The Return Rate Trend and Professional Heterogeneity of Higher Education in China

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Abstract: Existing research has examined the trends and heterogeneity of educational returns since China's economic reforms, but these studies have not integrated the two. Therefore, we focus on the development of higher education in China, combining the trends in educational returns with the heterogeneity of returns for different majors to explore three questions: 1) Using the latest cross-sectional data from `CGSS2018` and `CGSS2021`, we aim to explore the latest trends in the returns of higher education in China. 2) By using data on major selection and salary, we aim to explore the heterogeneity of educational returns across different majors, considering classic factors such as gender and region. 3) We aim to explore the heterogeneity in the trends of educational returns across different majors.

Key words: Education and Labor Economics, Return on Education, Specialization Heterogeneity, Propensity Score Matching

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1 Research Motivation

Theoretically, this study focuses on **the development of higher education in China, innovatively combining the analysis of trends in higher education returns with the heterogeneity of educational returns for major choices**. It aims to address three core issues: first, using the latest cross-sectional data from the `CGSS2018` and `CGSS2021` surveys, it dynamically tracks the evolving trends in higher education returns in China; second, by integrating data on major choices and salaries, it explores the heterogeneity of educational returns across different major categories, considering classic influencing factors such as gender and region; third, it analyzes the differences in the trends of educational returns across various major categories, revealing the underlying mechanisms and theoretical logic, thus providing new theoretical perspectives and analytical frameworks for research in the field of higher education economics.

At the empirical level, this study adopts the latest cross-sectional data of `CGSS2018` and `CGSS2021` to make up for the lack of timeliness in previous studies, realize the continuous and dynamic tracking of China's higher education return rate, provide more timely and accurate empirical basis for the academic community, and promote the further development of related research.

At the policy level, this study provides scientific guidance for students 'major selection by systematically analyzing the heterogeneity of returns from different majors. It guides students to choose majors and directions that align with national strategic needs, thereby maximizing their personal returns. Additionally, it aims to cultivate high-quality professionals for the 'Smart Manufacturing China' strategy, supporting the country's industrial upgrading and high-quality development, thus combining theoretical value with practical significance.

2 Literature Review

2.1 The Source of Education's Returns

Zhuo Guodong et al. (2024) analyzed the sources of economic returns of education from three perspectives.

They highlight that labor economics emphasizes **the role of education in enhancing individual human capital**. Through education, individuals can enhance their professional skills, better aligning with the demands of their careers. In the labor market, those with higher education levels often hold more advantageous positions, leading to greater economic rewards (Mincer, 1974; Harmon et al., 2003; Becker, 2009). Therefore, receiving quality education is often seen as a key path to escaping poverty and increasing income (Zhang Wenhong, 2023). Moreover, the improvement of individual human capital through education extends beyond specific professional skills to include non-cognitive abilities such as social skills and self-esteem (Manyu, 2017). Consequently, compared to vocational education, higher education has a more significant impact on boosting individual income. In different market environments, the labor selection mechanisms vary. In fully developed labor markets, there is a preference for 'appointing people based on talent' rather than 'appointing people based on personal connections.' Thus, during the transition from traditional socialist systems to market economies, the economic benefits of education have become increasingly evident (Nee, 1989).

Bourdieu (1998) argues from **the perspective of cultural capital that family background and other pre-given factors significantly influence an individual's educational opportunities and the extent to which they can benefit from their education**. Higher social classes not only invest more economic and cultural resources to ensure their children receive higher-quality education but also facilitate higher education and the acquisition of relevant diplomas, thereby forming a method of intergenerational transmission of cultural capital (Blau and Duncan, 1967). This process also involves a series of social rituals that transmit cultural symbols, gain class identity, and reinforce the existing social order (Nash, 1990). As a result, those who receive higher education are more likely to be accepted by higher social classes and gain a dominant position in the distribution of power and capital.

Some studies have explored **the endogeneity of educational returns from the perspective of sample selection**. This perspective suggests that individuals with higher education levels possess superior conditions and capabilities, which give them a natural advantage in market competition, leading to substantial economic rewards (Kenny et al., 1979; Heckman and Li, 2004; Gunderson and Oreopoulos, 2020). Quantifiable individual factors, such as IQ, act as confounding variables between educational attainment and economic income, leading to statistically spurious correlations (Ji Guodong and Chen Yunsong, 2022). In reality, an individual's educational level is merely a proxy for these capabilities and resources, and does not have a strong causal relationship with economic income.

The three perspectives mentioned above are not mutually exclusive; **they may interact to varying degrees and in different forms**. For instance, the 'signaling theory' in economics posits that academic qualifications and diplomas are seen as indicators of stronger capabilities in the market, which can lead to greater economic rewards (Riley, 1979; Li Fengliang et al., 2008). This perspective integrates both cultural capital and sample selection mechanisms.

