Return to Education and Education Mismatch in China

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I want to dedicate this thesis to my beloved parents, grandparents and friends.

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Summary

This thesis examines the connection between education and individuals' wages using China Family Panel Studies (CFPS) data, a national representative dataset provided by Peking University.

In Chapter 3, we estimate the return to education in China using the Mincer (1974) wage equation. Most of the previous studies only focus on urban China, but we conduct a regional comparison of returns between urban and rural areas in our analysis. Significant and positive returns to education are found for all the waged workers in the Chinese labour market. The return to urban workers is 4.6%, which is 2.1% higher than that for rural workers, and the gap is tested to be highly significant under the OLS method. However, the urban/rural gap is largely moderated after controlling for the sample selection bias among rural workers.

In Chapter 4, we examine the over-education condition for Chinese graduates doing waged jobs based on the fast expansion of Chinese higher education in recent decades. The over-education is defined as an individual's obtained education level exceeding the job requirement. We find up to 40% of graduate workers in China are over-educated, and these individuals would suffer from a wage penalty from 17.9% to 26.7% across different measures of over-education, estimated from a revised Verdugo and Verdugo (1989) model. In addition, the effect of over-education on wages cannot be explained mainly by individuals' skills heterogeneity.

In Chapter 5, we further examine the various returns to education qualities and subjects for graduate workers to test whether the assumption of a homogeneous return to colleges is still satisfied in the Chinese labour market. It is estimated that graduates from key and ordinary universities enjoy significant wage premiums to those in colleges, with 39.3% and 14.0%, respectively. However, significant disparities in wages between different subject groups are not found.

Table of Contents

List of Tables

List of Tables

List of Figures

List of Abbreviations

ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CCSS	China College Social Survey
CFPS	China Family Panel Studies
CGSS	China General Social Survey
CHNS	China Health and Nutrition Survey
CHFS	China Household Finance Survey
CHIP	China Household Income Project
CIA	Conditional Independence Assumption
COVID	Coronavirus Disease
COMB	Combined Degrees with More than One Subjects
CUHS	China Urban Household Survey
DWH	Durbin - Wu - Hausman
EU	European Union
FFM	Functional Form Miss-specification
GDP	Gross Domestic Product
GPA	Grade Point Average
HEI	Higher Education Institution
ISCO	International Standard Classification of Occupations
IQ	Intelligence Quotient
IRR	Internal Rate of Return
IV	Instrument Variable
LM	Lagrange Multiplier
LFS	Labour Force Surveys
LATE	Local Average Treatment Effect
LEM	Law, Economics and Management
MSB	Mean Absolute Standard Bias
MP	Madhya Pradesh
NBS	National Bureau of Statistics
NPSS	National Population Sample Survey
ORU	Over-Required-Under
OECD	Organisation for Economic Co-operation and Development
PSM	Propensity Score Matching
PhD	Doctor if Philosophy
PIAAC	Programme for the International Assessment of Adult Competencies
PCA	Principal Component Analysis
PGCE	Postgraduate Certificate in Education
QLFS	Quarterly Labour Force Survey
USR/FDS	Record/First Destination Surveys

List of Abbreviations

STEP	Skills Towards Employability and Productivity
STEM	Science, Technology, Engineering, Mathematics and Medicine
SUR	Seemingly Uncorrelated Regression
SY	Stock and Yogo
SSAH	Social Science, Arts, Humanities including Languages
TN	Tamil Nadu
UK	United Kingdom
USU	Urban Survey Unit
US	United States
V&V	Verdugo & Verdugo
WTO	World Trade Organization

Chapter1 General Introduction

1.1 Introduction, Motivations and Research Questions

The wage differences in labour markets are focused extensively by labour economics, and there is a long history of several researchers who would like to find a method to explain the observed wage disparities. Education is considered the main source of individuals' human capital achievements, which would increase individuals' efficiency and marginal products in the job markets. In recent decades, an increasing number of studies have focused on the connection between individuals' education achievements and labour market outcomes in worldwide countries, including China. The focus is to estimate the return to education to see how the wage disparities would vary by the different years (levels) of individuals' education.

China is a county with a land area of more than 9600 thousand square kilometres, which ranks second worldwide. China also has the largest population in the world, with more than 1.4 billion by the end of 2020. In the previous 20 years, the population in China increase continuously by 11.4%. The large population has contributed to the fast economic growth in China in recent decades. Over 60% of the total population are labour force, and over 95% of them can successfully be employed in the labour market. As such, human capital development becomes essential if China wants to maintain sustainable growth and the most crucial source of labourers' human capital is formal schooling.

The education evolution in China benefits largely from two different policies. Firstly, the Compulsory Education Law was first announced in 1986. The purpose of the law is to achieve a national spread of nine-year compulsory education, including the primary and lower middle periods of teaching. Under the requirements of the law, primary and lower middle schools are free of charge, which especially benefits those low-income families who cannot afford their children to go to school. Secondly, at the turn of the 21st century, the Chinese government conducts a higher education expansion policy which aims to increase the yearly enrollments of colleges and universities nationwide. The success of the policy is beyond expectation. The annual enrollments increase nine times in twenty years and by 2020, the gross enrollment rate of tertiary education in China already exceeds 50% (China Statistics Yearbook, 2020; World Bank, 2020). In fact, both the law and policy help increase the average education achievements for Chinese workers.

Based on backgrounds of education expansion, there is no surprise that both individuals and policymakers would be interested in how investments in education would be rewarded in the labour market. At the microeconomics level, there are two popular theories indicating that education achievements would affect individuals' wages. Firstly, the human capital theory argues that human capital investment is similar to other physical investments such as lands, plants, machines and equipment (see Schultz, 1961 and Becker, 1964). Human capital may include different varieties of production knowledge, labour and management skills, and health quality contained in people. Education is considered the main source of human capital achievements. Mincer (1974) forms the relationship between education years and log wages using a linear regression model based on the human capital theory, the so-called Mincer equation. Many researchers around the world conduct empirical analyses to estimate the return to education based on Mincer's method, and most of them confirm the original assumption that there is a significant and positive relationship between wages and education achievements. Secondly, the signalling theory also indicates the positive relationship between wages and education levels, but with different interpretations (see Spence, 1973). It assumes that education provides a signal to employers that individuals with higher innate abilities would invest more in education. These abilities would help with individuals' productivity in jobs and are reflected by their education levels. Therefore, employers would arrange individuals with higher education achievements into higher payoff positions. In the signalling theory, education just serves as a signal, and it is not necessarily to be true that education processes provide individuals with higher human capital. In fact, though with different interpretations, both human capital and assignment theory assume that higher educated individuals would earn higher wages in the labour market.

Following the contributions in the theoretical literature, this thesis focuses on empirically testing the return to education in China to see whether the wage return theories can be supported in the Chinese labour market. However, we extend our analysis into three different topics: return to education with the comparison between urban and rural areas, return to over-education and return to education qualities and subjects. These topics are correlated closely to the area of return to education but still need to be more focused on Chinese literature.

Firstly, in recent decades, there have been an increasing number of researchers trying to estimate the return to education in China, mainly using Mincer's method. However, many studies restrict the analysis to urban areas but exclude those individuals in rural areas. Nevertheless, till the year 2020, there are still more than 40% of individuals living in Chinese rural areas, and rural workers also comprise around 40% of the total labour force (China Statistics Yearbook, 2020). Some researchers may argue that the incomes of rural workers are difficult to clarify. However, even if only focusing on the waged market, around 40% of the total income of rural workers directly comes from wage earnings. Therefore, ignoring the education returns in rural areas and the comparison between labour markets with urban-rural differences would result in the lack of national representative in the analysis. Differentiated estimation on return to education would also provide suggestions to both policymakers and individuals on education investments in various areas.

In our analysis, the first empirical chapter, Chapter 3, estimates the return to education in current China to see to what extent individuals' wages can be explained by the achievements of years of education. We also compare urban and rural areas to see whether there would be enormous and significant differences in the payoff to education between urban and rural labour markets. In addition to these, we examine the return to education for subgroups such as gender and sector in both urban and rural areas. We also follow the literature to study the possible unobserved heterogeneity and self-selection problems often discussed when using the OLS method to estimate the Miner equation. Therefore, the research questions for the third chapter are: (1) What is the estimated return to years of education in most recent

China? (2) Are there any significant differences in the returns between rural and urban areas? (3) What are the returns to education for gender and sector in different areas? (4) Does the estimation on return to education suffer significantly from endogeneity and self-selection bias, and how do we solve these problems?

Secondly, besides the urban-rural difference in return to education, the consequence of the fast expansion of tertiary education to the labour market is also not largely focused on in China. The dramatic growth of graduates on the supply side may result in a disequilibrium in the labour market. The demand for graduates would not increase in the same proportion as the supply, and some graduates would fail to find suitable jobs that match their education levels. Arguments are often raised on the traditional Mincer's method that this method only covers the variations in the supply side of education and assumes a homogeneous return to a specific education level. However, it does not consider whether the education years individuals achieved would match the requirements of jobs on the demand side. If the education achievements exceed the required ones, the over-education problem will arise. In fact, over-education is costly for both the country and individuals. Every year the government provides a large amount of education spending for the expansion. However, if the labour market demand is saturated, this would be a waste of social expenditure. In addition, mismatched individuals would under-utilize their productivity in jobs. They may risk having lower returns than those with the same education level but taking the matched jobs. The wage penalty for over-education is confirmed mainly in other developed countries such as the UK (see Chevalier, 2003 and Walker and Zhu, 2010). These concerns show the importance of analysing the incidence of and return to over-education in China.

The second empirical chapter, Chapter 4, studies the return to over-education, which is the wage difference between over-educated and matched individuals. In this chapter, we specifically focus on the sample group of tertiary education, including graduates from vocational colleges and academic universities, corresponding to the background of the fast expansion of tertiary education in China. There are two main purposes for the empirical analysis. First, we would like to see whether there would be significant wage differences between over-educated and matched workers. Second, we want to find out whether over-education would generate a wage penalty. Usually, there are three different ways to define an individual's over-education status, which are subjective, objective and statistical methods where the reference (required) education levels rely on the job analysts' suggestion, self-assessment and statistical mean/mode, respectively. In fact, there are no agreements in the literature on the preferred method therefore, in our analysis, we compare these three measurements. After the over-education status can be successfully defined, we can also easily reach the incidence of over-education in China with three different methods. In this chapter, we also examine the connection between over-education and skills and use individuals' skills heterogeneity to explain the wage difference generated by over-education. Two existing theories could help explain the wage difference, based on the assumption that over-educated individuals will under-utilize their skills in jobs or suffer from significant gaps in skills proficiency. Therefore, the research questions for the fourth chapter are: (1) What is the estimated wage difference between over-educated and matched graduate workers? (2) What is the over-education incidence among Chinese graduates? (3) Do the empirical results vary largely according to different measurements of over-education? (4) Can individuals' skills heterogeneity help explain the over-education wage gaps?

Thirdly, in fact, the heterogeneous returns in the same education level are also correlated with education qualities and subjects. Some researchers argue that to comprehensively represent an individual's human capital, education achievements should be a function which takes into consideration both education years and qualities (e.g. Hanushek, 2002). However, in traditional Mincer's method, the original assumption indicates that the return would be the same for the same education level regardless of qualities and subjects studied, which can be considered another important limitation. The supply and demand for different education qualities and subjects would differ in the labour market. Also, in recent years, fast expansion in higher education has made it possible for more students to have the chance to be enrolled in colleges. However, the heterogeneous returns to individuals in the same tertiary education level would also drive the concerns because graduates from some specific types of institutions and subjects will be firstly disadvantaged by the possible disequilibrium in supply and demand. Therefore, estimating different returns according to education qualities and subjects would provide excess information before individuals invest in higher education. Some individuals and families would accept a trade-off between qualities and quantities of education, but they should be aware that they may face the risk of considerably lower returns.

The third empirical chapter, Chapter 5, examines the return to different education qualities and subjects. Similar to the second chapter, we focus only on graduates from tertiary education because the education qualities and subjects are mainly classified clearly in colleges or universities. The main purpose is to determine whether significant wage gaps exist between different education qualities and subjects. In our analysis, education qualities mainly refer to the qualities provided by different types of institutions. The classification of subjects is primarily based on the criteria from the "Catalogue of Subjects for Degree Awarding and Talent Training" officially published by the Chinese government. The interaction effect is also considered to see the effect of colleges on wages in different subjects or the effect of subjects in different college types. In this analysis, we also examine subgroups and study the differences in returns to education qualities and subjects according to gender and urban-rural disparities. Therefore, the research questions for the fifth chapter are: (1) what are the wage disparities between different education qualities and subjects for Chinese graduates? (2) What are the interaction effects between education qualities and subjects to wages? (3) Are there any differences in returns between gender and urban-rural subgroups?

Therefore, in summary, this thesis mainly focuses on the return to education in China. Still, we try to contribute to the current literature by incorporating the analyses on heterogeneity in the returns, for example, the differentiated returns between urban and rural areas, returns according to mismatch status, and returns to various education qualities and subjects. These analyses will be divided into three parallel chapters in the thesis. In the following subsection, we detail the dataset and methodologies used.

1.2 Dataset and Methodologies

The main restriction in China to conducting an empirical analysis on the micro level is the unavailability of datasets, and most of the data for individuals directly comes from social surveys. Thanks to the development of Sociology and social studies in recent China, we can find a dataset that would help with all the research aims of our thesis, which comes from the China Family Panel Studies (CFPS). CFPS is a national and comprehensive social tracking survey project designed by the research team of Peking University and funded by Peking University and the Natural Science Foundation of China. It aims to collect data from individual, family and community levels to reflect the changes in China's society, economy, population, education and health and to provide data basis for academic research and public policy analysis. CFPS focuses on Chinese residents' economic and non-economic welfare and many research topics, including economic activities, educational attainment, family relations and dynamics, population migration, and physical and mental health. The target sample size of CFPS is 16000 households and over 50000 individuals. The respondents are household members from 30 provinces/cities/autonomous regions in China (out of 34). Till 2018, CFPS has successfully conducted five rounds, every two years since 2010.

In fact, some other Chinese surveys also provide information on core variables for our analysis, such as individuals' education achievements and wages, including China Health and Nutrition Survey (CHNS), China General Social Survey (CGSS) and Skills Towards Employability and Productivity (STEP) Survey. However, CFPS hold specific advantages that can help solve our research questions in different chapters. For example:

(1) CFPS is a nationally representative survey covering nearly all of China's provinces. However, other surveys only include limited provinces, such as CHNS covering 12 provinces and STEP only focusing on one province, Yunnan. Though these provinces can be argued to represent different geographic areas in China, for a national-level analysis, it is better to rely on a survey that covers most of the provinces.

(2) CFPS provides detailed information on individuals' education achievements. Besides collecting data on individuals' levels of education, it further asks respondents about the actual years finished at that level and whether they have been awarded the qualifications. This would help mainly in the precise measurement of individuals' education achievements. In addition, more detailed information on each education level, such as the types of institutions graduated and subjects learned are also available, which would help us answer the questions in the third research topic on return to education quality and subjects.

(3) Regarding wages, CFPS is the only survey that provides information to measure individuals' hourly earnings. Other surveys only collect information on monthly or even yearly earnings. It is known that wages depend on both individuals' productivity and working hours, but higher wages based on working hours are not considered as driven by education or human capital achievements. Therefore, in our analysis, we decide to measure hourly wages based on the information on "total working hours in a week" in CFPS.

(4) CFPS provides information on individuals' skills achievements, which would help us disentangle the effect of education from skills. Also, individuals' educational outcomes and productivity variations could be represented by skills achievements in the same education level. In CFPS, cognitive skills, including two dimensions of numeracy and literacy, are measured objectively by formal tests, which are considered a more precise measure than self-assessments (Nieto and Ramos, 2017). CFPS also covers individuals' non-cognitive skills, including the "Big Five" personality traits and locus of control. However, different from cognitive skills, these non-cognitive ones are based on self-reported answers from respondents.

However, it is evident that CFPS also suffers from some limitations. For example, firstly, some core variables, such as cognitive skills and education qualities are only available for some survey years. Therefore, though CFPS is a longitudinal dataset with individuals followed in every wave, we cannot use panel analysis to solve all the research questions. We choose survey waves of 2010, 2014 and 2018 to conduct cross-sectional studies on the research topics separately. In fact, not all the research topics are suitable for longitudinal analysis. The fixed effect method is helpful for the elimination of biases generated from unobserved traits, but individuals' education levels are not time-variant. Secondly, in CFPS, income information is only available for those employed by others or wage earners but not for self-employed workers. This limitation is often seen in the social surveys in the literature since the self-employed workers' income is hard to clarify and would easily be contaminated by the companies' income. The distributions of education achievements in different employment statuses are quite different. The demand and supply condition of education in the labour market may also vary across employed and self-employed workers. Without the information on income for self-employed workers, we cannot analyse the comparison of return to education between them. Therefore, our analysis only focuses on the return to education in the waged sector.

