invest in their children's education through opportunities and capabilities. Thus, this paper also separates the samples based on household registration permits.

We use the same instrumental variable as in the previous section and the 2SLS method for heterogeneity analysis. From the results in Table 8, the influence of IGM on FEI is significant only in urban families and families with high economic and cultural capital.

In our view, this phenomenon reflects the presence of credit constraints from one side, meaning that families with low economic and social status are negatively affected by increased inequality. Conversely, an increase inequality will increase their expenditures on education. Likewise, for families with low socioeconomic status, the higher the degree of intergenerational mobility is, the greater the likelihood that their children will achieve more than their parents; therefore, these families will invest in the education of future generations. On the other hand, households with high socioeconomic status are typically less restricted by financial circumstances and may have lower incentives to invest. Due to the heterogeneity of these two factors in different families, the effect of intergenerational mobility on family education investment is significant only for families with high socioeconomic status.

This finding further highlights the significance of increasing intergenerational mobility. As an expensive activity, only families with a high level of economic and cultural capital invest in extracurricular tutoring (Becker and Tomes, 1986). Regarding rural families and families with low income and low cultural capital, who are subject to material conditions and the availability of educational resources, the proportion of these families participating in extracurricular activities is extremely low.

If intergenerational mobility declines, the education investment gap between families with high and low socioeconomic status will further widen, leading to a vicious cycle.

Mechanisms. What is the underlying reason for the reduction in FEI caused by IGM? We propose several possible mechanisms based on the literature. In the following section, we aim to validate these mechanisms through empirical research.

Degree of incentive. It is believed that equal opportunity refers to the fact that what an individual achieves is primarily due to his or her self-induced efforts. Consequently, in an environment where equal opportunities exist, individuals should have a stronger belief in their ability to succeed. We measure this incentive by examining the level of agreement with the statement "hard work can be rewarded" in the CFPS individual questionnaire. The answer ranges from 1 to 5. A higher value indicates a greater agreement with the idea of effort having a positive effect on outcomes. Using the answers provided by children's parents, we conduct a 2SLS regression to test whether children's parents are incentivized. Columns (1) and (2) in Table 9 show the results for the effect of IGM on the degree of incentive of children's mother and father, respectively. Addressing the endogeneity concerns using the instrumental variables, we find a significant positive effect of IGM on the incentives of fathers. This result suggests that increased equality of opportunity can indeed enhance confidence in achieving goals.

Table 9 Mechanisms.

	(1) 2SLS	(2) 2SLS	(3) IVPobit	(4) 2SLS	(5) 2SLS
VARIABLES	DIM	DIF	EEA	SSM	SSF
IGM	0.506	0.855*	−0.213*	0.389	−1.689*
	(0.556)	(0.472)	(0.128)	(0.537)	(0.925)
Individual vars	Yes	Yes	Yes	Yes	Yes
Family vars	Yes	Yes	Yes	Yes	Yes
City vars	Yes	Yes	Yes	Yes	Yes
Province fe	Yes	Yes	Yes	Yes	Yes
F statistic in the first stage	221.468	192.178	122.890	221.468	192.234
Observations	1041	861	751	1041	860
R-squared/ Pseudo R-squared	0.018	0.034		0.015	0.017

Significance levels ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors clustered at the city level appeared in parentheses.

The reason intergenerational mobility does not significantly affect the incentives of mothers is likely due to prevalent societal norms in China, where the notion of men being responsible for providing for the family and women being responsible for caregiving is more common. Fathers are typically more involved in social activities than mothers, which may contribute to a higher perception of intergenerational mobility among fathers than among mothers.

Excessive educational anxiety. A review of the international literature on school choice shows that the educational market can contribute to parents' excessive anxiety, leading them to invest significant energy and mental effort in selecting the right school (Cucchiara, 2013). Chen and Xiao (2014) pointed out that the purpose of education in China is regarded as competition for higher education. Parents who have excessive educational anxiety display several inappropriate educational behaviors to compete. One of these behaviors involves helping their children choose schools. This phenomenon is not limited to China and is also observed in developed countries such as the United Kingdom and the United States, where social transformation leads to uncertainty and risk for middle- and upper-class parents. A widely adopted strategy that parents use to alleviate the anxiety associated with the "fear of lagging " involves choosing schools for their children based on their class affiliations (Ball, 2003). Therefore, from an empirical perspective, this paper determines whether parents have excessive educational anxiety about their children as a result of school choice, which is inappropriate educational behavior.

Specifically, we utilize data from the 2018 CFPS child proxy questionnaire to investigate parents' educational anxiety, focusing on the following question: "Have you or your family paid fees or extra fees for this child to attend school?" Parents who answered "yes" were classified as having excessive educational anxiety, while those who responded "no" were considered to have ordinary educational anxiety. To represent this classification, we introduced a binary variable called EEA. As shown in Table 9, Column (3) presents the results from the IV probit model for estimating the impact of IGM on EEA. Based on the estimated coefficient of IGM, IGM can effectively alleviate parents' excessive educational anxiety.

Degree of status-seeking. To test whether the degree of status-seeking behavior might also contribute to the effect of IGM on FEI, we first need to measure the degree of status-seeking. According to aspiration level theory, the pursuit of wealth can be seen as a status-seeking behavior. This concept was proposed by Inglehart (1988) and Michalos (1991), and this behavior is primarily influenced by past income or consumption levels, as well as income comparison (Stutzer, 2004). The comparison of income has a significant impact on the development of the pursuit of wealth, which subsequently influences individual economic decisions and levels of well-being (Ferrer-i-Carbonell, 2005; Ball and Chernova, 2008). People's relative income status will change as a result of widening income disparity, strengthening their motivation to compare incomes and increasing their pursuit of wealth (Stark, 2006). Thus, the extent of status-seeking behavior can be reflected by a comparison of people's subjective evaluation of income to their actual income status.