2.2 Discussion on the Trend of Educational Returns in China

The methods for studying the returns to education primarily fall into four categories.

The first is **the classic application and extension of the Mincer income equation** (Mincer, 1974), which uses individual income (logarithmic) as the dependent variable and educational level and years of work experience as the core independent variables. This equation forms the foundational framework for research on the returns to education. Current studies have expanded this framework by incorporating multiple dimensions, such as gender, urban-rural differences, the nature of the employer, and relative educational status, to analyze their correlation with the returns to education and their interactions (Li Chunling, 2003; Li Fengliang et al., 2008). For example, urban-rural disparities can lead to a differentiation in the returns to education within the labor market, with urban residents typically enjoying a higher educational premium compared to rural residents.

Second, **the exploration of causal inference through quasi-experimental methods**: By employing techniques such as breakpoint regression, propensity score matching, and instrumental variables, researchers aim to identify the causal relationship between education and income, while controlling for confounding factors like ability. Based on policy impacts such as the implementation of the Compulsory Education Law in 1986 and the expansion of university enrollment in 1999, researchers used breakpoint regression to examine the economic returns associated with different levels of education. For instance, Liu Shenglong et al. (2016) found that the Compulsory Education Law significantly increased individual years of education, with an educational return rate of 12.8%, and higher returns for high-income groups, which supports the 'Matthew effect.'

The third aspect involves **a multi-dimensional analysis of the impact of heterogeneity**: it focuses on how individual attributes influence the differential returns to education, controlling for proxy variables of individual ability (such as place of birth and type of employment). Li Xuesong and Heckman (2004) found that the place of birth and the nature of employment significantly affect the economic returns from education. Jian Bixi and Ning Guangjie (2013) used propensity score matching to confirm that there are sample biases in the returns between high school and college graduates, as well as between urban and rural birth cohorts.

The fourth aspect involves **a long-term tracking of the trend of longitudinal changes, by integrating data from multiple surveys to reveal the dynamic evolution of educational returns**: After the restoration of the college entrance examination in 1977, the size of the higher education population gradually expanded, and this process accelerated with the expansion of enrollment in 1999. In the early stages of reform and opening up (the 1980s), there was a phenomenon known as 'the inversion of brain and body' (Li Chunling, 2003), but after the 1990s, educational returns significantly improved:

Li Shi and Ding Sai (2003) analyzed data from 1995 to 1999 and found that the educational returns for urban residents continued to rise, with the return on higher education significantly outpacing other levels of education.

However, the income growth from primary and lower education stagnated. He Yiming (2009), using data from the China Health and Nutrition Survey (CHNS) from 1991 to 2006, noted that the 'brain-body inversion' in the early 1990s was reversed, with education levels positively correlating with income. However, the return on higher education stagnated from 2004 to 2006. Liu Zeyun (2015) analyzed data from 1988 to 2007 and found that the return on higher education increased more slowly after 2002.However, after adjusting for factors such as the education level of spouses using instrumental variables, the increase remained consistent with earlier periods. The stagnation observed in the linear regression was mainly due to women and younger groups.

The dynamic evolution of the return on education has been characterized by two phases: a period of phased growth and structural differentiation. From 1988 to 2002, with economic reforms, the return on education for urban residents rose rapidly (Chen Chunjin et al., 2013), particularly in higher education. For instance, Zhang Weiwei et al. (2014) found through MLE estimation that the return on university education increased significantly from 1992 to 2000, followed by a slight increase from 2000 to 2009, with significant heterogeneity in the sample data —— groups more likely to attend university saw higher returns on education. After 2002, the growth rate of higher education returns slowed and even fluctuated. Yuan Yuan and Zhang Wenhong (2023) found that the income returns for the 'post-80s' and 'post-90s' generations in higher education were lower than those of the '60s and 70s' generations, showing a 'U-shaped' trend with the lowest returns around 2013. Wang Jun (2016) analyzed the CHNS data from 1989 to 2011 and found that the overall trend of higher education returns was upward but with fluctuations.

There are group differences and income distribution effects in the returns to education. The gender gap has shown a trend of narrowing over time. According to Chen Chunjin et al. (2013), the gender gap in educational returns has gradually decreased since 2002, but disparities among occupational classes, ownership sectors, and regions remain fluctuating. The educational premium is more pronounced among high-income groups. Zhang Chi et al. (2016) noted that after 2012, the overall return on education increased, but high-income groups benefited significantly more from higher education, indicating that the expansion of higher education has not effectively reduced income disparities. Liu Shenglong et al. (2016) also confirmed that high-income groups have higher returns on education compared to low-income groups, exacerbating the 'Matthew effect' in income distribution.