In terms of the methodologies, the linear regression model is the main method used in this thesis, and the coefficients are estimated by the Ordinary Least Square (OLS) method. For example, in the first empirical chapter, the Mincer wage equation to estimate the return to education is a linear regression model, which connects education and individuals' log wages. The estimated coefficient(s) for the education years or levels are the so-called return to education. However, arguments are often raised regarding the robustness of the OLS method that the coefficients estimated may suffer from bias, generated mainly by endogenous independent variables and self-selection. These concerns are also correlated with the limitations in the dataset that we mentioned before. The Education variable would be endogenous in the OLS model because unobserved heterogeneity would be included in the error term, such as innate ability, affecting both the individuals' education achievements and wages. In fact, no dataset can provide perfect information to measure innate ability. Therefore, our analysis uses a statistical method of Instrument Variable (IV) to solve this problem. We find instruments correlated with education achievements but not the innate ability to break the connection between education and unobserved heterogeneity. In addition, since we are only able to observe the income of waged workers, the self-selection bias may exist because this group of people may take the waged jobs because of self-selection and may not be a random draw from the population. The income of other individuals such as self-employed workers and those self-selected not to participate in the labour market are missing, resulting in a problem that observations in the OLS regression model are not representative and lead to a bias on the estimated coefficients. To solve this problem, we implement the Heckman (1979) two-step method by adding an inverse Mills ratio in the wage equation as a correction term to eliminate the bias.

The methodologies covered in the second empirical chapter are comparatively more complicated. We start from a revised Mincer equation proposed by Verdugo and Verdugo (1989), which further considers individuals' mismatch status alongside education years. The mismatch means that an individual's education is higher or lower than the job requirement. Since we only focus on a specific education level and our core purpose is to examine over-education, the specification remains a dummy variable indicating whether an individual is over-educated. Skills variables, including skills utilisation and proficiency, are further added into the model to check whether the effect of over-education can largely be explained by skills heterogeneity. In addition, to test the robustness of results obtained from linear regression and OLS, we further implement a Propensity Score Matching (PSM) method in this chapter. This is a non-parametric method based on matching techniques where the estimators are obtained from the average treatment effect. However, the treated (over-educated) and non-treated (matched) groups may not be randomised regarding different characteristics. Therefore, matching techniques are used to control the effect of covariates that may lead to different probabilities of being treated, with the help of propensity score.

Similar to the first empirical chapter, we also implement linear regression models and the OLS method in the third empirical chapter. However, since we only focus on the tertiary education level, the independent variables are the dummies of education qualities and subjects. According to the method often used in Chinese literature, education qualities are defined roughly according to institution types, including vocational colleges, ordinary universities and key universities. In CFPS, graduates' subjects are classified into 12 groups, consistent with the "Catalogue of Subjects for

Degree Awarding and Talent Training" officially published by the Chinese government. However, the reclassification is also implemented to group some subject units together due to the sample size limitation. Consistent with the first empirical chapter, we also include the Heckman method to solve the possible selection bias problem.

1.3 Structure of the Thesis

The structure of the thesis is as follows: Chapter 2 covers the backgrounds of Chinese education and the labour market. We specifically introduce the policies that help develop Chinese education and economy. Chapter 3 examines the return to education in China with the urban-rural differences by using the Mincer wage equation. IV method and Heckman method are also included to solve the possible endogeneity and self-selection problems. Chapter 4 estimates the return to over-education to determine whether there would be a significant wage penalty for over-education among Chinese graduates. Three different measurements are used to define over-education status, and the comparisons of the wage effects of over-education are made between different measurements. In addition, we also examine to what extent the results of over-education can be explained by skills heterogeneity. Chapter 5 studies the return to different education qualities and subjects to find out heterogeneous returns between graduates in the same tertiary education level. Finally, in Chapter 6, we provide the conclusion for the thesis, covering concluding remarks, implications and limitations.

Chapter 2 Background

Our focus on the analysis is the economic payoff to individuals' education achievements, which covers both the area of education and the labour market in China. Therefore, in this part, we provide some detailed background on the development of the Chinese education and labour market, with the help of related statistics in different reports and databases. We also cover a subsection to provide background on the socioeconomic development of China.

2.1 General Introduction to Economic and Social Development in China

China is a country with the second largest land area (9600 thousand square kilometres) in the world, consisting of more than 30 provinces and municipalities (province-level cities directly under the central government). In Table 2.1, we provide detailed information on the number of cities and land areas for each province and municipality. We divide the country into four regions, including northeast, east, middle and west, which follow the criteria provided by China Statistics Bureau (2011) based on geographic and economic development conditions. The table shows that China's western areas have the largest land area and the largest number of cities.

In terms of demographics, China ranks top in the total population of the world, with more than 14 billion people by the end of 2020. Figure 2.1 shows the time trend of the development of the total population in China, with gender and regional differences. It can be seen that the total population has increased continuously across the years from 2000 to 2020. In Table 2.1, we also illustrate the population in each province, and we find an unequal population distribution in different areas. Western China enjoys the largest land area, more than seven times of eastern regions, but has a smaller total population. In addition, big cities in China also attract people to work and live, having a high population density, such as Beijing and Shanghai.

Table 2.1: Land areas, demographics and economic developments in different areas of China

Provinces and municipalities	Number of cities	Number of counties	Number of towns /villages	Land areas (10 thousand square kilometres)	Population (10 thousand)	GDP (100 million yuan)	GDP per capita (yuan)
Northeast							
Heilongjiang	13	121	1292	47.3	3171	13698	42635
Jilin	9	60	951	18.74	2399	12311	50800
Liaoning	14	100	1355	14.59	4255	25114	58872
Total	**36**	**281**	**3598**	**80.63**	**9825**	**51123**	**50769**
East							
Beijing	1	16	343	1.68	2189	36102	164889
Tianjin	1	16	250	1.13	1387	14083	101614
Shanghai	1	16	215	0.63	2488	38700	155768
Hebei	11	167	2254	18.77	7464	36206	48564
Shandong	16	136	1822	15.38	10165	73129	72151
Jinagsu	13	95	1258	10.26	8477	102718	121231
Zhejiang	11	90	1365	10.2	6468	64613	100620
Fujian	9	85	1107	12.13	4161	43903	105818
Guangdong	21	122	1611	18	12624	110760	88210
Hainan	4	25	211	3.4	1012	5532	55131
Total	**88**	**768**	**10436**	**91.58**	**56435**	**525746**	**101399.6**
Middle							
Shanxi	11	117	1396	15.63	3490	17651	50528
Henan	17	158	2453	16.7	9941	54997	55435
Hubei	13	103	1251	18.59	5745	43443	74440
Anhui	16	16	1501	13.97	6105	38680	63426
Hunan	14	122	1940	21.18	6645	41781	62900
Jiangxi	11	100	1566	16.7	4519	25691	56871
Total	**82**	**616**	**10107**	**102.77**	**36445**	**222243**	**60600**
West							
Neimenggu	12	103	1024	118.3	2403	17359	72062
Xinjiang	14	106	1128	166	2590	13797	53593
Ningxia	5	22	241	6.64	721	3920	54528
Shanxi	10	107	1313	20.56	3955	26181	66292
Gansu	14	86	1356	45.44	2501	9016	35995
Qinghai	8	44	403	72.23	593	3005	50819
Chongqing	1	38	1031	8.23	3209	25002	78170
Sichuan	21	183	3230	48.14	8371	48598	58126
Xizang	7	74	697	122.8	366	1902	52345
Guangxi	14	111	1251	23.6	5019	22156	44309
Guizhou	9	6	1509	17.6	3858	17826	46267
Yunnan	16	129	1410	38.33	4722	24521	51975
Total	**131**	**1009**	**14593**	**687.87**	**38308**	**213283**	**55373**

Source: China Statistics Yearbook, 2020

Note: In the last column of GDP per capita, "total" indicates the average GDP per capita of total provinces in one area. Provinces exclude Hong Kong, Macao and Taiwan.

For the subgroups, China has a clear gap in population between genders. There are about 3-4 per cent more males than females in the whole country, but the gap does not change largely across the years. The population gender imbalance is striking, and possible explanations may rely on the consequence of the one-child policy and liberal birth control policies. In addition, from Figure 2.1, we could also find the variations in the population distributions across regions. In 2000, residents in rural areas are nearly two times higher than those in urban areas. However, the post-2000 period witnesses the fast urbanisation of China. After 2010, the number of urban residents exceeds that of rural ones. In 2020, more than 60% of the population is covered by urban areas.

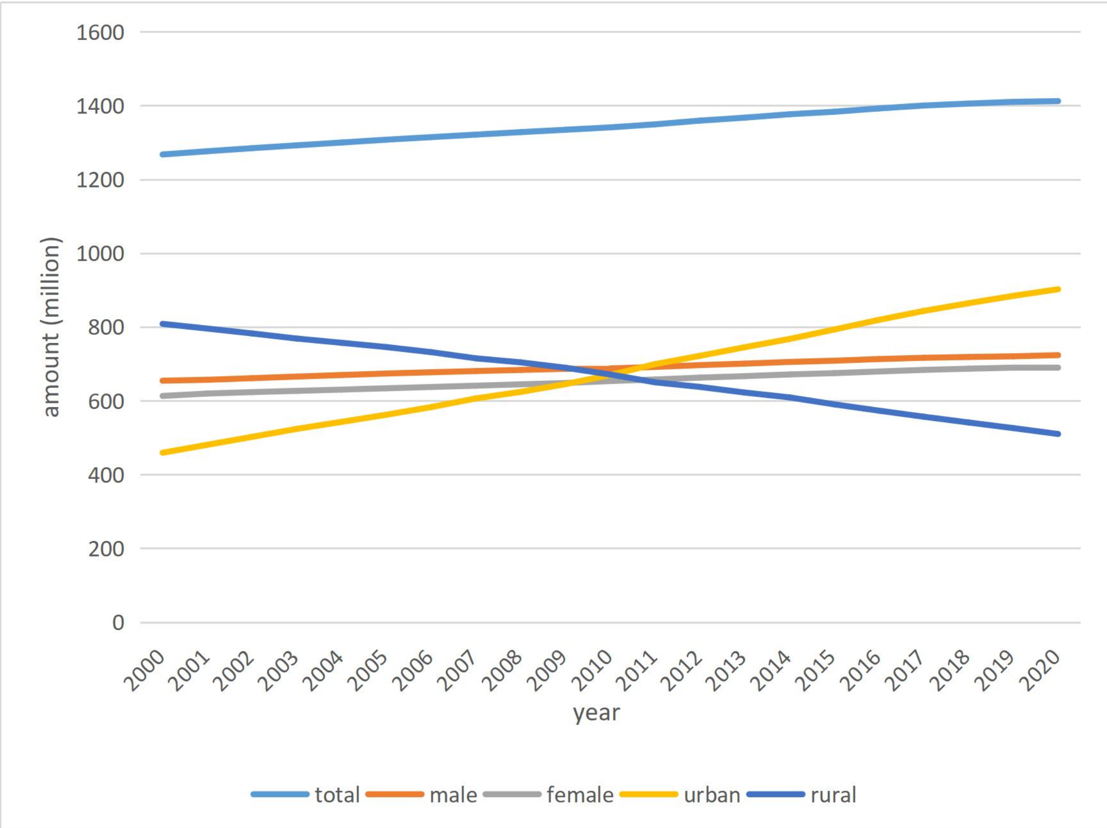


Figure 2.1: Population of China in millions across years with gender and urban/rural differences
Source: China Statistics Yearbook, 2000-2020
Note: Urban and rural are classified according to geography

GDP and its growth rate are good indications of the general economic development of a country. Figure 2.2 illustrates the scale of the Chinese GDP and its growth rate between 2000 and 2020. Across the period of 20 years, the total GDP has increased by ten times. In fact, in 2010, China became the second-largest economy in the world, just following the US. The growth rate is always positive across the years, reaching the highest in 2007, with 14%. However, the growth rate fluctuates across the years and decreases rapidly after 2010. This may reflect a slowdown in the Chinese economy.

In Figure 2.2, we also show the amount of GDP per capita with a time trend. It can be seen that the GDP per capita also increases continuously, and the growth pattern is quite similar to that of total GDP. Though the overall scale of the Chinese economy is large, the GDP at the average level is relatively small, which only ranks 63rd in the whole world. The fast economic growth in China would also result in a problem of unbalanced development, and the most obvious is the gaps in different regions. From Table 2.1, we can see that the average GDP per capita in eastern areas is about two times higher than in western areas. Beijing enjoys the highest GDP per capita, with more than 160 thousand yuan per year, which is closely followed by another eastern city, Shanghai, with more than 155 thousand per year. The lowest GDP per capita exists in Gansu province, which is located in western areas. The GDP per capita is around 36 thousand yuan annually, which is only about one-fifth of that in Beijing.

In Figure 2.3, we show the composition of Chinese GDP according to different industries. All of the industries show an increasing pattern in total amount but with different growth rates. In 2000, the primary sector is still an important component of the Chinese economy, which accounts for around 15% of the total GDP. However, in 2020, the importance of the primary industry is largely moderated. The scales of secondary and tertiary sectors are quite similar until 2012. Starting from 2013, the scale of the tertiary sector exceeds the secondary sector and becomes the most important source of total GDP, accounting for more than 50% in 2020. In fact, Figure 2.3 shows the pattern of industrial transformation and upgrading in recent decades.

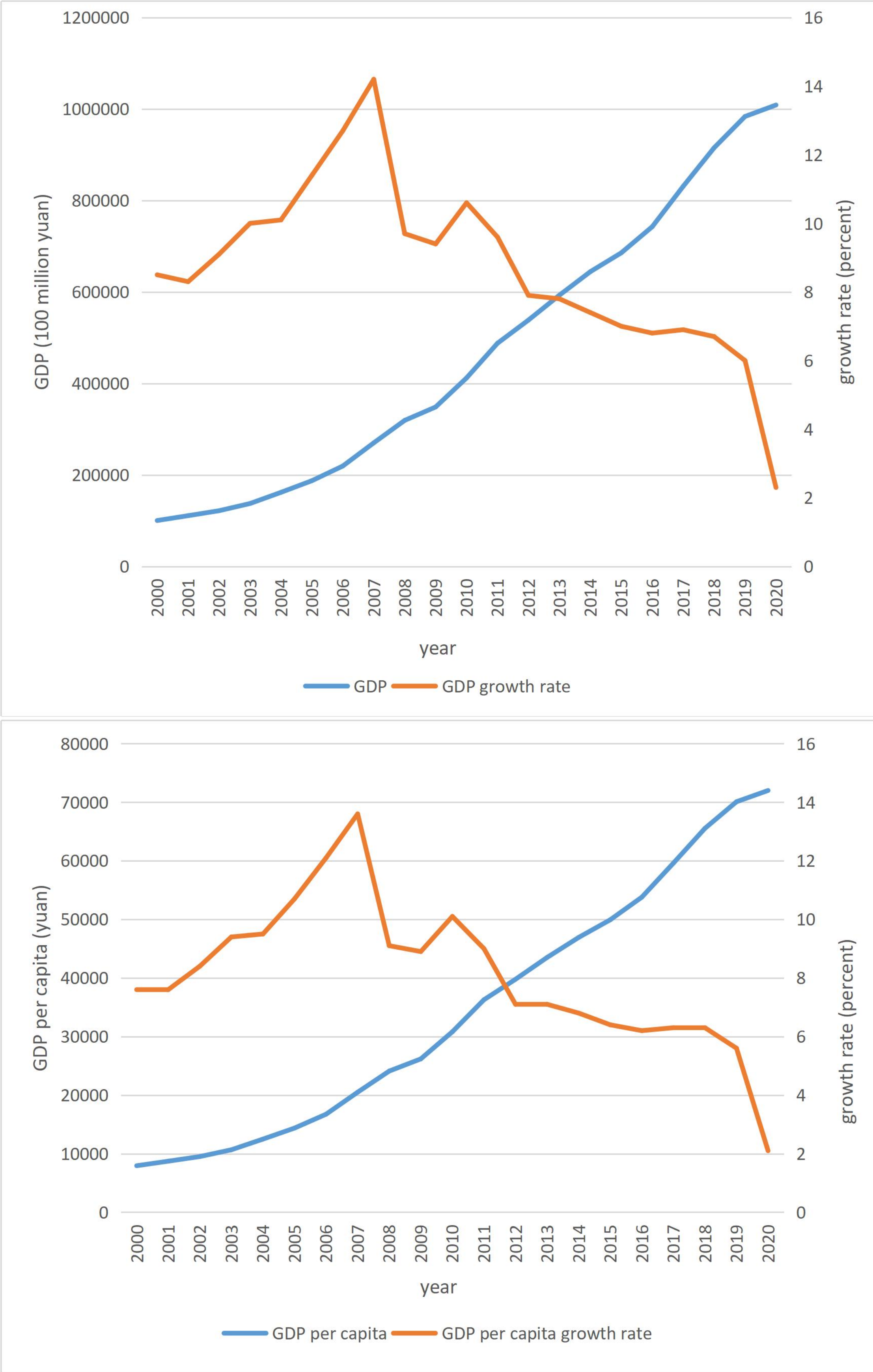


Figure 2.2: GDP and GDP per capita across the years with growth rates
Source: China Statistics Yearbook, 2000-2020