In the CFPS individual self-report questionnaire, participants are asked to state their self-rated economic status based on the following: "What personal income bracket do you belong to locally?" The response scale ranges from 1 to 5, with 1 representing very low scores and 5 representing extremely high scores. The purpose of this question is to obtain information about parents' self-perceived income status. Furthermore, using the actual wage income of parents, we can accurately determine their economic status. Specifically, we rank the samples in a city based on their income levels from lowest to highest, and we then divide them into 10 groups with values of 1–10. Equation (7) calculates the difference between self-assessed and actual economic status. This value is used to measure an individual's desire for wealth. The larger the value is, the lower the self-assessed economic status is relative to actual economic status, denoting an individual's higher degree of status-seeking behavior.

$$\text{status seeking} = \frac{\text{actual economic status}}{\text{self}-\text{rated economic status}} \tag{7}$$

Therefore, we use the degree of parents' status-seeking behavior to regress on IGM. In Table 9, Columns (4) and (5) represent the results of 2SLS estimations, and the discussion of the IV is the same as that above. The estimated coefficient of IGM on the status-seeking degree of fathers is significantly negative, indicating that increased intergenerational mobility may result in fewer parents seeking status, reducing investment in their children's education. At the same time, the lack of impact of intergenerational mobility on the status-seeking degree of mothers also supports our conjecture in the previous Section 4.5.1.

Conclusions and discussion

Given the limited research on the relationship between macro-level opportunity inequality and micro-level family education investment, this study utilizes data from a Chinese population sample survey conducted in 2015 to calculate the intergenerational mobility of cities, and it uses the 2018 China Family Panel Studies survey to estimate family education investment. This study is one of the first to research the causal effects of intergenerational mobility on family education investment. Our empirical analysis employs multiple models and robustness tests. The results confirm our findings that intergenerational mobility has a negative effect on family education investment, indicating that inequality of opportunity increases family education investment.

According to our heterogeneity analysis of intergenerational mobility, the negative effect of intergenerational mobility is particularly prominent among urban families and families with significant economic or cultural capital. In other words, as intergenerational mobility increases, families with higher socioeconomic status tend to invest less in their children's education.

However, families with lower socioeconomic status are not affected by this trend, as they are more incentivized and may be subject to credit constraints. Furthermore, our mechanism analysis suggests that this effect is primarily driven by a decrease in parents' excessive educational anxiety and status-seeking behavior.

These findings are particularly important in light of the increasing inequality of opportunity and growing competition for educational resources. Recent changes to China's "Double Reduction" policy, aimed at reducing student burdens and extracurricular activities, underscore this issue. Several theoretical studies have argued that to fully realize the potential of this policy, it is crucial to not only address issues within the education system but also enhance equal opportunities for all students to succeed academically (Jin and Sun, 2022; Eryong, Li (2022); Zhang, 2022). Our research supports this view. Moreover, our findings show that households with high socioeconomic status tend to invest less in education when intergenerational mobility improves. On the other hand, families with low socioeconomic status often face credit constraints and suffer relative disadvantages when competing for educational resources. Therefore, increasing intergenerational mobility can help mitigate the widening gap in human capital among children from different backgrounds, creating a positive cycle. In light of these results, our research suggests that the Chinese government should increase public spending on education, more efficiently allocate resources for educational purposes, and reduce parental anxiety about education. These measures will aid in effectively implementing the "Double Reduction" policy and promoting intergenerational mobility.

Our main findings are different from those of Wen and Witteveen (2021), who believe that people will increase their investment in education when they feel a higher degree of intergenerational mobility. Notably, however, the independent variables and dependent variables used by Wen and Witteveen (2021) are based on people's subjective feelings, and only OLS regression and quantile regression are used for analysis, which may have endogeneity problems such as measurement error and reverse causality. In this paper, the independent variable, the intergenerational mobility level, and the dependent variable, family extracurricular tutoring expenditure, are both objective data, and the measurement of the independent variable is earlier than that of the dependent variable at the regional level and in terms of the year. In addition, based on OLS regression, the instrumental variable is further used for 2SLS regression, which better alleviates the endogeneity problem. The conclusion can better represent the causal effect of intergenerational mobility level on education investment. Finally, Wen and Witteveen's (2021) explanation of how intergenerational mobility affects education investment considers only the incentive effect of equal opportunity, while this paper also explores the impact of other mechanisms, such as status-seeking and educational anxiety, which means that his study is more comprehensive.

However, this paper still has several limitations. First, although we have enriched our understanding of the mechanisms through which intergenerational mobility affects household education investment from different perspectives, such as status-seeking and educational anxiety, there may still be other potential impact mechanisms, such as the rate of return on education and family income. Second, due to data limitations, we used only cross-sectional data for our analysis. In future studies, researchers can further use panel data and combine fixed effect models to better alleviate endogeneity issues. Finally, our study found that increasing intergenerational mobility can alleviate the fierce competition for extracurricular education in Chinese families. However, with the increasingly serious issue of class rigidity, how to effectively promote intergenerational mobility still needs further research.

Data availability

The data that support the findings of this study are available from China Family Panel Studies but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of China Family Panel Studies.

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