Secondly, the policy impact and the transformation of the return model have influenced the structure of returns due to the expansion of university enrollment. Guo Ran and Zhou Hao (2020) analyzed CGSS data from 2003 to 2015 and found that, after controlling for the probability of obtaining higher education, the expansion of enrollment shifted the educational returns from favoring the lower-middle class to being significantly beneficial only to the middle class, forming an 'inverted U' pattern. This means that in the early stages of enrollment expansion, the lower-middle class could improve their returns through higher education, but as education became more widespread, the benefits of higher education concentrated among the middle class.

2.3 Discussion on the Heterogeneity of Education Return Rate

2.3.1 Professional Heterogeneity of Educational Returns

Hu Dexin et al. (2024) found, based on the principles of quality function deployment, rational choice assumptions, and related research findings, that the material and non-material educational returns for engineering majors are significantly higher than those for other majors. This is closely linked to the inherent characteristics of engineering majors and the evolving external environment in recent years. Engineering majors have promising employment prospects and development trends, high social status, and competitive salaries, providing engineering students with excellent career opportunities and rewards.

2.3.2 University-level Heterogeneity of Educational Returns

Zhou Yang et al. (2020) used data from the China Family Panel Studies to investigate the heterogeneous income returns and their classification mechanisms in the context of higher education expansion. They found that during the pre-expansion elite phase, there was no significant difference in income returns between key universities and non-key universities, both significantly higher than those from high school education. Upon entering higher education, students would see higher returns, known as "threshold" returns. However, in the post-expansion mass education phase, key universities had significantly higher income returns compared to non-key universities, while non-key universities showed no significant difference in income returns from high school education. At this stage, the income return differences within higher education were greater than the differences between the university and high school stages, known as "elite maintenance" returns.

2.3.3 Heterogeneity of Education Return Rate Between Urban and Rural Areas

Xing Chunbing et al. (2021) used data from five rounds of the China Household Income Survey (CHIS) between 1995 and 2018 to calculate the educational returns in urban and rural areas, examining the differences and trends in these returns across regions. They found that when migrant workers and those who permanently moved to cities were reclassified as rural residents, the educational returns in rural areas significantly increased. Regarding regional differences in educational returns, economically developed provinces had higher returns, and the disparities in urban areas were narrowing, although inter-provincial differences in rural areas remained significant. When the migrant samples were reintegrated, the inter-provincial differences in rural educational returns further increased. If the examination is based on prefecture-level cities, the educational returns in urban and rural areas of different prefecture-level cities showed a gradual dispersion, indicating that regional differences in educational returns are more pronounced between cities than between provinces.

Chu Shuai et al. (2017) used data from the China Household Income Survey (2007 and 2013) to analyze the impact of the university expansion policy implemented in 1999 on the years of education, income, and educational returns for urban and rural residents using a breakpoint regression design. The results indicate: First, the implementation of the university expansion policy increased the average years of education for both rural and urban residents, with the increase being higher for urban residents than for rural ones. Second, under the breakpoint regression design, the educational returns for both rural and urban residents were higher than those estimated by Ordinary Least Squares (OLS). Empirical findings show that there is no Matthew effect in educational returns between urban and rural areas. Third, the university expansion policy significantly boosted the educational returns of low-income urban residents, effectively curbing the ”Matthew effect” that could have led to a widening income gap among urban residents. On the other hand, it also increased the educational returns for high-income rural residents compared to those of low-income residents, contributing to the ”Matthew effect” that could have widened the income gap in rural areas.

2.3.4 Family Background Heterogeneity of Educational Return Rate

Zhang Shiwei et al. (2008) noted that family background significantly influences individual income, and overlooking the educational background of the family can lead to an overestimation of the educational returns for individuals. As individuals ”education levels rise, the impact of their family”s educational background on their educational returns increases; compared to the father”s educational background, the mother”s educational background has a more significant impact on personal educational returns. As parents ”education levels improve, their positive influence on personal income also increases; compared to the father”s educational background, the mother”s educational background has a more significant impact on personal income. Therefore, investing in education not only boosts the income of workers but also positively impacts the income of their children.

2.3.5 Combination of Major Selection and Family Background

Yang Shuai et al. (2022) used cross-sectional data from the `CGSS2003` and `CGSS2000` surveys to examine the impact of family background on major choices from a rational choice perspective. They further explored how differences in family background influence major choices through the mechanism of professional diversion and income returns. The study found that family background primarily influences major choices through two aspects: ”resources” and ”preferences”. On one hand, individuals from better-off families have more advantages in their major choices and a wider range of options. On the other hand, they tend to prefer applied majors like finance and engineering, while those from less affluent backgrounds are more likely to choose foundational majors such as humanities, social sciences, and science, leading to a certain degree of professional stratification. Additionally, the study found that different majors have varying income returns, with finance and engineering majors offering higher returns compared to humanities and social sciences majors. Therefore, individuals from better-off families leverage their resource advantages and personal preferences to enter higher-income applied majors, thereby achieving the intergenerational transmission of advantages.