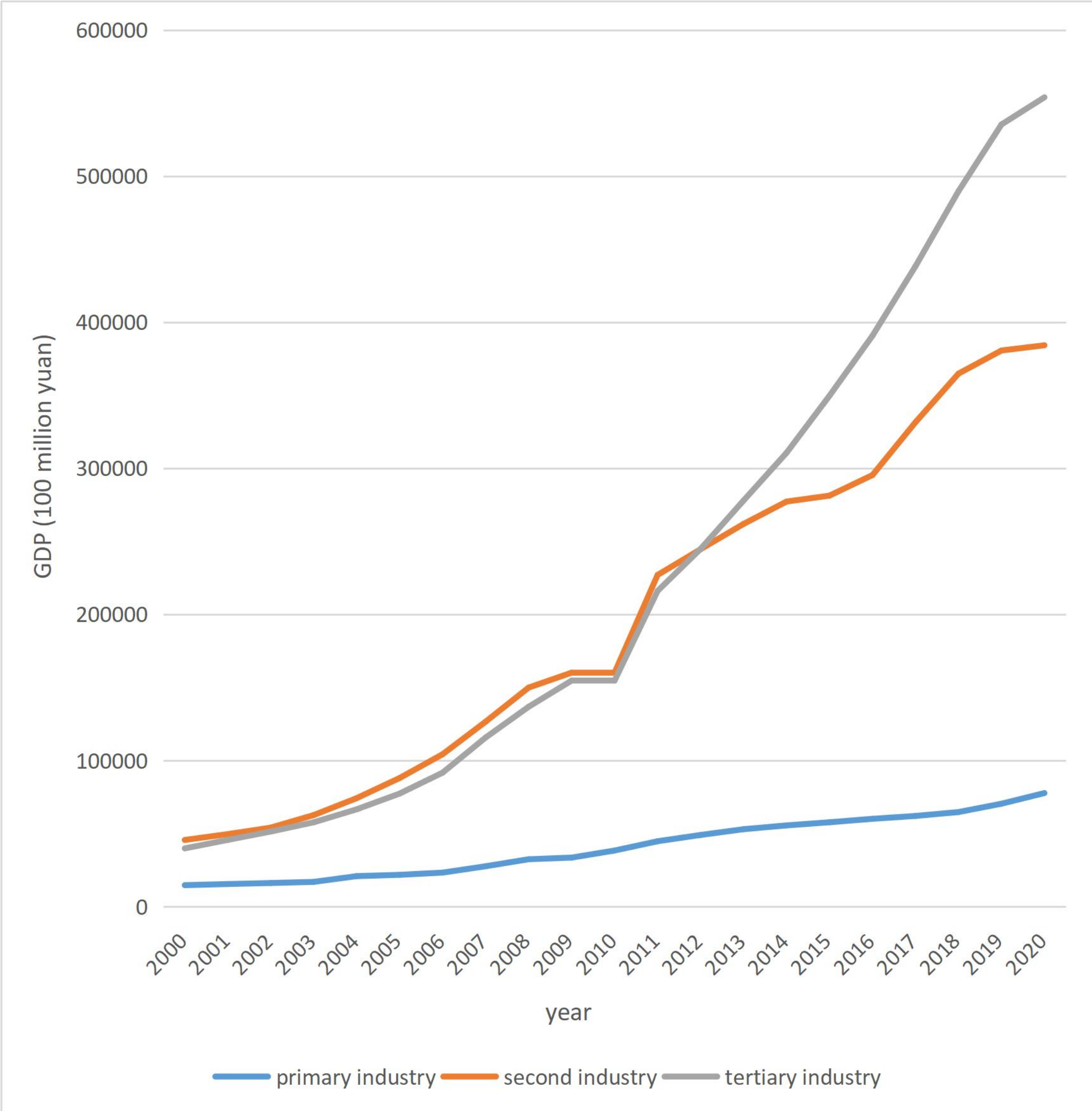


Figure 2.3: Composition of GDP by different industries
Source: China Statistics Yearbook, 2000-2020

2.2 Backgrounds on Education

2.2.1 Education System in China

Figure 2.4 shows in detail the education system in China. In general, Chinese education for 6+ years old children can be roughly divided into four parts: compulsory primary school, compulsory lower middle school, upper middle school and tertiary colleges and universities.

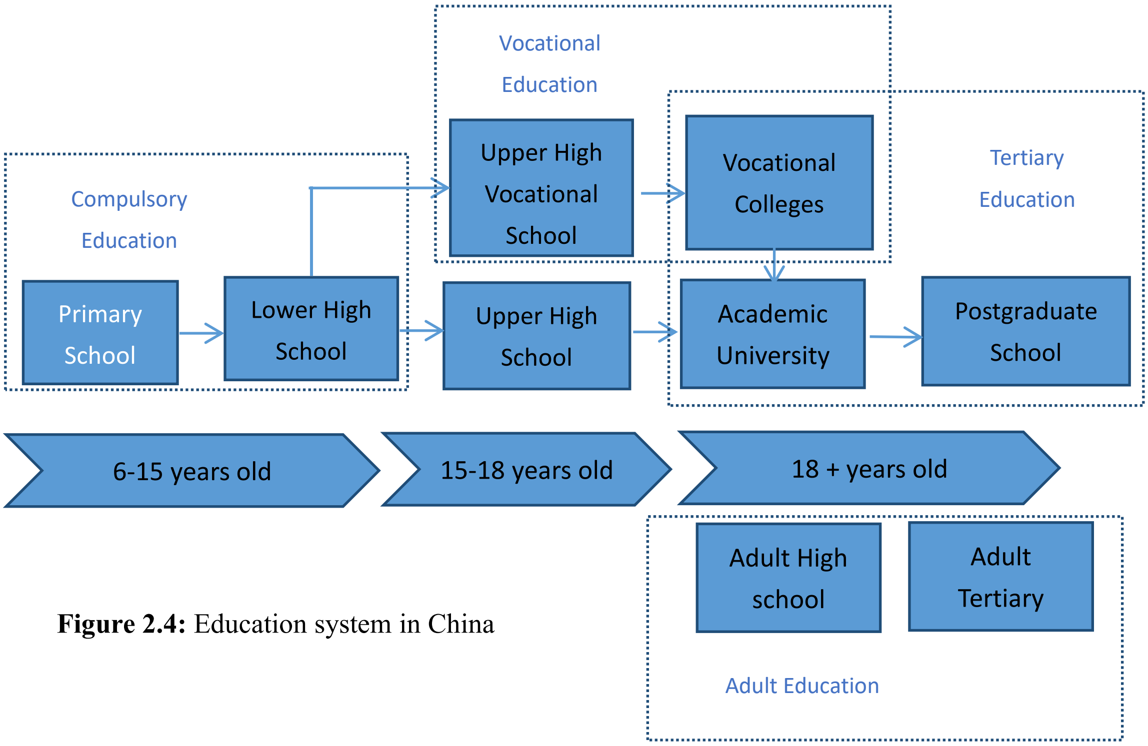


Figure 2.4: Education system in China

Firstly, children exceeding six years old are able to enter primary school with a duration of 6 years. In fact, according to the requirement of the Compulsory Education Law that was first proposed in 1986 (explained in detail in the following subsection 2.2.3), all children over 6 years old are compulsory to be enrolled in primary schools. In addition, also based on the law, primary education is free of charge of tuition fees. After 6 years of learning, students are able to be promoted to lower middle school, with a duration of 3 years. Similar to primary school, a lower middle school in current China is also compulsory and free of charge. No entrance requirements are needed, and students would be allocated to schools that are nearest to their family residential locations.

Secondly, after finishing the period of compulsory education, students will normally have two options: continue to study in high schools for a duration of 3 years or leave school and try to find jobs in the labour market. However, according to the provisions for using child labour in China (also explained in the following subsection 3.3.2), individuals are not able to find formal jobs before 16 years old. Therefore, most of the graduates from lower middle school are promoted to take at least one year of upper middle school education. There are three main differences between the non-compulsory and the compulsory period of education. First, in the non-compulsory education period, students could choose different education types: vocational and academic schools. Academic education often aims to teach fundamental and advanced academic knowledge, which would help with research jobs or the promotion to the next stage of education, for example, upper middle school to tertiary level. However, vocational education normally focuses on specific skills that would be directly used in the labour market. Second, entry examinations are required to apply for non-compulsory education. For example, most of the students need to take the entrance examination before going to upper middle school, and the examination results would determine whether they are able to be enrolled in academic or vocational schools. In fact, in current China, only 50% of students could have the chance to take the academic type of education. Third, non-compulsory education is not free of charge. Students need to pay tuition fees and also service fees (accommodation, food, etc.) if needed. However, since most of the high schools are publicly funded, the charges for these fees are quite low.

2.2.1.1 Tertiary Education in China

After 12 years of schooling, high school graduates can apply to colleges and universities through a centralised admission system that directly leads to tiers based on the scores in the standardised National College Entrance Examinations, known as "gaokao" (Zhu 2014). Colleges and universities in China can be classified into three tiers in descending order of prestige (quality) and entry requirements: Key Universities, Ordinary Universities, and Vocational Training Colleges. Whether students are able to enter institutions with higher qualities is almost totally determined by the exam scores obtained in "gaokao". The duration of study for the Key Universities and Ordinary Universities is typically four years, leading to a bachelor's degree and qualification. The duration of study for Vocational Training Colleges is three years, leading to a vocational college qualification but no degrees.

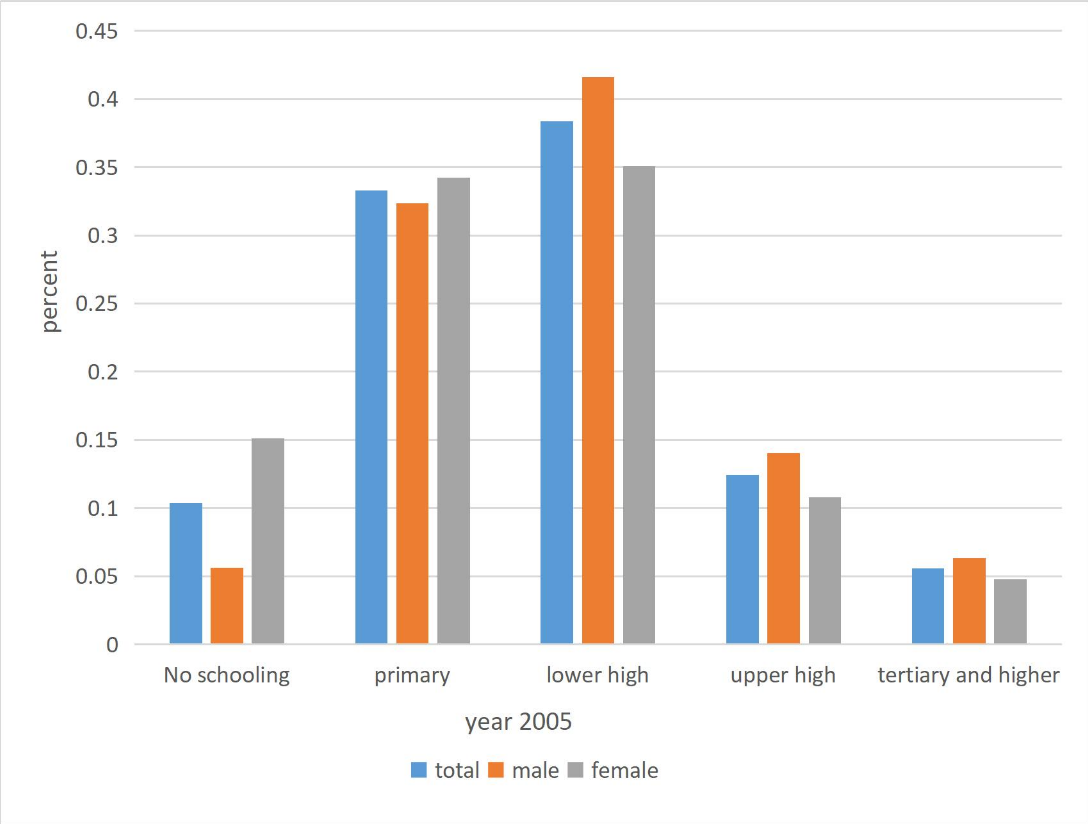
Higher education admissions in China also follow orders. Admissions in the second-tier universities start only after the assignments in the first tiers are finalised, and so forth. Each applicant submits a lexicographic list that indicates their HEI (Higher Education Institution) preferences and then their preference regarding subjects within each HEI. Whether they can be admitted to schools in better tires or better-ranked institutions in the same tier depends mostly on the marks obtained from the College Entrance Examination. Importantly, applicants must consider the tier of the HEI and the subject at a given HEI simultaneously, which defines a higher education course.

Graduates from academic universities also have opportunities to achieve the education level of postgraduate, leading to a master's degree or PhD. A master's degree often takes three years to achieve, and a PhD normally takes 3-4 years, depending on the variations in subjects. Adult education in China is also very common, including adult middle school education and also adult tertiary education. However, different from normal tertiary education, the teaching of adult tertiary education often takes the forms of self-taught, online courses or correspondence courses rather than full-time teaching on campus. However, students who successfully finish their adult education are also formally provided with similar degrees or qualifications.

2.2.1.2 Overall Education Achievements in China

In the following Figure 2.5, we show the distribution of the highest education levels (including undertaking) for the 6+ years old population in China. We can find out that the leading education level in China is still the lower middle school from 2005 to 2020. The rate of no schooling in China decreases over the years, and by 2020, there are still 5% of the population who do not take any formal schooling. Non-compulsory education also develops quickly, especially tertiary education. In 2005, only 5% of the total population achieve tertiary education. However, in 2020, the proportion grows rapidly to over 15%.

In terms of gender differences, a clear gap is the proportion of individuals with no schooling. In year 2005, we find the proportion of females with no schooling is three times higher than that of males. With the variations of time, both males and females have fewer populations with no schooling, and the decreasing rate is clearly higher for females. However, in 2020, there are still 5% of females who have not undertaken any level of education, which is two times higher than that among males. We cannot see large gaps between gender at other levels of education. Females have slightly higher proportions to achieve primary school education, but more male individuals have the chance to go further to the high school level. In addition, we find a small gender gap in tertiary education level, especially the proportions for males and females becoming closer and closer to each other with the time variation. In 2020, we even find out the proportion of females taking tertiary education is higher than males, but to a very small extent.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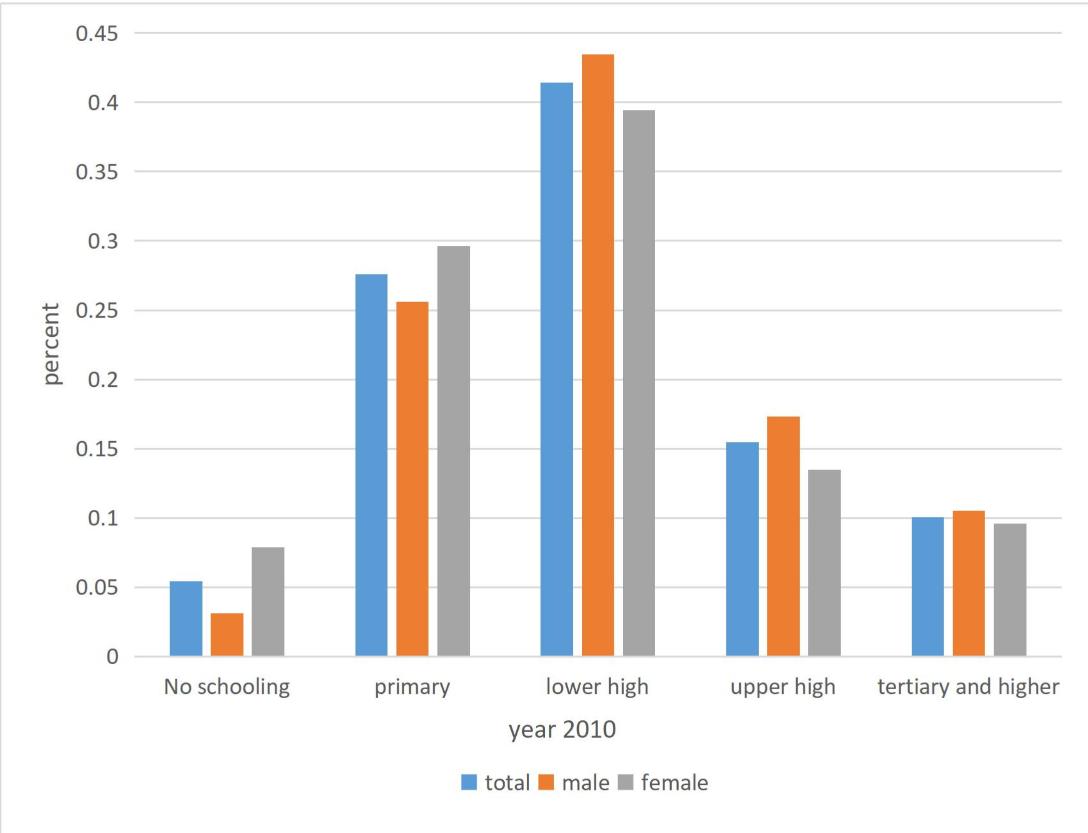
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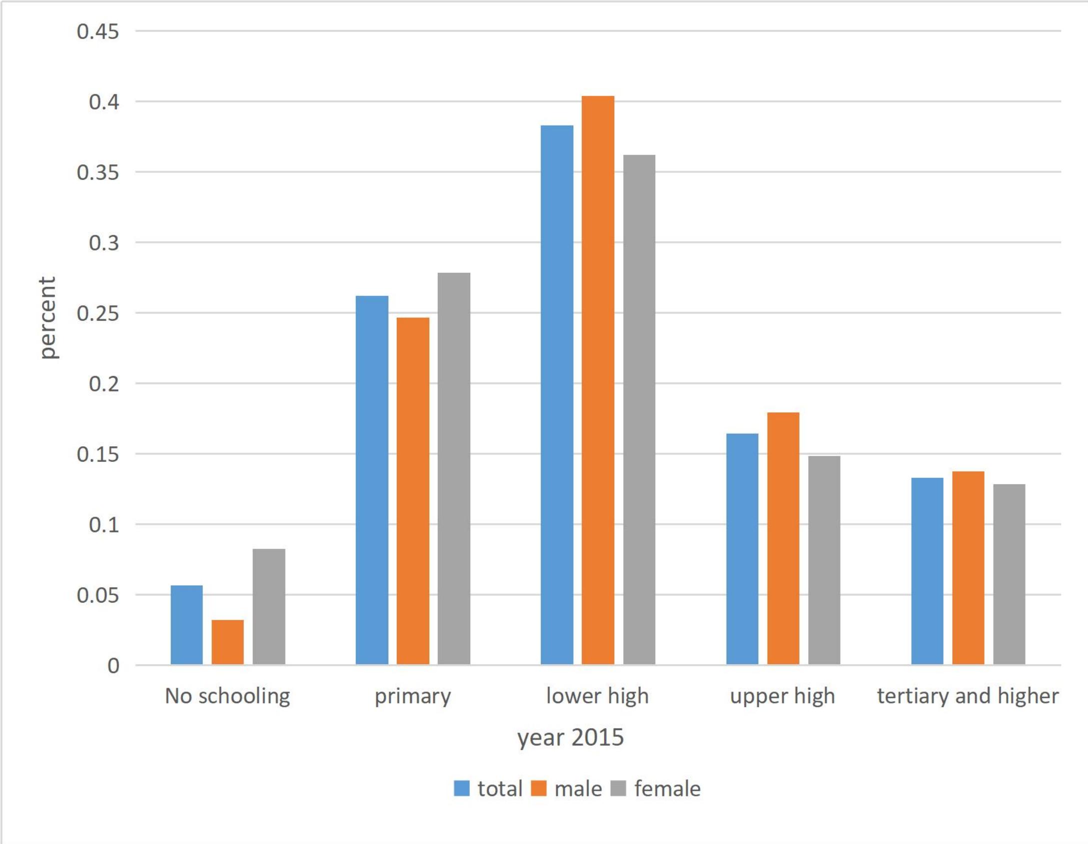


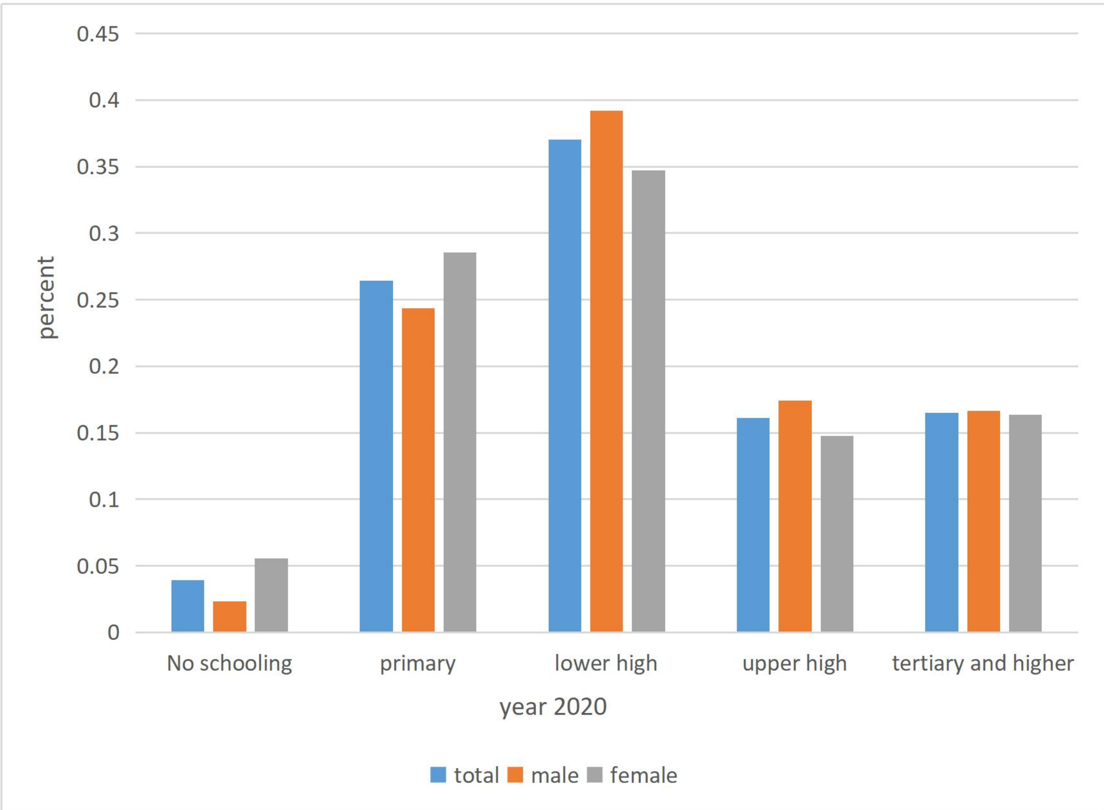


Figure 2.5: Proportion of highest education levels for 6+ years old individuals with gender differences
Source: China Statistics Yearbook, 2005,2010,2015,2020.

2.2.2 Teachers, Students and Education Institutions

In the following Table 2.2, we illustrate the number of teachers, pupil/teacher ratios and institutions for different education levels in China. It can be seen that primary education has the largest scale in China, with over 6 million formally registered teachers and over 160 thousand primary teaching institutions. However, the lowest pupil/teacher ratio shows up in the lower middle education level, where one teacher is responsible for around 13 students. It can also be seen that current China has a considerable number of teachers in tertiary education, which is close to the number of those at the middle school level. However, middle schools still enjoy a significantly lower pupil/student ratio than tertiary institutions. From the table, we can also figure out the gaps between the two different systems of vocational and academic education. For middle school, the scale of academic education is clearly larger, having a larger number of institutions. However, at the tertiary level, the number of institutions is quite similar across different categories of education. In addition, the academic education institutions seem better resourced because it enjoys a significantly lower pupil/student ratio.

There are several requirements for becoming a teacher in current China. Teachers employed in all levels of education need to acquire a tertiary education qualification. All the teachers need to take the assessment of the Teaching Qualification Test before formally registered in schools. For the compulsory education level, all the teachers need to be graduates from specially designed normal subjects. The requirement for teachers in colleges/universities is much higher. Normally, only individuals with postgraduate qualifications (mostly PhD) would have a chance to be employed as full-time teachers in tertiary education institutions. From Table 2.2, we can see that China clearly does not suffer from an over-supply of teaching resources. In fact, in many rural places, schools are facing the problem of a shortage of teaching resources, especially long-term employed teachers (Xuehui, 2018).

Table 2.2: Teachers, students and institutions for Chinese different education levels

	Primary	Lower middle	Higher middle (vocational)	Higher middle (academic)	Tertiary (vocational)	Tertiary (academic)
Number of teachers	6441585	3862083	857401	1934997	556424	1276101
Pupil/teacher ratio	16.67	12.73	19.54	12.90	25.32	18.37
Number of institutions	162601	52998	9896	14561	1468	1270

Source: China Statistics Yearbook, 2020

Note: Tertiary level excludes those of postgraduate and adult tertiary education

2.2.2.1 Institutions and Education Qualities for Tertiary Education

As mentioned in the introduction part, the fourth and fifth chapters of our thesis focus mainly on graduates from tertiary education, including colleges and universities. Therefore, in this subsection, we provide more detailed backgrounds on the institutions in China's tertiary education, including postgraduate and adult tertiary education and their fund status.

In Table 2.3, we can see that most of the tertiary education institutions in China are publicly funded. However, privately funded institutions are also important components of Chinese tertiary education. About 25-30% of undergraduates are from private schools. For postgraduate education schools, some of them are combined with undergraduate institutions (around 70%), and some of them are separate institutions that only admit postgraduate students (around 30%). It is shown that most of the postgraduate institutions are publicly funded, which is similar to adult tertiary education in China.

Table 2.3: Education institutions at the tertiary education level

	Tertiary (vocational)	Tertiary (academic)	Postgraduates	Adult tertiary
Publicly funded	1131	936	822	263
Privately funded	337	334	5	2
Total	1468	1270	827	265

Source: China Statistics Yearbook, 2020

In terms of education qualities, it is often considered that in China, there are differences between vocational colleges and academic universities. Firstly, on the supply side, the entry requirements on examination scores are often considerably lower for vocational colleges compared with academic universities, which may reflect the differences in skills or innate abilities between students. In addition, since the education focus is not academic research, colleges are often smaller in scale and locally based. They have lower funds than universities and may suffer from the shortage of good quality teaching resources, such as campus, facilities, and teachers (Wang, 2010). From the previous subsection, we can see that in the number of teachers, academic universities are clearly better resourced. Therefore, based on the differences on the supply side, students from different tertiary education institutions are also not treated the same on the demand side. Many occupations or job vacancies with better working environments and benefits in China (for example, white-collar jobs) are only available for university graduates, and significantly higher earnings are found in the literature for university graduates compared with college graduates.

Even if at the academic tertiary education level, there are also differences between key and ordinary universities that are often recognised in the Chinese labour market. Key universities include institutions from two important projects of “211” and “985”. The aim of the “211” project is to enhance the quality of 100 colleges in the 21st century. The project first indicated 100 universities as examples, and in practice, there are 116 universities included as high-quality ones. The purpose of the “985” project is to build first-class Chinese universities with international reputations. In fact, requirements are higher for schools to be included in this project. Initially, there were only nine universities, including the two highest-ranked schools, Peking University and Tsing Hua University. Till now, there are in total 39 universities covered by the project, and all the schools from the “985” project are also members of the “211” project. In the following Table 2.4, we illustrate the top 10 universities in China, according to QS rankings and also rankings based on TS (Times Higher Education World University Rankings) criteria. It can be seen that good universities in China are also recognised internationally, and all ten universities rank in the top 500 worldwide across different criteria.

Table 2.4: World Rankings for the top 10 Chinese universities

	QS rankings	TS rankings
Tsinghua University	16	23
Peking University	22	24
Fudan University	40	109
Zhejiang University	54	107
Shanghai Jiaotong University	60	157
University of Science and Technology of China	89	80
Nanjing University	120	144
Wuhan University	257	351-400
Tongji University	265	401-500
Beijing Normal University	277	301-350

Note: QS World University Rankings, 2020; Times Higher Education World University Rankings, 2020

2.2.3 Education Expansion Policies in China

The fast expansion of overall Chinese education and higher average education achievements of the population benefit largely from the proposed education policies. In fact, there are a number of policies that boost the expansion of different levels of education. In the following, we introduce two representative ones with essential influences corresponding to compulsory and also non-compulsory education.

2.2.3.1 Compulsory Education Policy

In China, the 9-year Compulsory Education Law was first enacted on April 12, 1986, and officially went to effect on July 1, 1986. The purpose of the law is to boost the expansion of primary and lower high school education. There are three important elements of this law. First, nine-year education is compulsory for all young children under 15 years old. Second, primary school enrollment is also compulsory when children reach the age of 6. Third, compulsory education is free of tuition fees. Based on these elements, a considerable number of children under 15 years old would be motivated to have more years of schooling than they would otherwise have had.

However, though the law was proposed in 1986, the implementation of it varies across different provinces. Evidence shows that in some of the provinces, the law took effect until 1991 (Campos et al., 2016). Also, compulsory education is a long-term ambition rather than a goal to be fulfilled immediately. In fact, there is also an important supplement policy which boosts the students younger than 15 years old to finish 9-year compulsory education, which is the Provisions on the Prohibition of Using Child Labour. The provision was enforced in April 1991, just after the proposal of the Compulsory Education Law, which forbids any work unit to employ children under 16 years old. The provision significantly decreases the dropping out rate of young children from primary and lower high schools and makes sure each child finishes at least lower middle school before entering the labour market. The provision enjoys the advantage of immediate implementation and effectiveness because it carries much harsher penalties on work units which violate the provision, including imposing fines and revoking licenses.

In the following Figure 2.6, we show the variations in net enrollment rates of primary education and also the promotion rates to lower middle school for young children across the years. We can see clearly the effect of the policies, especially on the enrollment rate of lower middle schools. Primary school's net enrolment rate was boosted to around 100% after 2010. In addition, for the lower middle school, 20 per cent more students have the chance to take the 9-year education in 15 years. After 2005, the promotion rate to lower middle school is over 98% yearly. These statistics show the success of the policies on compulsory education in China.

2.2.3.2 Tertiary Education Expansion Policy

It is often considered that in China, the fast expansion of tertiary education starts from the year 1999. The purpose of expanding tertiary education is to increase every year's enrollments in academic universities and vocational colleges. Implementing the policy would help with the unemployment problem that existed in the Chinese labour market in the late 1990s and allow young adults to avoid the fierce competition in the labour market. The expansion policy is based on the "Action Plan for Revitalizing Education in the 21st Century" proposed by the Chinese Ministry of Education by the year-end

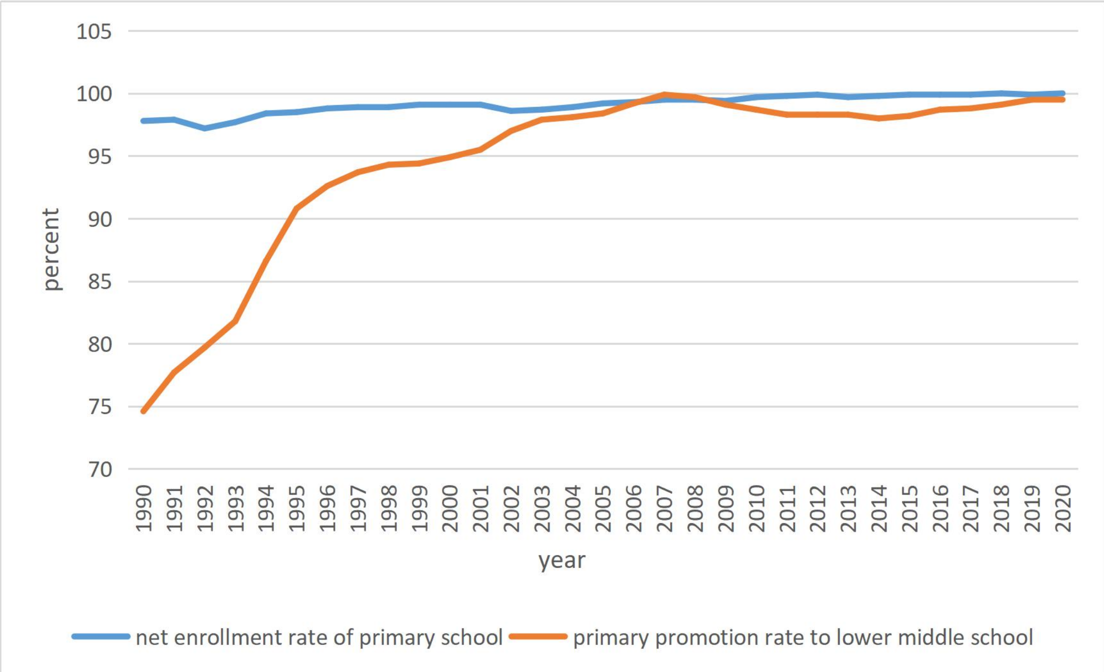


Figure 2.6: Enrollment rates of primary and lower middle school
Source: China Statistics Yearbook, 1990-2020
Note: Net enrollment rate of primary education is calculated by the number of enrolled school-age children divided by the total number of school-age children

of 1998. The original goal is to increase the gross enrollment rate of tertiary education to 15% by 2010. However, the success of the expansion policy is beyond expectation. In 2010, the gross enrollment was boosted to 26.5% and by 2020, more than 50% of young adults of corresponding ages had the chance to take tertiary education. The following Figure 2.7 shows the variations in annual enrollments in tertiary education. It can be seen that after 1998, the annual enrollments grow rapidly at a high rate. From 1990 to 1998, students enrolled in tertiary education only increase from 0.6 million to 1 million. However, from 1998 to 2000, the number of new entries increase more than nine times, which can be seen as a boom of expansion. In addition, from the figure, we can see that after 2000, both vocational colleges and academic universities expand at a similar rate, though at the starting point, the scale of vocational colleges is smaller.

In Figure 2.8, we further illustrate the comparison of gross enrollment rates worldwide in 2018. It can be found that compared with those advanced countries, the enrollment rate in China is still lower than that in the US but similar to the UK. When compared with Asian countries, especially those in southern Asia, China enjoys a higher gross enrollment rate of tertiary education relative to, Indonesia, India and the Philippines.