2.3.6 Gender and Age Heterogeneity of Education Returns

Ge Yuhao (2007) used a partial linear model to investigate the heterogeneity of educational returns, concluding that: women have higher educational returns than men; the older one gets, the lower the educational returns tend to be; female vocational education yields higher returns than high school education; young women have higher returns from junior high school, while young men have lower returns from the same stage.

Furthermore, Zhang Yongli et al. (2018) used propensity score matching to analyze the educational returns of rural male and female labor forces in 15 impoverished villages in Gansu Province in 2017. The study found that education in impoverished areas has a strong income effect and a significant intergenerational transmission effect. Specifically, women"s education levels have a significant positive impact on their children"s high school and college education. There is a notable gender gap in the returns from education in impoverished areas, with women receiving significantly higher returns for junior high school, high school, and college education compared to men, while they receive significantly lower returns for primary school education. Both genders achieve the highest returns during high school. Some capable workers have the potential to earn higher incomes but do not pursue higher-level, better-quality education, a phenomenon more prevalent among female workers.

2.3.7 Heterogeneity of Educational Returns by Degree

Based on the data from the China Health and Nutrition Survey (CHNS) in 1997 and 2006, Jian Bixi et al. (2013) used propensity score matching to estimate the educational returns for high school and university education in China over two decades, taking into account selection bias and individual heterogeneity. They found significant differences among individuals; the average returns for all educational stages over the decade were significantly higher; the annual return for high school was consistently higher than that for university, and there was a trend toward narrowing the policy effect gap in university education.

2.4 Identify Gaps and Our Study

From the previous summary, we can see that existing research has examined the trends and heterogeneity of educational returns since China's economic reforms, but these studies have not integrated both aspects. Therefore, we focus on the development of higher education in China, combining the trends in educational returns with the heterogeneity of returns for different majors to explore three questions: 1) Using the latest cross-sectional data from `CGSS2018` and `CGSS2021`, we aim to explore the latest trends in the returns of higher education in China. 2) By using data on major choices and salaries, we aim to explore the heterogeneity of educational returns across different majors, considering classic factors such as gender and region. 3) We aim to explore the heterogeneity in the trends of educational returns across different majors.

3 Research Methodology and Key Challenges

3.1 The Mincer Equation Extension (Heterogeneity of Returns to Education Across Majors)

From the previous review, we understand that both Ordinary Least Squares (OLS) and Instrumental Variables (IV) methods can introduce biases. Specifically, OLS tends to underestimate the returns to education, while IV tends to overestimate them. To address these biases, existing literature employs methods such as propensity score matching, breakpoint regression using exogenous policy shocks, logit regression, and Tobit truncation models.

$$
\begin{aligned}
lnY_i = \beta_0 + \beta_1 Year_i + \beta_2 Major_i + \beta_3 Edu + \beta_4 Year_i \times Edu_i \\
+ \beta_5 Major_i \times Year_i \times Edu_i + \beta_6 Exp + \beta_7 Exp^2 + Controls_i + u_i
\end{aligned}
$$

The two surveys we studied did not cover a sufficiently broad range of exogenous policy shocks, thus the design of breakpoint regression can be ruled out. We will use the logit model from the Mincer equation as the baseline regression and gradually add control variables and interaction terms to capture trend heterogeneity. Finally, we will attempt to further our research using propensity score matching. This approach fully leverages the effectiveness of quasi-experiments while also addressing their limitations.

Table 1: Variable Description and Processing Specifications

Var	Calculation	Description
Dependent Variable		
`income`	2021 income deflated by 2018 CPI	Real income adjusted by price index
Independent Variables		
`Year`	$2021 = 1$, $2018 = 0$	Survey year dummy variable
`Major`	Categorical variable	Major category: Arts, Science, Engineering, Economics, Others
`Edu`	$A7c(graduation\ year) - A3\_1(birth\ year) - 6$	Years of education (calculation logic)
`Exp`	$\max\{0, \min\{\text{Age} - 6 - \text{Edu}, 60\}\}$	Potential work experience (calculation logic: Age - years of education - 6, capped at 60)
Control Variables		
`high_school_type`	1 if key high school	Whether the high school is a key school (binary variable)
`female`	1 if female	Gender (binary variable)
`ethnic`	1 if Han Chinese	Ethnicity (binary variable)
`health`	Categorical variable	Health level (1-5, higher value indicates better health)
`hukou`	1 if usual residence at age 14 was urban	Household registration type (binary variable)
`happiness`	1-5 integer	Happiness (higher value indicates greater happiness)
`edu_level`	Categorical variable	Education level (original variable)
`age`	$Survey\ year - A3\_1(birth\ year)$	Age (calculated from birth year)
`party_member`	1 if Party member	Whether a Party member (binary variable)
`college_level`	1 if central or provincial university	Type of university (binary variable)
`parental_education`	Father's education level (mother's if missing)	Parental educational background
`parental_class`	Father's occupational class (mother's if missing)	Occupational class classification based on Goldthorpe framework (5 categories)
`major_category`	Categorical variable	Major category (original variable)
`research_year`	2018/2021	Survey year identifier

4 Data Sources and Types

The data we study comes from the **China General Social Survey (CGSS)**, which represents a continuous cross-sectional social survey in China. Through annual survey data, it provides a comprehensive and systematic description and analysis of Chinese society, revealing changes in various aspects such as the economy, politics, society, and culture, as well as trends in institutional, structural, behavioral, and attitudinal development at different levels. It also reveals changes in the relative status, roles, and perceptions of social members and groups, and describes and analyzes the actual conditions of Chinese social strata and various social groups. CGSS uses historical and internationally standardized data to promote longitudinal and cross-national comparative studies. Additionally, CGSS promotes the openness and sharing of basic data for scientific research in China, fostering a data-driven empirical research model and providing high-quality basic data resources for scientific research, teaching, and policy-making.

This dataset is based on households and includes all key variables we need, such as university major choices, which are relatively difficult to find. However, as it is cross-sectional data, there may be some

Table 2: Main Identification Challenges in the Model

Challenge	**Cause**	**Impact on Estimation**
Endogeneity of Educational Attainment	Unobserved ability (e.g., cognitive skills) or family background correlated with both Edu and lnY; potential reverse causality (higher income enabling further education)	β_3 (education return) biased; interaction terms (β_4, β_5) may reflect ability premium rather than true educational effect
Measurement Error in Income	Self-reported income in CGSS subject to underreporting (e.g., tax avoidance) or recall bias; CPI deflation may not fully adjust for regional price differences	Attenuation bias in all coefficients; inconsistent estimation of real income elasticity
Multicollinearity in Interaction Terms	High correlation between $Year_i \times Edu_i$ and $Major_i \times Year_i \times Edu_i$, especially when major categories have different educational distributions over time	Inflated standard errors; unstable coefficient estimates for interaction terms; difficulty in interpreting marginal effects
Sample Selection Bias	CGSS sampling may underrepresent certain populations (e.g., migrant workers, self-employed) with distinct educational attainment and income patterns	Non-representative parameter estimates; biased conclusions about heterogeneous returns across majors
Functional Form Misspecification	Assumption of linear additive effects for Exp and Exp^2 may not capture true experience-income profile; potential need for higher-order polynomials or splines	Inconsistent estimation of experience returns; omitted variable bias through misspecified functional form
Heteroskedasticity and Serial Correlation	Income variance likely increasing with education level; possible temporal correlation in unobserved shocks across 2018-2021 waves	Inefficient estimates; invalid standard errors leading to incorrect inference
Policy Endogeneity in Year Effects	Educational policies (e.g., university enrollment expansion) or economic reforms between 2018-2021 may be correlated with $Year_i$ and Edu_i	$Year_i$ coefficient capturing policy effects rather than pure time trends; biased estimation of return trends
Ambiguity in Major Categorization	"Arts/Science/Engineering" classifications may aggregate heterogeneous disciplines; "Other" category lacking clear definition	Misclassification of majors; biased estimates of major-specific return differentials

potential errors, and the lack of specific surveys for individuals with higher education levels results in an unsatisfactory sample size. In terms of data type, it is continuous cross-sectional data.

The data requires basic processing: first, review the questionnaire instructions, construct the required variables using the questionnaire information, and then screen out the necessary fields. For the missing values that cannot be made up, we use the direct deletion method to deal with them; for the missing values of numerical type, we use linear interpolation or fill the average value method; for the extreme outliers, we delete them.