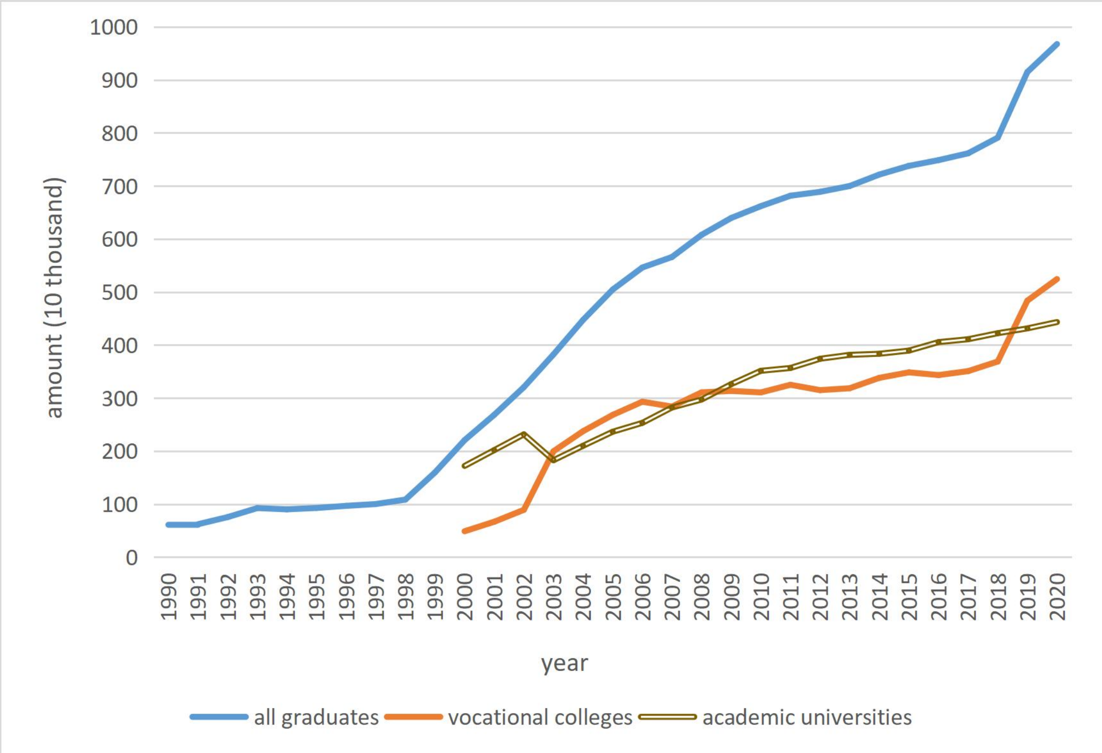


Figure 2.7: Annual enrollments of tertiary education

Source: China Statistics Yearbook, 1990-2020

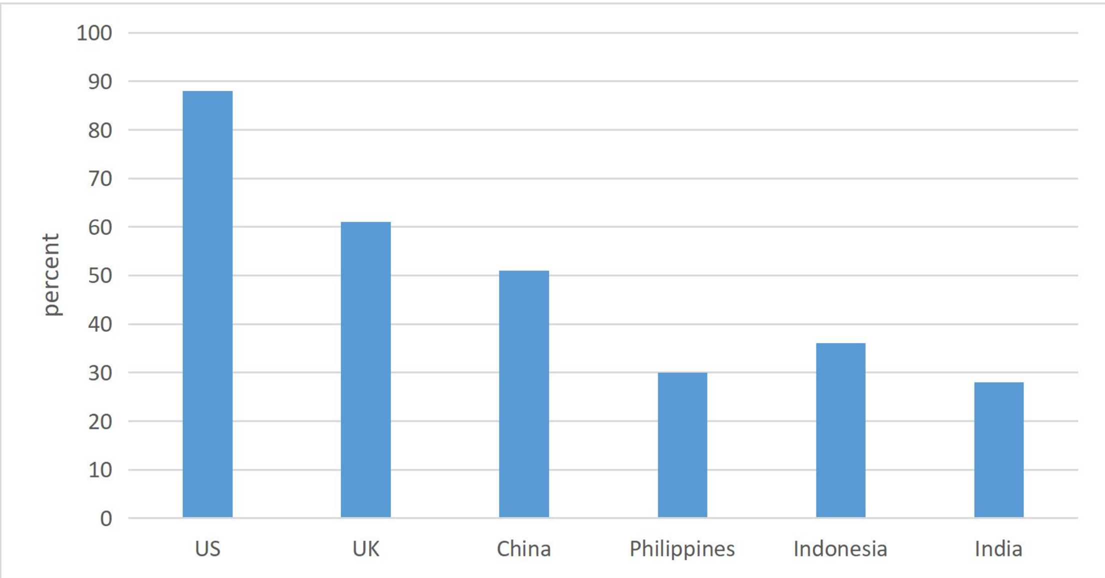


Figure 2.8: Gross enrollment rates of tertiary education in worldwide countries

Source: World Bank, 2018

2.2.4 Education Spending

Education expansion is often focused on by researchers, but fewer studies would focus on the cost of expansion. In Table 2.5, we illustrate different sources of education spending across the years. It can be seen that the total spending contentiously grows with the variations in time. In addition, most of the education spending directly comes from the government fiscal expenditure. In fact, in 2020, education expenditure is the largest among all the government expenditures in a year. Aside from the resources the government provides, income from non-compulsory education is also an important component of education spending. Other resources come from private investment and social donations but on a small scale. Despite the change in the real amount of expenditure, we also illustrate the proportion of total education expenditure to GDP in the last column. It is found that the proportion of expenditure is quite large each year, with more than 5% after 2015, and generally increases over the years.

Despite focusing on the education expenditure from the government or units, individuals are also concerned with the money to be paid for students to get different levels of education. In fact, with the different economic and social development conditions, education fees would vary across different provinces and urban/rural areas in China. However, according to the requirement of the Compulsory Education Law, 9-year compulsory education, including primary and lower middle schools, is free of charge nationwide, covering all urban and rural areas. However, schools could charge service fees such as fees for uniforms and activities. In the period of non-compulsory education, fees mostly consist of tuition and accommodation payments. In Table 2.6, we illustrate the fee standards for upper middle school and tertiary education, using Jiangsu province as an example. We can see the annual tuition and accommodation fees are quite low for upper middle schools. Charges are slightly higher for tertiary education but are significantly lower than those in advanced countries such as the UK and the US. In public schools, students only need to pay 6800 yuan per year for tuition fees. The charge in private schools is about two times higher than in public schools, but the accommodation fees are the same, with only 1600 yuan per year. In addition, we cannot find large differences in fees between vocational colleges and academic universities. Therefore, it can be seen that in China, students do not need to pay higher fees when enrolled in better quality schools. This may generate a larger gap in the net payoff to different kinds of tertiary education.

Table 2.5: Education spending across the years with different sources

	Government fiscal expenditure	Private investment	Social donation	Income	Other investment	Total	The proportion of total education expenditure to GDP
2000	2563	85	114	938	148	3848	3.84%
2005	5161	452	93	2339	372	8417	4.49%
2010	14670	105	108	4106	572	19561	4.75%
2015	29221	187	86	5810	823	36127	5.24%
2019	40047	220	101	8723	1086	50177	5.09%

Source: China Statistics Yearbook, 2005-2019
Note: Amount unit, 10 thousand yuan

Table 2.6: Students' yearly education fees standards

		Upper high school	Tertiary (vocational)	Tertiary (academic)
Publicly funded	Tuition fees	1700	6800	6800
	Accommodation fees	200	1500	1500
Privately funded	Tuition fees		16500	15000
	Accommodation fees		1500	1500

Source: Bureau of Price of Jiangsu Province, 2020
Note: Amount unit, yuan

2.2.5 Overseas Education

In the previous parts, our discussions are mainly based on the students studying in China. However, an important feature of Chinese education in recent years has been the increasing number of young Chinese students choosing to study abroad. Since the "open and reform" policy was proposed in the 1980s, the connection in the education field between China and international countries has also been strengthened. Studying abroad is more acceptable in Chinese society by the government, employers, and families. In addition, with the fast economic growth in recent decades, Chinese families become wealthier at a fast speed and can afford their children to take education overseas. In the following Figure 2.9, we show the number of overseas students from 2010 to 2020, including the number of new students and a total number of students studying abroad at all levels of education. It can be seen that the number of students studying abroad has increased continuously over the years. In 2020, more than 0.6 million new students go abroad to take an education, and in total, there are 1.27 million students studying outside China. According to the statistics also provided by the Education Ministry (2020), about 82% of overseas students are taking tertiary education. 48% of students are at the postgraduate level, and the rest 34% are at the undergraduate level. It can be seen that overseas education for current Chinese students is mainly restricted to tertiary education.

The Chinese government can provide formal authentication for overseas students indicating that they have finished specific levels of education, serving as a signal in the labour market for employers to review. The Ministry of Education also provides the information that from 2000 to 2020, about 84% of overseas students who have finished their education would choose to return to China for their future career development. In addition, Li and Brey (2007) argue that employers often consider these return students to hold several advantages compared with domestic students, including language skills, communication and writing skills and skills for fast adaption to new working environments.

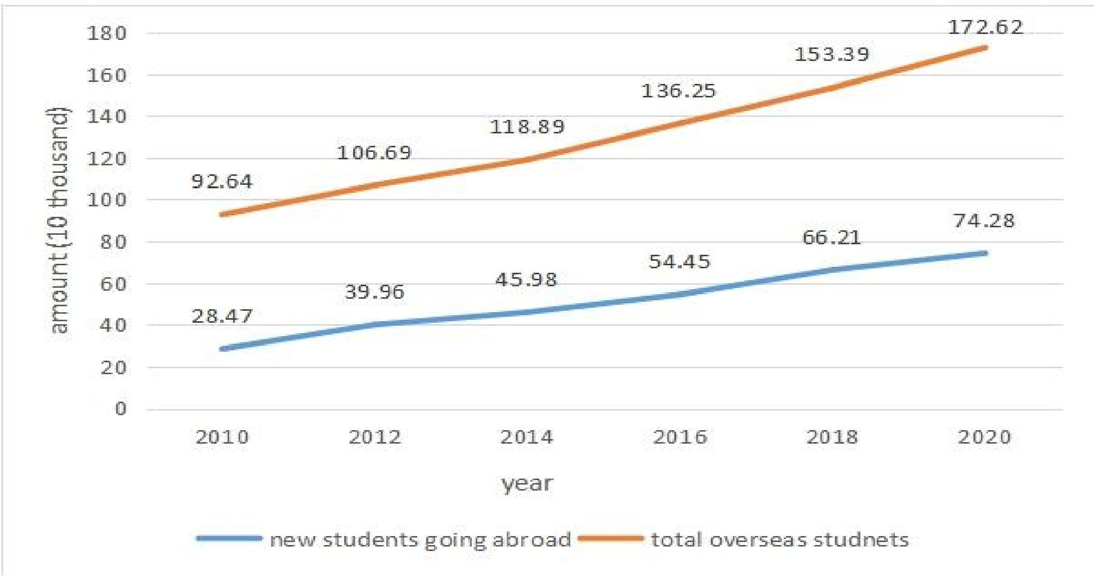


Figure 2.9: Number of overseas students

Source: China Statistics Yearbook, 2010-2020

2.3 Background to the Labour Market in China

2.3.1 Labour Market Indicators

The following Table 2.7 illustrates some important indicators for the Chinese labour market across the years. It can be seen that the total labour force decreases from 2014 to 2020. However, as shown in the previous subsection, the total number of population continuously increases over this period. This circumstance can be explained by the decreasing labour force participation rate. From Table 2.7, the proportions of the labour force to the whole population show a clear decreasing pattern after 2014, from 0.579 to 0.555, which may reflect a problem of the ageing population in China. However, the unemployment rate is quite low in China and does not vary largely across the years. At least 95% of the total labour force is employed each year. The unemployment rate is slightly higher in 2020 compared with previous years, reaching 4.24% for the first time in a decade. This may be driven by the influence of the COVID that happened at the start of 2020. We also provide the urban registered unemployment rate, which only shows the unemployment conditions in urban areas. We find the urban registered unemployment rate is only slightly higher than the total unemployment rate and remains quite stable across the years.

The distribution of the employed labour force across urban and rural areas is also illustrated. After 2014, there are more people employed in urban areas than in rural areas, and until 2020, people working in urban areas are around 1.5 times higher than those working in rural areas. This finding is consistent with the increasing urbanisation rate in China, shown in subsection 2.1.

In Figure 2.10, we specifically focus on the unemployment conditions for graduates from tertiary education. Employment Report on Chinese Graduates provides statistics by collecting employment data after half year of students' graduation. From the report's illustration, vocational college students suffer from a high unemployment rate in 2010, which exceeds 10%. However, with the variations of years, the unemployment condition is better for college students, and the ratio decreases to 8% until 2018. Regarding graduates from academic universities, the unemployment rate continuously increases after 2014 at a speed of one per cent every two years, which may imply an over-supply of academic students in the labour market. The unemployment rate for all types of graduates increases slightly from 2018 to 2020, and this finding is consistent with the previous growth in unemployment for all the workers in a country.

Table 2.7: Labour market indicators across the years

	2010	2012	2014	2016	2018	2020
Total labour force	78388	78894	79690	79282	78653	78392
Employed labour force	76105	76704	77253	76254	75782	75064
Employed labour force (urban)	34687	37102	39310	42051	44292	46271
Employed labour force (rural)	41418	39602	37943	34194	31490	28793
The proportion of labour force to the whole population	0.584	0.580	0.579	0.569	0.559	0.555
Unemployment rate	3.02%	2.78%	3.06%	3.82%	3.66%	4.25%
Urban registered unemployment rate	4.1%	4.1%	4.09%	4.02%	3.8%	4.24%

Source: China Statistics Yearbook, 2010-2020

Note: Urban registered unemployed people are those urban residents over 16 years old but with no job offers and officially registered as unemployed in public service agents; Labour force amount unit, 10 thousand people.

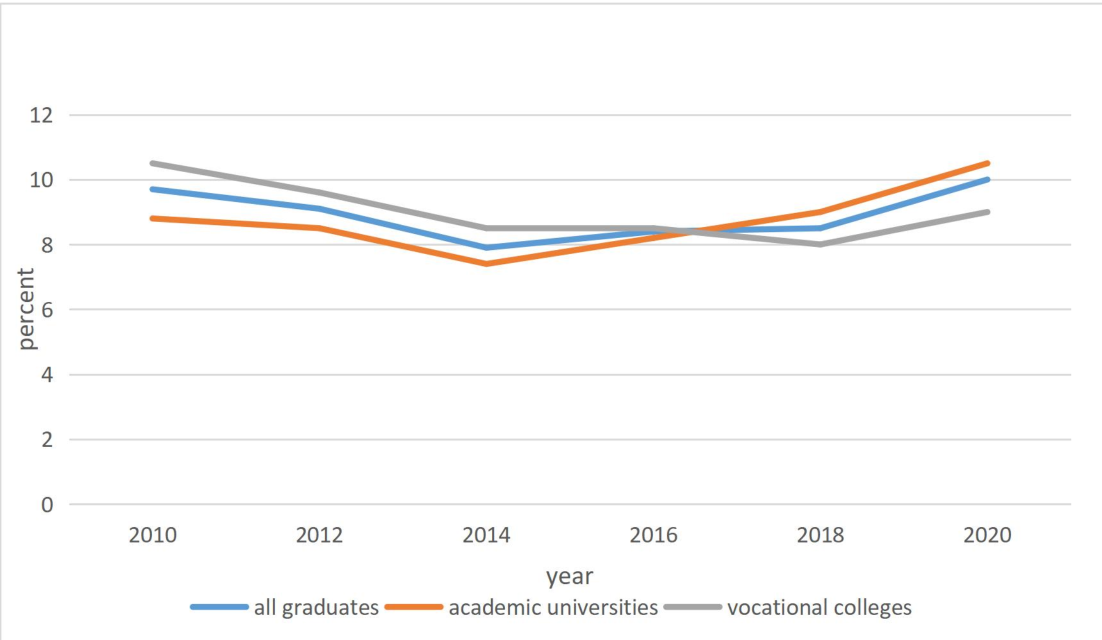


Figure 2.10: Unemployment rate of tertiary education after half year of graduation

Source: Employment Report on Chinese Graduates, 2010-2020

In the previous subsection 2.2, we show the distribution of different education levels for the population in China. Since in this subsection we mainly focus on the labour market conditions, we further illustrate education achievements for the employed workers in Table 2.8, with the help of the CFPS dataset. It can be seen for total employed workers, the lower middle school education is still the leading education level. However, we find that there are about 13% of individuals do not finish primary school education but still successfully find jobs in the Chinese labour market. Employed workers with non-compulsory education account for around 33% of all workers. Among them, 17% have finished tertiary education.

It is feasible for us to clarify the differences between self-employed workers and employees by using the CFPS dataset. In fact, we can find large differences in the distribution of education levels between the two employment statuses. Workers with no schooling mostly exist in the self-employed group. More than 20 per cent of self-employed workers are categorised as having no schooling. In addition, only 3.93% of the self-employed workers have achieved tertiary education, showing that being waged workers would be the main choice of college/university graduates. In terms of employees, we find very few individuals with no schooling would have a chance to be employed by companies or institutions. Though the leading education level is still lower middle in the group of employees, we find non-compulsory education is the most important component of employees' education, accounting for around 50%. Among them, 28% of individuals hold the qualification of colleges/universities.

Table 2.8: Education distribution of employed workers

	Total employed workers	**Employees**	**Self-employed**
No schooling	13.15%	05.80%	22.38%
Primary	19.04%	13.49%	26.01%
Lower middle	34.14%	32.37%	36.36%
Upper middle	16.17%	20.05%	11.30%
Tertiary and higher	17.47%	28.26%	03.93%
Total	100%	100%	100%

Source: CFPS data, 2018, author's calculation

Note: Education levels are based on individuals' highest finished education

2.3.2 Economic Transformation and Public Sector Development

When the People's Republic of China was first established, the central government implemented a policy of planned economy. Private units were not allowed in China, and nearly all the workers were employed in public-owned institutions. However, after the "Open and Reform" policy proposed in 1980, China experienced fast industrialisation and modernisation, and the economy has grown rapidly in recent decades. The development of the private sector also largely benefits from the policy. Private-owned institutions appear in the labour market, and a number of workers transform their working sectors from public to non-public. In addition, China joined the WTO at the turn of the 20th century, which further strengthened the open economy. The increasing amount of foreign direct investments and foreign institutions also further boost the development of the non-public sector.

Table 2.9 shows the number of institutions in the current Chinese labour market with different ownership statuses. Here the institutions refer to those with the rights to own assets, bear liabilities, and independently engage in socioeconomic activities. They include both business organisations and public-owned bodies, such as hospitals and schools in the public sector. It can be found that only smaller than 2 per cent of institutions are publicly owned. The private sector accounts for 98% of the labour market, which covers both inland and international institutions.

Table 2.9: Number of institutions with different ownership

	Number of institutions	**Proportions**
Publicly owned (nation)	293473	1.17%
Publicly owned (community)	180550	0.72%
privately owned (inland companies)	24034163	95.92%
Privately owned (international companies)	102477	0.40%
Others	444793	1.77%
Total	25055456	100%

Source: China Statistics Yearbook, 2020

The importance of the private economy is clearly shown in terms of the number of institutions. However, it does not mean that very few workers are employed in the public sector. Publicly owned institutions are often large in scale, but privately owned institutions consist largely of self-employed units with a small firm size. In Figure 2.11, we compare the number of employed workers in different sectors in 20 years. The proportion of workers in the private sector continuously increases over the years. After 2008, the number of workers employed in the private sector exceeds the public sector. By 2020, the proportion for the private sector reaches 67%, which is two times higher than that of the public sector. The number of employed workers clearly confirms the importance of the private economy in current China. However, individuals in private institutions suffer from considerably lower earnings than those in public institutions. Details are shown in the following subsection 2.3.4.

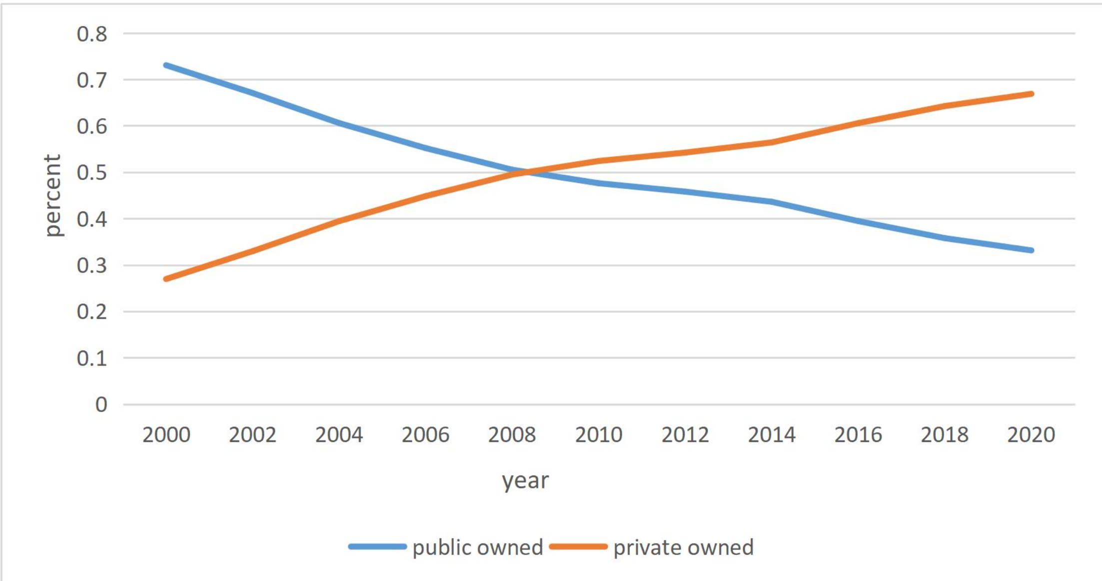


Figure 2.11: Proportion of employed workers in different ownership of institutions
Source: China Statistics Yearbook, 2000-2020

2.3.3 Population and Education Achievements in Different Areas

The dual society and the unequal development between urban and rural areas in China are often pointed out by a number of researchers. In fact, China suffers from a long-term separation in the labour market and economic developments between urban and rural areas, mainly driven by the registration system proposed by the government several decades ago. Each person in China needs to be registered as an urban or rural resident at birth. The free flow of labourers is restricted, especially to big cities, which decreases the communication between urban and rural areas and finally results in a dual society in China. Though the Chinese government has been trying to reform the registration system and loosen the restrictions on the inflow of labourers to city areas in recent years, the long-term effect of the separation in the labour market would not be easily eliminated in a short period.

Figure 2.12 shows the population proportion in urban and rural areas with residential and registration status. We can find there are increasing numbers of people living in urban areas, which increases the urbanisation rate in China. However, according to survey results from the CFPS, a small proportion of new entries to the urban areas obtain the official urban registration status. As many researchers argued, these immigrants may be treated differently in health care, social insurance, children's education and even job occupations (Zhu, 2015).

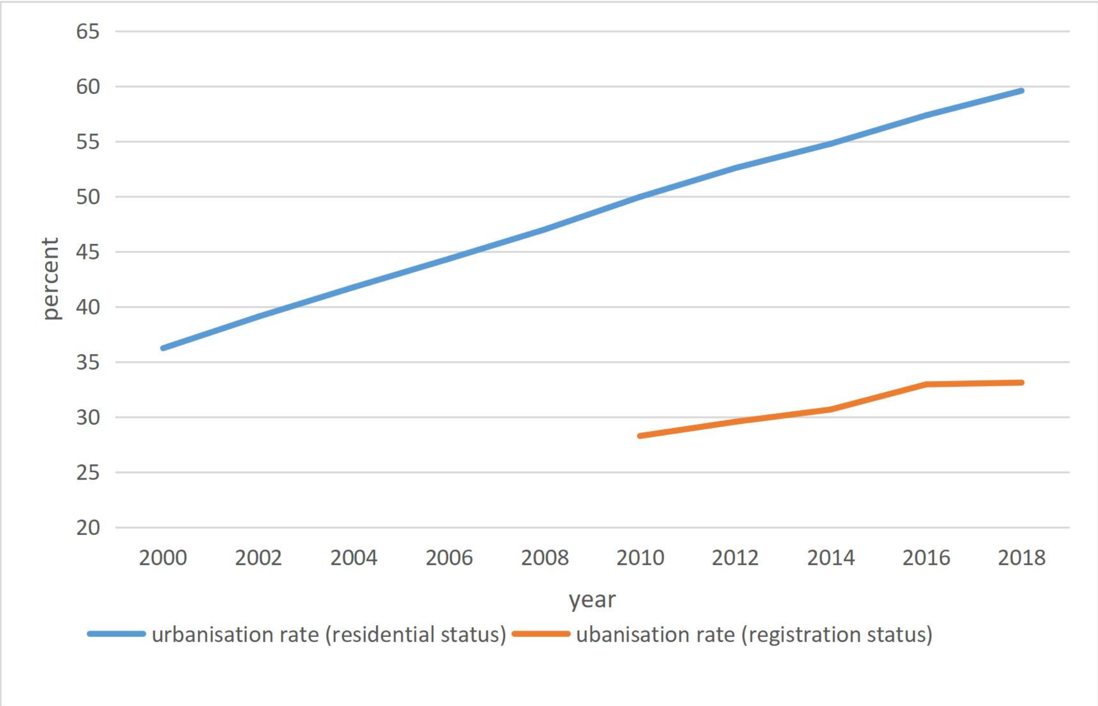


Figure 2.12: Population distribution across urban/rural areas
Source: China Statistics Yearbook, 2000-2018; CFPS data, 2010-2018, author's calculation

Differences between urban and rural areas can also be reflected in the educational achievements. Figure 2.13 clearly shows the gap in average education years for urban and rural working age individuals (using residential status). In 1990, the average years of education for rural individuals are only six years. However, in urban areas, individuals have finished lower middle education on average. The gap between human capital achievements does not change largely across years, though average years of schooling both increase in different areas across the years. By 2020, there is still more than two years difference in average education achievements between areas. The lower education achievements may lead to lower productivity and marginal product for rural workers, which can be considered an important explanation for income gaps between areas. In the following subsection, we detail the income conditions in urban and rural areas.

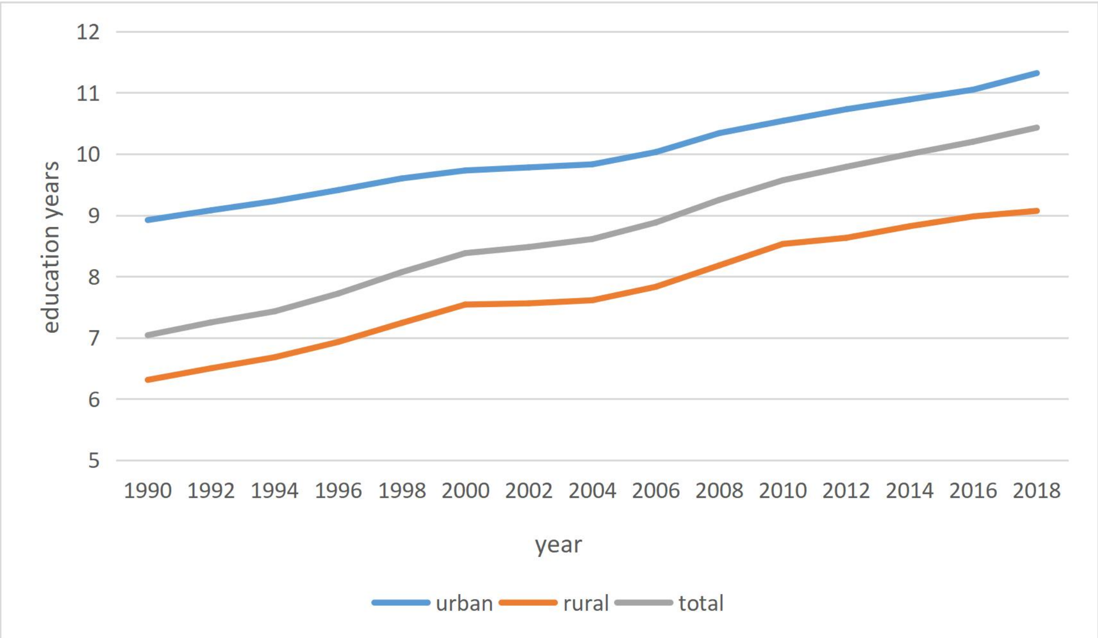


Figure 2.13: Average education years for urban and rural working age individuals
Source: China Human Capital Report, 1990-2018

2.3.4 Income and Wages

In this subsection, we focus on individuals' income and wages in the Chinese labour market, comparing urban/rural areas and sectors. Firstly, Table 2.10 illustrates the residents' average and waged disposal income in different areas. It can be found that both incomes continuously increase from 2010 to 2020. However, a large gap is observed between areas where the average disposal income in urban areas is more than two times higher than that in rural areas. However, we find a decreasing urban/rural income ratio trend across the years. We cannot directly compare the amount of average disposal waged income between areas because the proportions of the population doing waged jobs are quite different. However, we can see in recent decades, waged income is an important source of income in rural areas, accounting for around 40% of total disposal income.

Table 2.10: Average disposal income and average disposal waged income for urban and rural residents

	Average disposal income			Average disposal waged income	
	Urban	**Rural**	**Urban/rural ratio**	**Urban**	**Rural**
2010	21033	5919	3.55	13707	2431
2012	26959	7916	3.40	17335	3447
2014	28843	10488	2.75	17936	4152
2016	33616	12363	2.71	20665	5021
2018	39250	14617	2.68	23792	5996
2020	43833	17135	2.55	26380	6973

Source: China Statistics Yearbook, 2010-2020

Disposal income may have many sources, such as wage income, business income, financial income, transfer income, etc. In Figure 2.14, we specifically focus on the labour market earnings for employees in urban and rural areas. It is clear that urban workers also have higher labour market earnings than rural workers, but the gap is considerably smaller than that found in the level of average disposal income. This may reflect that the large gap in total income is mainly driven by those not doing waged jobs in rural areas, such as farmers or self-employed workers. However, attention needs to be paid that with the variations in periods, the gap in labour market earnings between urban and rural areas shows an increasing pattern.

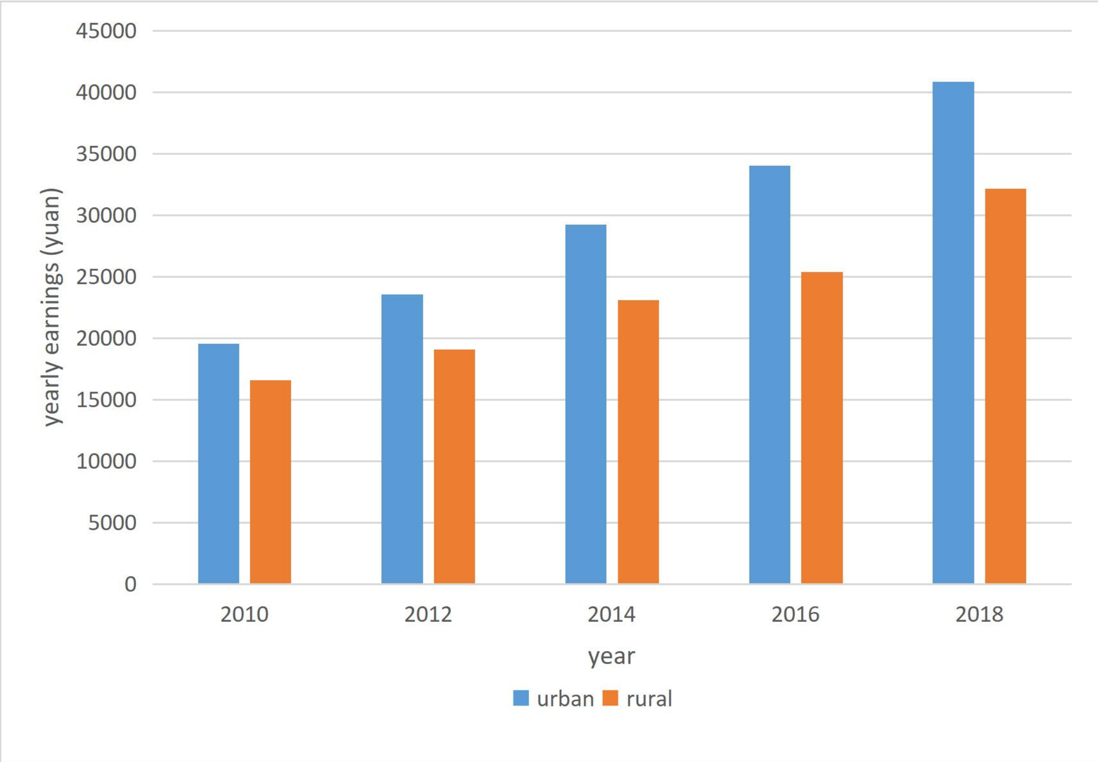


Figure 2.14: Average yearly earnings for employees in urban and rural areas across the years
Source: CFPS data, 2010-2018, author's calculation
Note: Earnings from CFPS are after-tax, but are gross ones including different kinds of benefits, rewards and subsidies

In the following Figure 2.15, we cover the differences in earnings between workers employed by institutions with different ownership statuses (China Statistics Yearbook only provides earnings in urban areas). In the previous subsection, we find that there is a higher proportion of workers employed in private institutions. However, employees in private institutions suffer from considerably lower earnings than those in public institutions in a 10-year period. In 2010, the average payoff in the public sector is around 40000 yuan, which is 20000 yuan higher than that in the private sector. In fact, we find an increasing gap across the years, and when it comes to 2020, the earning gap between sectors grows to 40000 yuan per year. It can be seen that though the private economy shows a larger scale in current China in terms of the number of institutions and employed workers, the public sector still takes the advantage that they can provide a higher payoff to employees, which would explain why public institutions still keep the attraction to job seekers in China.

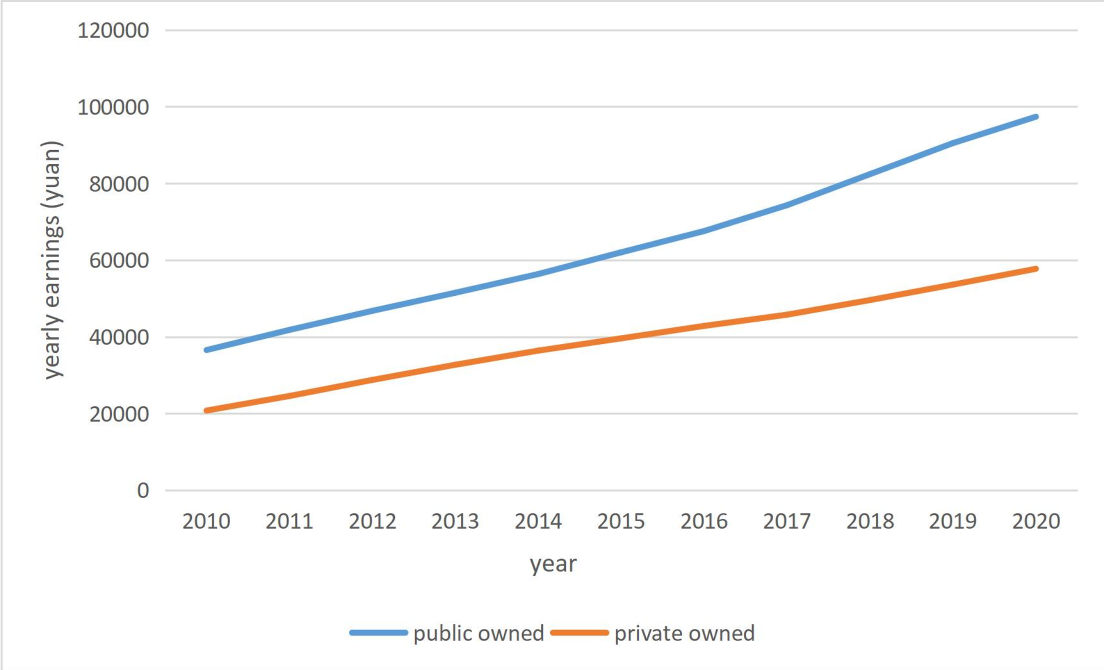


Figure 2.15: Average yearly earnings for employees in institutions with different ownership (urban areas)
Source: China Statistics Yearbook
Note: Earnings in the Yearbook are before-tax gross earnings, including benefits, rewards, bonuses, allowances, subsidies, overtime wages and wages paid under special circumstances; Employees exclude those who are not registered as formal staff.