5 Basic Data Description

5.1 Fundamental Statistical Information

Table 3: Summary Statistics of Processed Dataset (N=2,219)

Variable	Missing	Min	1st Qu.	Median	Mean	Max
`income`	0	0	30,000	60,000	104,638	9,999,996
`happiness`	0	1.000	4.000	4.000	4.064	5.000
`high_school_type`	0	0.000	0.000	1.000	0.558	1.000
`age`	0	18.00	27.00	35.00	37.80	94.00
`ethnicity`	0	0.000	1.000	1.000	0.945	1.000
`health`	0	1.000	4.000	4.000	3.994	5.000
`residence_14`	0	0.000	0.000	1.000	0.564	1.000
`party_member`	0	0.000	0.000	0.000	0.273	1.000
`college_level`	0	0.000	0.000	0.000	0.477	1.000
`female`	0	0.000	0.000	0.000	0.481	1.000
`education_year`	0	0.00	15.00	17.00	18.38	47.00
`research_year`	0	2018	2018	2018	2019	2021

Notes:

- All variables show complete cases with zero missing values
- Monetary values in original units (yuan), note extremely high maximum income value
- Binary variables (0-1): `high_school_type`, `ethnicity`, `residence_14`, `party_member`, `college_level`, `female`
- Ordinal scales: `happiness` (1-5), `health` (1-5)
- `education_year` range (0-47) includes non-traditional education paths
- Categorical variables (`edu_level`, `parental_education`, `parental_class`, `major_category`) excluded from numerical summary
- Age distribution shows right skew (median 35 < mean 37.8)

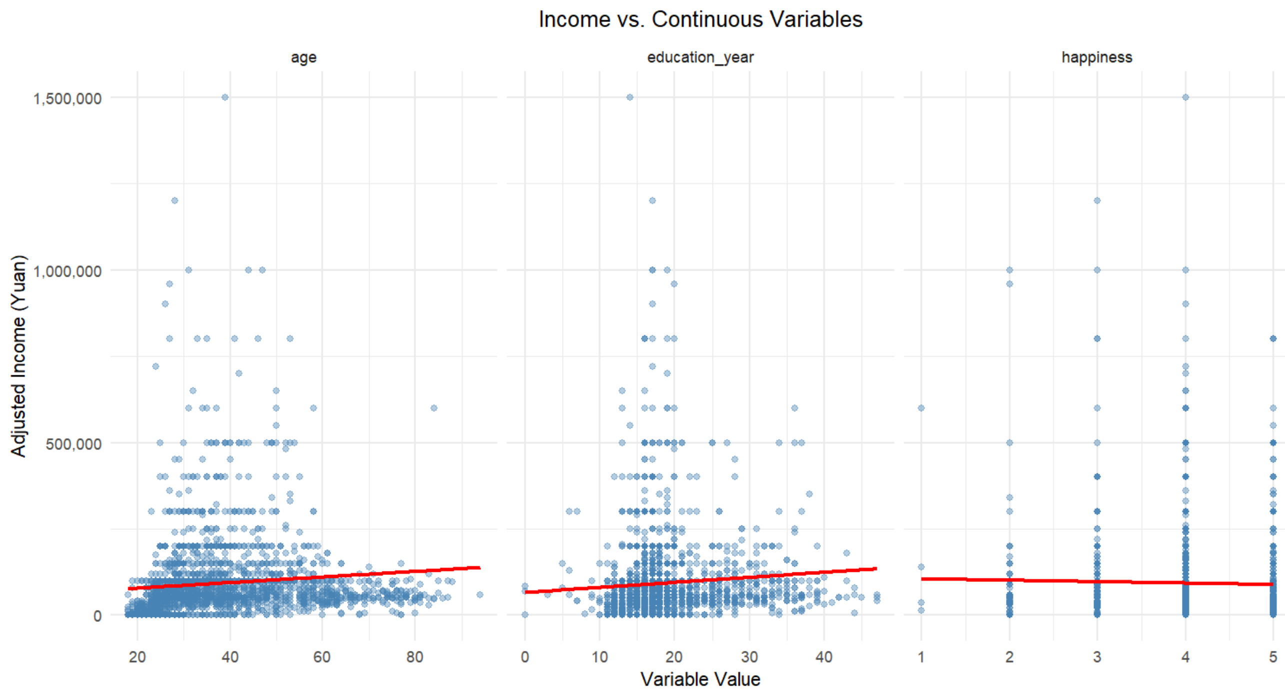
5.2 Conduct Mean Difference Analysis Between Groups