2.4 Human Capital, Economic Growth and Individuals' Wages

2.4.1 The Effect of Human Capital Achievements on the Economic Growth

In the previous section 2.1, we illustrate statistical evidence of Chinese efforts in promoting the population's human capital achievements. Why do China and many developing countries worldwide focus on education and human capital development? In fact, economic investments are traditionally restricted to physical capital, such as land, plants and machinery. However, a number of researchers have realised the importance of human capital to a county's economic growth, which is the capital that exists in people, including knowledge, skills and physics (health). In the existing literature, there are many theories that support this idea, and we illustrate some important theories in the following.

(1) Schultz's Theory

Schultz (1961) argues that human capital accumulation can help countries adapt to global economic changes. In a rapidly changing world, where new technologies and ideas are constantly emerging, countries that invest in human capital can be more resilient and adaptable. They can more easily restructure their economies and shift resources to emerging industries, which can help them to remain competitive and grow over the long term.

(2) The Bowles-Gintis View

Bowles and Gintis (2002) point out that "human capital" is the capacity to work in organisations, obey orders and adapt to life in a hierarchical/capitalist society, which would also help with fast economic development. According to this view, the main role of schools is to help individuals develop the "correct" approach towards life.

(3) Neoclassical Model

The standard neoclassical model suggests that if educated and uneducated workers are imperfect substitutes, an increase in the share of educated workers will raise the productivity of uneducated workers (Katz and Murphy, 1992). Educating a worker is often argued to generate knowledge spillovers that benefit others. Agents can acquire skills through informal interactions with their peers.

(4) Endogenous Growth Theory

According to the economic endogenous growth theory, technological progress and innovation are endogenously determined by the investments that people make in human capital. In endogenous growth models, the economic growth rate is determined by the choices and behaviours of economic agents within the system, including individuals, firms, and governments (Aghion and Howitt, 1992). As Acemoglu (2009) argued, unlike traditional growth models that assume exogenous technological progress, the endogenous growth model emphasises the role of factors such as human capital accumulation, research and development (R&D) investments, innovation, and knowledge spillovers as drivers of economic growth.

The importance of human capital to economic growth is also found in China. Evidence from growth accounting studies (e.g. Yan and Yudong, 2013) confirm that the accumulation of human capital during the 1980–2010 open and reform period contributed significantly to Chinese economic growth. In addition, various studies have highlighted the key role that the expansion of the education system, in particular, the higher education (HE) system, has played in China's remarkable economic growth over the last four decades, accounting for at least 10–15% of per capita GDP growth (Zhu, 2012; Whalley and Zhao, 2013).

2.4.2 The Effect of Human Capital Achievements on Individuals' Wages

At the micro level, education development also benefits individuals' labour market outcomes. In recent years, Becker's (1964) idea has been widely accepted that human capital achievements, such as education and training, would make individuals more effective in doing jobs and increase their marginal products and wages. The Chinese economy grew at an unprecedented rate from 1980 to 2010. The country's transition to a market economy was facilitated by a wide range of economic reforms introduced in the 1980s and 1990s. During the planning era, wages were low because of the country's socialist labour system, which suppressed returns to schooling (Chen and Feng, 2000; Fleisher and Wang, 2004). In post-reform years, substantial physical capital investment and the relocation of labour and capital through privatisation and market liberalisation increased the demand for skills and schooling (Meng et al., 2013). As argued by many researchers such as Hung (2008) and Heckman and Yi (2012), consistent with the experience of other transition economies in Central and East Europe, China would also have rising returns to education in post-reform years. With sufficient demand in the labour market, human capital accumulation is an essential way to increase individuals' income. This can be achieved successfully by individuals with the help of fast national education development in recent China.

2.4.2.1 Alternative Explanations of Return to Education

Based on the human capital theory argued by researchers such as Becker (1964) and Mincer (1974), many researchers conduct analyses to empirically estimate the wage return to human capital. In econometric models, education is often treated as the proxy of individuals' human capital and assumed to have a positive and significant effect on individuals' wages. However, it should not be ignored that the human capital aspect is only one way to explain the effect of education on wages. In the literature, there are two other lines of theories that can explain the positive connection between education and wages.

Firstly, Spence (1974) proposes a signalling theory. It is argued that higher-educated individuals would be more productive not only because they gain knowledge or training in the education process but also because they have higher innate abilities than those lower-educated individuals. If these innate abilities and characteristics persist in the labour market, these individuals would have higher marginal products and be rewarded with higher wages. Employers believe they can distinguish those high and low-productive employees just by using their educational achievements as a signal and provide more capable employees with better-paid positions. Under Spence's signalling theory, education can be used only as a signal to divide individuals' innate abilities, even if it has no real help with individuals' marginal product. In addition, the signalling can also arise in the form of the credential effect, that employers only treat education as a true reflection of individuals' actual productivity (Hungerford and Solon, 1987; Clark and Martorell, 2014). They will pay wages to the productivity that the qualifications imply rather than rewarding individuals' true skills or abilities. This theory does not argue that the achievements on human capital are unnecessary, but it assumes that information problems may exist in the screening procedure on individuals' actual productivity when only qualifications are used as a signal.

Secondly, another theory to explain the positive return to education is based on the achievements in social capital or networks, reflected by the fact that well-educated workers often have social networks with other workers who are also well-educated

(Knight and Yue, 2008). It argues that education generates returns beyond the acquisition of human capital. Social networks can contribute to enhanced employment outcomes and economic benefits through two main mechanisms. Firstly, well-educated individuals will more easily obtain ideas, information, job opportunities and even financial support from networks with other well-educated individuals James and MacLeod (2007). Through these networks, individuals can also gain insights, guidance, and recommendations that can enhance their employment prospects and overall success. Social networks can also be provided by their families because, in recent years, more evidence confirms a positive relationship between family backgrounds and individuals' educational achievements. In addition, well-educated workers could fast enhance their productivity by formally cooperating with other talented workers through the so-called "learning by doing" process (Thompson, 2010). By connecting with peers who have similar educational backgrounds, individuals can engage in knowledge-sharing, professional development, and collaborative projects. This collective learning and support can increase productivity and success in the workplace.

The effect of social capital would make individuals more innovative and productive and help them quickly adapt to the labour market dynamics, leading to better job performance and higher wages. This theory can also be used to explain the existing higher return to better education qualities (especially at the tertiary education level) found in the literature. For example, individuals graduated from top universities such as Harvard and Oxford would have significantly larger social capital than other graduates. This capital may not be correlated with academic achievements in schools, which is distinguishable from the traditional human capital explanation of a positive return to education.

2.5 Labour Market Segmentation between Chinese Urban and Rural Areas

2.5.1 Labour Market Segmentation Theory

Labour market segmentation is the division of the labour market according to a principle such as occupation, geography and industry. According to Reich et al. (1973), segmentation is to define groups "with little or no crossover capability", such that members of one segment cannot easily join another segment. This can result in different segments, for example, men and women, receiving different wages for the same work (Lips, 2008). 19th-century Irish political economist John Elliott Cairnes referred to this phenomenon as that of "non-competing groups".

Traditionally, LMS is characterised by a labour market that is divided into two segments, often referred to as ‘primary’ and ‘secondary’, though it can include more. The rewards of primary jobs, in terms of earnings, working conditions, job security, training opportunities and career prospects, are high; those of secondary jobs, are low (Demekas, 1990). Rumberger and Carnoy (1980) argue that a key element in labour market segmentation relates to mobility, specifically the limited mobility between primary and secondary segments. As a result, the differences are not only relevant to an individual’s first entry or even their re-entry into the labour market but rather persist over time.

Anderson et al. (1987) hold the idea that segmented labour markets exist because of barriers which prevent the free movement of workers between different sections of the labour market. In practice, there is not one labour market but several different and distinct markets for labour. The most obvious barrier is skills and qualifications, but candidates might consider others such as location, the existence of discrimination, finances, lack of information, etc. It is further argued by Davia and Hernanz (2004) that segmentation may arise from particularities of labour market institutions, such as governing contractual arrangements (segmentation along permanent/temporary nature of employment contracts), from lack of enforcement, as well as types of workers concerned (such as migrant and non-migrant workers).

A typical example of the segmented labour market is the segmentation between locations or geography. In China, there is a man-made separation between urban and rural areas because the Chinese government has set up a unique household registration system. Labourers in different areas are not allowed to flow freely, and especially, there is a barrier for rural residents to migrate to urban areas. Workers in different areas suffer from the problem of "little or no crossover capability", pointed out in the labour market segmentation theory, and urban and rural workers have become non-competing groups. The segmentation results in the different economic development and labour market conditions between urban and rural areas. As illustrated in the previous subsections, we find statistical evidence of the significant differences in population, educational achievements and wages between urban and rural areas. Further, as Zhu (2015) argued, even if there are migrants from rural to urban areas, they are not treated equally with local urban residents in occupations, work benefits, social care and children's education.

2.5.2 Return to Education in the Geographically Segmented Labour Market

A considerable amount of researchers have focused on the different economic development conditions between urban and rural areas and the labour market segmentation. However, most of them focus on wage differences or educational achievements solely at the descriptive level. In fact, the segmentation in the geographic labour market can also be reflected in how individuals' human capital and skills can be rewarded in the labour market. In the following, we list several factors from the literature that can be used to explain the return to education gap between areas, which can also be the theoretical evidence to support the empirical analyses on various returns to education between geographic locations.

(1) Demand and Supply

Firstly, the transition period since the early 1980s witnessed the fast economic growth of China with rapid industrialisation and market liberalisation, mostly in urban areas. The increasing number of technology-based industries and foreign direct investments generate the demand side shock on educated and skilled workers, resulting in a rising return to education. However, in rural areas, the economic development is much slower. With the lack of physical investment inflow and low level of industrialisation, the demand for human capital investment is relatively lower, and the wage gap between high and low-educated workers may be largely moderated (Ann et al., 2015).

(2) Agglomeration

According to this theory, there are benefits to firms and workers associated with clustering in urban areas. One of the main benefits of agglomeration is the availability of a larger pool of skilled labour needed to drive innovation and productivity. The concentration of high-skilled labour in urban areas may be due to the proximity of research institutions, large firms, and other key economic drivers (Florida, 2002). As a result, firms in urban areas may be willing to pay higher wages to attract the best talent.

(3) Education Quality

Secondly, some scholars are worried about the quality of education attainment in Chinese rural areas. Weng et al. (2010) find out that there is a significant gap in education quality between rural and urban areas. Students who take primary or high school education in rural areas normally suffer from worse learning conditions (shortage of qualified teachers and hardware facilities) and, therefore, worse academic performance than urban students. The teaching quality will affect the quality of human capital accumulated and the future productivity of rural workers even if they have the same level of education as urban workers, which could be an important reason to explain the difference in return to education between areas (Yang et al., 2010).

(4) Labour Market Functionality

Some other researchers argue that the labour market functionality may be lower in rural areas, and employees suffer from the effects of asymmetric information (Bharadwaj, 2015). On the one hand, employers may lack information on the actual skills and abilities of rural workers as they are not confident to use the qualifications obtained in rural areas as a signal, based on the low education qualities. In addition, each year, there are amount of workers coming back from urban to rural areas. They may claim they have achieved better education and training in city areas, but it is still hard for rural employers to determine the actual abilities of these return immigrants. In such cases, to avoid adverse selection, the employers would offer a pooled wage to all workers, skilled or unskilled, until they are tested (Kar, 2009). The pooled wage offer leaves skilled workers with lower than their desired returns.

On the other hand, with insufficient employment information and limited help from employment services in rural areas, skilled workers may lose bargaining power with employers and have fewer access to job opportunities. This will lead to skilled workers having an imperfect expectation of their wage returns in the labour market. They may accept misallocation between job characteristics and actual skills or abilities due to the lack of alternatives or negotiating skills, which lower their wage payoff. Li et al. (2005) also provide an extension to this theory that in rural areas, wage returns can be explained more by other factors besides actual productivity, such as social relationships, employers' preferences and job information acquisitions.

2.5.3 Waged Work Participation and the Self-employment Choices

The segmentation in the labour market also results in differences in the employment choices for workers in urban and rural areas.

In the following table 2.11, we show the composition of Chinese working age individuals' employment statuses in urban and rural areas and the difference in waged and non-waged job participation. From the data information provided in CFPS, it can be seen that from 2010 to 2018, most individuals in urban areas take waged jobs, and the waged work participation rate is much higher than that in rural areas. For example, in 2018, about 62% of urban residents are waged workers. However, for rural residents, the number is only 37%. Turning to other employment statuses, we find very close proportions of individuals who are unemployed and not in the labour market across different areas. Therefore, it can be seen that the main issue that drives the various waged job participation rates is the individuals' choices to become self-employed workers in rural areas. The unemployment rate in CFPS is shown to be quite low because of the unique definition of unemployment in CFPS. Only those individuals who have tried to find jobs in the previous month and at the same time can start a job in two weeks if received the offer can be classified as unemployed.

The large number of non-wage participants may result in a concern in the empirical analysis of individuals' wages in rural areas. In most Chinese surveys, only income for wage earners is available to researchers. This means we are conducting analysis on a small than 50% of rural residents, and these individuals may be self-selected and not a random draw of the population, which may result in a self-selection bias of the estimated coefficients in econometric models.

Many reasons could explain why self-employment plays a more important role in the rural labour market, including limited demand for waged workers, higher return to education in the self-employed sector and the motivation from return urban-rural migrants. We provide more detailed explanations in the following.

Table 2.11: Distribution of employment statuses for working age individuals in urban and rural areas

		Wage earners	Non-wage earners			Total
		Employed by others	Unemployed	Self-employed	Not in the labour market	
Year 2010	Urban	60.28%	1.72%	27.21%	10.79%	100%
	Rural	31.97%	1.18%	59.61%	7.42%	100%
Year 2014	Urban	58.07%	1.89%	28.26%	11.78%	100%
	Rural	30.53%	1.11%	57.65%	10.71%	100%
Year 2018	Urban	62.85%	1.42%	25.78%	9.96%	100%
	Rural	37.59%	1.00%	53.69%	7.71%	100%

Source: CFPS data, 2010-2018, author's calculation

Note: in CFPS, self-employed individuals also include those having self-owned agricultural businesses (farmers) and those in the informal sector, such as domestic workers, home-based workers, street vendors and waste pickers.

(1) The Liberalisation of Rural Labour Force

Before China's reform and opening up in the late 1970s, individual employment and income were linked to the commune-based production system, and non-agricultural activities were almost non-existent in rural China (Meng, 2012; Zhang et al., 2004). After the Household Responsibility System was implemented in the early 1980s, the traditional system was abandoned. Each family is responsible for a fixed amount of agricultural production. The ownership of land still belongs to the collective, while the management right is subcontracted to farmers in rural areas for independent management on a family basis. This system does not require collective production, and the rural labourers have been gradually freed from traditional agriculture to non-agricultural activities, thus promoting the growth of the non-farm sector in China (Hu, 2015).

However, low industrialisation in rural areas makes labourers not easy to find waged jobs in rural markets; therefore, they are more motivated to do self-employed. Self-employment is not restricted to the agriculture industries. It also includes the simple manufacturing and services sector, but often on a small scale. Self-employment also slowly benefits industrial development in rural areas. Statistical evidence shows that the share of rural industries represented by township and village enterprises (TVEs) and other rural private enterprises has increased rapidly from 9% to 36% of the national industrial output during 1979–93 (Jin and Qian, 1998). According to de Brauw and Rozelle (2008), the self-employed accounted for 16.2% of the total rural labour force, highlighting the possible contributions of rural entrepreneurs to local economic activities. In addition, the share of non-agricultural income from household business in per capita rural household income has grown steadily from about 2% in 1978 to 12% in 2012 (National Bureau of Statistics of China, 2013).

(2) Higher Return to Education

In waged jobs, because of the lack of sufficient demand, skilled labourers cannot find jobs that fully utilise their knowledge and skills and suffer from a lower return to education. However, an increasing number of evidence show that a significant return to education also exists in self-employment and in rural areas, the return to education for self-employed jobs is higher than for waged jobs (Hu, 2015; Tokila and Tervo, 2011). Since there is an increasing number of educated individuals in rural areas, self-employment is a method that can be selected to increase wages under the problem of limited waged job positions.

(3) The Return Immigrants

Han and Cui (2007) argue that the size of China's rural internal return migration (from urban to rural areas) accounts for nearly one-quarter of the total rural migration flow and 10% of the total rural labour force in recent years. These return immigrants acquire better experience and skills in urban areas, and most return immigrants choose to become entrepreneurs rather than wage earners. One of the reasons is that these individuals often have financial capital earned from urban areas, and they have the ability to create their own businesses after coming back.