Table 4: Analysis of Income Differences by Major Category and Control Variables

Variable	Category	N	Mean Income	Mean Log Income	F-statistic	p-value
Major Category	Science	177	112,773	9.97	6.09	<0.001
	Engineering	533	104,491	9.85		
	Business/Econ	705	96,563	9.81		
	Humanities	588	80,837	9.72		
	Other	48	74,792	10.00		
	Medical	168	62,257	8.35		
Gender	Male	1,152	109,898	10.10	54.4	<0.001
	Female	1,067	73,768	9.24		
Education Level	Postgraduate	169	168,921	10.10	20.7	<0.001
	Adult Bachelor	278	98,460	10.70		
	Regular Bachelor	945	94,942	9.25		
	Adult Associate	284	76,199	10.20		
	Regular Associate	523	70,227	9.59		
	Technical School	20	65,170	9.75		
Significant control variables ($p < 0.05$):						
Party Member	No	1,614	85,948	9.27	19.0	<0.001
	Yes	605	110,070	10.80		
College Level	No	1,160	81,950	9.69	20.1	<0.001
	Yes	1,059	104,109	9.72		
Residence at 14	Rural	968	85,616	9.51	6.03	0.014
	Urban	1,251	97,871	9.85		
High School Type	Vocational	982	86,836	9.90	4.19	0.041
	Academic	1,237	97,041	9.54		

Notes:

- Income values in Chinese Yuan (¥). Mean income calculated after extreme value treatment
- Science majors earn 81% more than Medical majors (¥112,773 vs ¥62,257)
- Gender income gap: Males earn 49% more than females (¥109,898 vs ¥73,768)
- Postgraduates earn 2.4× more than technical school graduates
- Party members earn 28% more than non-members
- Complete ANOVA results available in supplementary materials
- Non-significant variables: Ethnicity (p=0.216), Health (p=0.089), Parental Class (p=0.336)

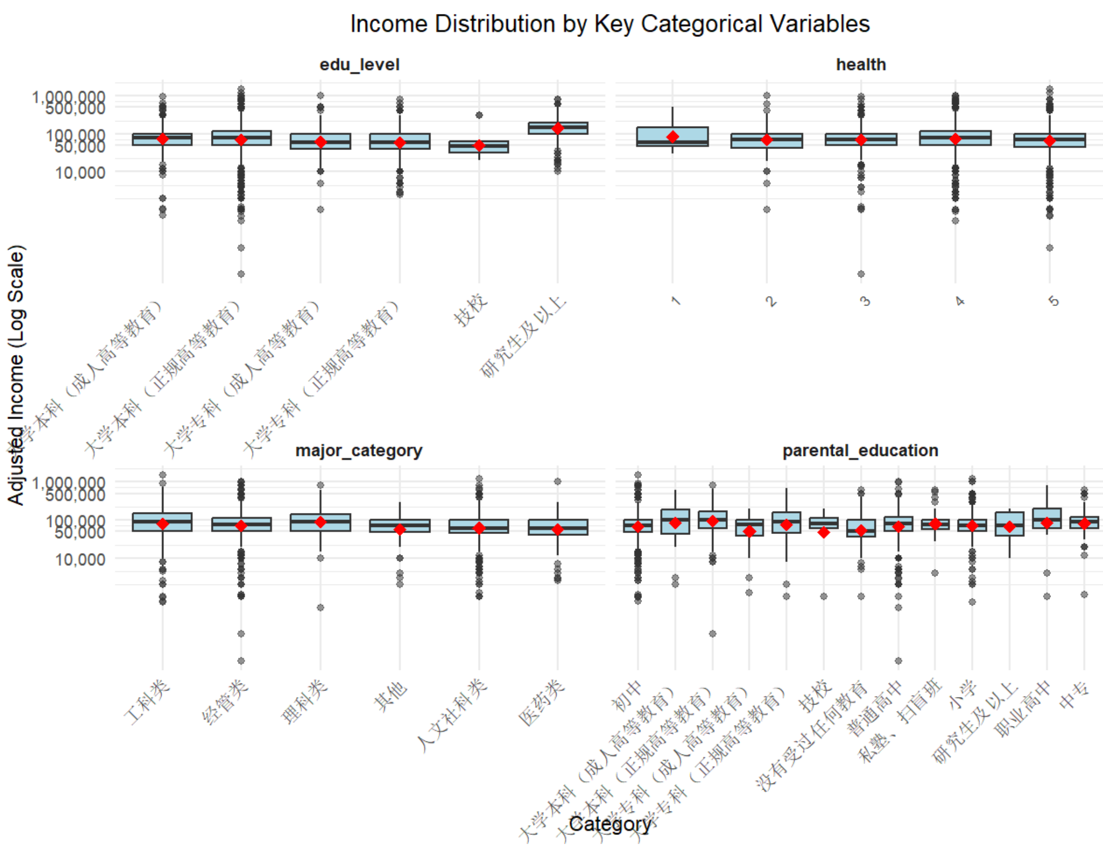


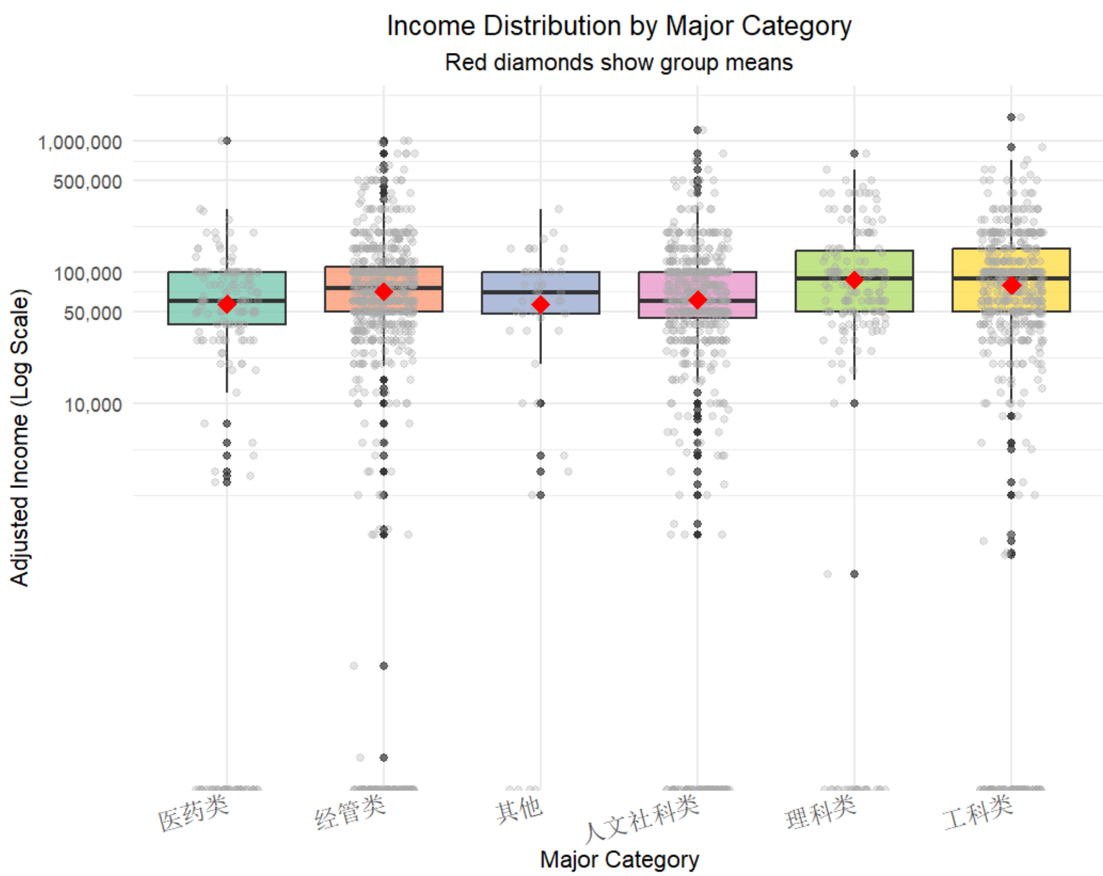
6 Expected Results

- The return rate of higher education tends to decline, that is, with the increase of graduation year, the real income under the same conditions decreases.
- There is professional heterogeneity in the return rate of higher education, that is, the return rate of education in each major category has a downward trend, but the degree of flattening is: engineering majors < economic and management majors < science majors < liberal arts majors.

Our research addresses the current gaps in the study of higher education returns, which have not integrated the trends and heterogeneity of these returns. This gap is particularly significant for guiding professional choices and national talent needs. If our findings are confirmed, they will assist the government in formulating educational training plans to improve the return on investment for college students. Additionally, by adjusting the heterogeneity of returns across different majors, we can better align university major selections with national strategies and the demand for specialized talents.

Potential limitations: there must be unobservable omitted variable bias, which can be improved by matching and instrumental variable regression results; secondly, the sample size and research time are not large enough, so we can expect the subsequent CGSS data.


Income Distribution by Key Categorical Variables
edu_level
health
major_category
parental_education
Adjusted Income (Log Scale)
1,000,000
500,000
100,000
50,000
10,000
大学本科（成人高等教育）
大学本科（正规高等教育）
大学专科（成人高等教育）
大学专科（正规高等教育）
技校
研究生及以上
1
2
3
4
5
工科类
经管类
理科类
其他
人文社科类
医药类
初中
大学本科（成人高等教育）
大学本科（正规高等教育）
大学专科（成人高等教育）
大学专科（正规高等教育）
技校
没有受过任何教育
普通高中
私塾、扫盲班
小学
研究生及以上
职业高中
中专
Category



Income Distribution by Major Category
Red diamonds show group means
Adjusted Income (Log Scale)
1,000,000
500,000
100,000
50,000
10,000
医药类
经管类
其他
人文社科类
理科类
工科类
Major Category