(4) Taking Care of Family Members

One of the advantages of taking self-employed jobs is to work in a flexible way and can have more time to take care of family members. Though in the previous decades, China proposed a one-child policy, the implementation of this policy was argued to be slow and not strict in rural areas (Wang et al., 2016). Therefore, rural families often have more children to care for than families in urban areas. In addition, because of the imperfections of the social security system in rural areas, many old farmers suffer from low or even no pensions and bad medical care. Therefore, family care is essential for these people in rural areas. These factors motivate rural individuals, especially females, to participate in a job with more flexible working arrangements.

2.6 Conclusion

In this chapter, we provide statistical evidence on Chinese education and labour market conditions. With the fast development of education in recent years, an increasing number of Chinese residents have the opportunity to increase their educational achievements. Many researchers argue that the growth of human capital would benefit the economic development of a country. In addition, the human capital theory proposed by Becker also points out that at the micro level, human capital achievements would increase individuals' marginal product and efficiency and, therefore, their wages. Many researchers conduct analysis to empirically estimate the wage return to human capital. However, based on the theoretical contributions in the literature, the human capital aspect is only one way to explain the effect of education on wages. Signalling theory also argues that education may only serve as a signal to individuals' innate abilities, and social capital can also be accumulated through education processes.

However, the complication of the Chinese labour market will also affect the analysis of the wage payoff to human capital in China. For example, firstly, though China has transformed from a planning economy to a modernised and liberalised economy, the public sector and public-owned institutions still play an essential role in the market and control the key economic factors such as electricity, water and mines. It is often argued that the private sector is more marketised, and the wage payoff would be closer to the marginal product. It is still not clear in China whether or to what extent the return to skilled workers would be affected by the existence of large-scale public institutions and whether there would be a significant sector-oriented return to education. Secondly, China suffers from a labour market segmentation between urban and rural areas, driven by the strict household registration policy proposed by the government. Under the segmented labour market, the free flow of labourers is restricted, and urban and rural workers become non-competing groups. The labour market conditions, especially the supply and demand conditions for skilled workers, would vary across areas, affecting the wage return to education. Thirdly, though China has experienced economic growth for decades, the payoff to human capital will adjust to the new condition of both educational supply shock as well as shifts in the demand side. As Asadullah and Xiao (2020) argued, there are emerging concerns about declines in economic growth rates, and after years of high growth, China's economy is slowing down. However, the supply side shock education has been shown in China, especially with the fast expansion of tertiary education. In 2018, the gross enrollment rate of tertiary education achieved over 50%. Therefore, rising concerns should be focused on whether skilled labourers can be correctly used in the labour market. An updated analysis of return to education is needed for the contemporary Chinese labour market, with the consideration of the possible over-supply of skilled workers and the match between education achievements and job requirements.

Based on the wider context of China, we conduct empirical analyses on the wage payoff to education in China in the following chapters. We also take into consideration the different explanations for returning to education and address the effect of innate ability by using econometric methods. We examine the urban/rural differences in return by including the measurement of self-selection bias, especially in the rural labour market driven by the high number of self-employment participation. In addition, we study whether the match between individuals' education achievements and job characteristics can have a significant effect on individuals' wages.

Chapter 3 Return to Education for Workers in the Waged Sector in China: A Comparison between Urban and Rural Areas

3.1 Introduction

Since the human capital theory proposed by conventional wisdom such as Schultz (1960) and Becker (1964), there is an increasing number of scholars realising the importance of investment in human capital to economic development. Many econometicians try to examine how the human capital investment would be rewarded at the individual level, such as Mincer (1974), who used education as an important proxy of human capital and empirically estimated the marginal effect of education years on individual wage levels, which is the so-called “return to education”. The topic of return to education is long researched for several decades globally, and it is not surprising that there is an increasing number of studies on return to education in China after the “open and reform” policy when the planned economy ended and the modern market economy was first established. Studies examining how human capital can be rewarded in the Chinese labour market find clear trends. For example, many scholars argue that after the tough transition period in the late 1970s and early 1980s, when the return rate is considerably low, there is a clear pattern from the late 1980s to the early 2000s that the return to education continuously increases, which corresponds to the fast development of the Chinese economy during this period (e.g. Li and Ding, 2003; Wang and Yue, 2008). However, when it comes to the 21st century, the growth in return to education seems moderated because some researchers find out that starting from 2000, there is an indifferent or even insignificant decrease in return to education (Ding et al. 2012).

Compared with studies in Chinese urban areas, the analyses in rural areas are much fewer, and the direct comparison between rural and urban areas is rather limited, especially in most contemporary China. Nevertheless, in other Asian countries that are also developing ones, the difference between rural and urban areas is more focused such as India (Rani, 2014), Pakistan (Aslam et al., 2012) and Thailand (Warunsiri and Mcnown, 2010). This gap in Chinese literature is also emphasised by some of the researchers. For example, when reviewing the analysis results of the return to education in China, Guo et al. (2019) state that the studies on rural-urban differences are too few to examine the geographic isolation. In addition, Asadullah and Xiao (2020) point out that no study documenting changes in both rural and urban China, particularly for the period after 2010. This apparent gap in Chinese literature encourages us to conduct a specific analysis of geographic differences.

It is often pointed out by many scholars (e.g. Wu and Treiman, 2004; Chan, 2010) that China suffers from a man-made, policy-based segmentation between rural and urban areas. The strict household registration system, which is rarely seen in international countries, prevents the free flow of labourers and creates a dual society in China. Even until most recently, with the fast growth of the Chinese economy and industrialisation, the dual society still exists and is considered the main source of the large income inequalities between rural and urban areas and possibly hinder long-term economic growth in the future (Wu, 2011).

The separation of development and labour market conditions would also be a reason for the heterogeneous returns to education between urban and rural areas. For example, firstly, the transition period since the early 1980s witnessed the fast economic growth of China with rapid industrialisation and market liberalisation, mostly in urban areas. The increasing number of technology-based industries and foreign direct investments generate the demand side shock on educated and skilled workers, resulting in a rising return to education. However, in rural areas, economic development is much slower. With the lack of physical investment inflow and low level of industrialisation, the demand for human capital investment is relatively low, and the wage gap between high and low-educated workers may be largely moderated. Secondly, some scholars are worried about the quality of education attainment in Chinese rural areas. Secondly, Weng et al. (2010) find out that there is a significant gap in education quality between rural and urban areas. Students who take primary or high school education in rural areas usually suffer from worse learning conditions (shortage of qualified teachers and hardware facilities) and worse academic performance than urban students. The teaching quality will affect the quality of human capital accumulated and the future productivity of rural workers, even if they have the same level of education as urban workers, which could be an important reason to explain the difference in return to education between areas. Thirdly, some scholars, such as Li et al. (2005), propose the idea that the rural labour market may suffer from more severe imperfect information and lower functionality than the urban market. The rural labour market may reward human capital less, but other non-market factors (such as social relationships and backgrounds) are used in assigning jobs and wages, which largely hinder the degree of return to education in rural areas.

The differentiated estimation on return to education between regions would guide the education investment for both individuals and the government. For example, firstly, individuals or families would decide on how many financial resources to be invested in education according to the payoff rate to human capital in the labour market. The urban and rural residents would react differently if there is a significant return gap. Secondly, the government is also quite sensitive to the cost/benefit ratio of the education expenditure, and adequate and differentiated estimation of return to education would help them adjust the education policies in both rural and urban areas. If there are large gaps in the return to human capital investment between areas, it would be hard for the government to promote consistent national policies.

In this analysis, we take advantage of a newly formed survey, China Family Panel Studies (CFPS), which is designed by the research team of Peking University and funded by Peking University and the Natural Science Foundation of China. CFPS is a nationally representative survey covering 30 (out of 34) provinces in China. It provides detailed information on important variables such as individuals' hourly wages and education achievements, which are essential for the estimation of return to education. The main methodology used in this analysis is Mincer's (1974) wage equation and Ordinary Least Squares (OLS) method. However, arguments are often raised by researchers that results obtained from the OLS method would possibly suffer from significant biases, such as those resulting from omitted variables and non-random sample selection. To address these problems and achieve robust conclusions to the most extent, we further conduct the Instrument variable (IV) and Heckman two-step method in our analysis.

In detail, our analysis has the following research questions:

(1) Estimate return to education in contemporary China in both urban and rural areas

(2) Find out whether there are significant differences in returns between urban and rural areas

(3) Examine the heterogeneity in return to education between subgroups, including gender and sector.

(4) Study whether the estimated returns would suffer significantly from an omitted variable or self-selection bias.

The structure of the chapter is formed as follows. In the first part we introduce the backgrounds and specific research aims. In the second part, we provide a review of the related literature. In part three, we illustrate the methodologies. In the fourth part we explain the data, sample selection and provide detailed introductions and summary statistics for the variables we use. In the fifth part we provide empirical results on return to education with urban/rural comparison. In the last part we conclude.

3.2 Literature Review and Hypotheses

3.2.1 Theoretical Literature on Return to Education

3.2.1.1 Human Capital Theory

According to many economists, economic investments are traditionally restricted to physical capital, such as land, plants, machinery, equipment, currency and other securities. However, in the 1960s, some economists, such as Schultz (1961) and Becker (1964), proposed the ideas of human capital theory, which argues that human capital is also essential to individuals' productivity and countries' economic development. These human capitals may include different varieties of production knowledge, labour and management skills, and health quality contained in people. Human capital can also be invested in and improved through formal or informal education and different kinds of training such as skills or management training.

Firstly, In 1961, Schulz gave a speech entitled "Investment in Human Capital" at the annual meeting of the American Economic Association, in which he made a very systematic discussion on the viewpoint of human capital. It is also known as the "Declaration of Independence" in the new field of capital research, which clearly distinguishes physical and human capital. Generally speaking, there are three core ideas in Schultz's human capital theory:

(1) Human capital exists in people, which is the sum of values of knowledge, skills and physics (health). A country's human capital can be measured by its workers' number, quality and working time.

(2) Human capital is formed by investment in nutrition and health care, school education, personnel training, etc.

(3) Human capital investment is the main source of economic growth. The productive effects of human capital on the economy are determined by different levels of workers' knowledge, technology and labour skills, which result in various degrees of national income growth.

Taking education as a representative, Schultz (1961) made a quantitative macroeconomic study on the relationship between American education investment and economic growth in 1929-1957 and illustrated the following conclusions:

(1) the average return rate of education investment for all education levels, including primary, secondary, and tertiary levels, is 17%;

(2) the education investment contributes to 70% of labour income growth;

(3) the education investment contributes to 33% of national income growth.

One of the limitations of Schultz's theory is that his research is only restricted to the macroeconomic level. Following Schultz, another Nobel Prize winner in Economics, Becker used systematic microeconomics analysis to examine the relationship between human capital and individual income distribution. Becker (1964) developed the first model to measure the return to education, which is the internal rate of return or IRR.

The IRR is the discount rate for the present value of additional future income from higher education investment. The IRR can be achieved when the present value of additional income from education equates to the opportunity cost. Opportunity cost can be divided into two parts: the forgone earnings for not being employed and the direct cost of studying. This investment is considered worthy if the IRR exceeds the market interest rate at which individuals can borrow loans.

There are also some implications of the human capital theory. For example, firstly, Becker (1964) argues that in a person's life, the optimal amount of investment decreases with age. With the growth of age, the wage and the marginal cost of further investment both increase. With the growth of age, the expected income decreases because the number of years left to collect these investments is limited. Therefore, everyone should strengthen their investment in human capital when they are young. Secondly, the greater the depreciation rate of human capital, the less the motive force of investment. Because with the increase in depreciation rate, the marginal income will decrease, and the human capital investment will drop as well.

Becker (1964) also conducts some empirical analyses based on his theoretical contributions. He estimates the rate of return to white male college graduates, focusing on the 1939 and 1949 cohorts, using the national level data of the 1940 and 1950 censuses. The returns and costs of the cohorts are adjusted by mortality, growth and taxation. It is concluded that the private rate of return to the 1939 cohort is 14.5%, whereas to the 1949 cohort, it is 13%.

However, the human capital theory also experiences some limitations and arguments. Firstly, it put aside the education quality factors, which would be an essential issue to affect individuals’ labour market outcomes. Secondly, Teixeira (2014) argues that the human capital method deals with average benefits instead of specific returns to each individual’s investment. Thirdly, Heckman et al. (2006) also note that the internal rate of return requires lifetime earning profiles, and it is difficult to calculate non-market benefits and non-pecuniary costs.

Based on the Human capital theory and the arguments from Becker (1964) on the internal rate of return, Mincer (1974) develops a common single-equation model to measure the relationship between individuals' education achievements and wages in the labour market, which is the so-called Mincer Wage Equation. This method is often used in the literature because of the critical advantage that it is a linear regression equation, where the return to education can be directly estimated from econometric methods, such as Ordinary Least Squares (OLS).

In the extended Mincer wage equation, individuals' labour market experience and its quadratic form also serve as explanatory variables to capture the on-the-job training investment. There are two other important extensions to Mincer's equation. Firstly, some researchers use education levels (categories) to represent education years. They focus on various education returns at different levels rather than a homogeneous return to education years. Secondly, other control variables are added to the wage equation to distinguish different characteristics of individuals, for example, personal characteristics such as sex, marital status and urban/ rural area residents. In addition, job-related characteristics are also considered, such as tenure, firm size and industries.

However, Mincer's method to estimate the return to education may also suffer from some limitations and restrictions, mainly on the econometric aspect, for example:

(1) Endogenous issue driven by omitted variables

(2) Measurement error on education which would lead to biased estimates on return to education

(3) Sample selection issue driven by the non-random selection of worked workers

(4) The non-linear relationship between education and wages

In our analysis, we will focus on the issue of endogenous bias and self-selection bias in the estimation process. Detailed explanations are provided in the following section 3.3.

3.2.1.2 Signaling Theory

Spence (1973) provided a sensible economic explanation for the positive correlation between education and wages. It is argued that higher educated individuals would be more productive not only because they gain knowledge or training in the education process but also because they have higher innate abilities than those lower-educated individuals. If these innate abilities and characteristics persist in the labour market, these individuals would have higher marginal products and be rewarded with higher wages. Employers believe they can distinguish those high and low-productive employees just by using their educational achievements and provide more capable employees with better paid positions.

There are two main assumptions for the signalling theory to be satisfied. Firstly, there is asymmetric information between employers and employees regarding the proper skills of workers. Therefore, the signalling mechanism plays a vital role in accurate job-market matching. Secondly, it is assumed in the theory that the signalling cost (cost of education) is negatively correlated with productivity, which means high-ability individuals would have lower costs of education, whereas low-ability individuals would have higher costs. Individuals would make decisions to invest in education to maximise the income from wages net of signalling costs. The employer's initial belief is confirmed, and the signalling equilibrium occurs when more productive employees choose to obtain higher education qualifications and less productive employees prefer to receive lower levels of education, considering their different education costs.

Though both human capital and signalling theories indicate a positive relationship between education and individuals' wages, they have very different interpretations. Under the signalling theory, education can only be used as a signal to divide individuals' innate ability and productivity, even if it has no real help with individuals' marginal product. The different implications between the two theories drive the concerns in the empirical analysis. The estimated return to education may only reflect the effect of individuals' innate ability rather than the human capital achieved in education. Some researchers try to distinguish these two kinds of effect, but few of them conclude that the signalling theory is largely supported. For example, Harmon et al. (2000) find some positive effects of ability on individuals' wages, but education also plays an essential role in individuals' productivity enhancement. Also, Chevalier et al. (2002) support the human capital explanation that the effect of human capital achievements in education on wages is relatively large, with 10%. Aslam et al. (2012)

also distinguish education and ability by using Raven test results for ability at individuals' young age. No significant effect on ability is found to affect wages, but the positive and significant effect of human capital achievements is concluded.

3.2.2 Empirical Literature on Return to Education

In recent decades, several researchers have used the Mincer wage equation to empirically estimate the return to education. In the traditional study, Mincer (1974) used 1960 US Census data to examine the linear relationship between individuals' education achievements and wages. Mincer finds out that the return to one year of schooling is 10%, with a return to experience around 8%. Psacharopoulos and Layard (1979) follow this method but focus on the case of the United Kingdom by using the data from General Household Survey in 1972. They find the return to schooling of a similar level, around 10%.

In a more recent study, Bonjour et al. (2003) also examine the return to education in the UK, focusing on the data provided by the Twins Research Unit, St. Thomas' Hospital, London. The mincer wage equation is also used. The return to education is estimated to be 7.7% if only experience variables are controlled. After adding other controls such as region, marriage status, tenure and part-time/full-time job status, the return to education decreases slightly to 7.3%. Silles (2007) estimates the Return to education in the UK, also using the General Household Survey, similar to Psacharopoulos and Layard (1979). In the study, full-time and part-time employed wage earners are included. From the pooled analysis from 1985 to 2003, the return to education is estimated to be 5.7% and 8.7% for males and females, respectively. According to variations across the years, the return to education fluctuates for both males and females. The return to male workers shows a clearer increasing pattern. In the year 1985, the return to male workers is 5.5%. However, in the year 2003, the return increases to 7.0%. Reisel (2013) compares the return to education between the US and Norway to study the different labour market conditions between the two developed countries. For the US, the data from the National Education Longitudinal Study of 1988 is used. The sample is focused on the 10^{th}-grade cohort in 1989, and the income information is measured ten years later in 1999. For Norway, the data comes from the “The Educational System in Norway: Putting it to the Test of the Labour Market” project, based at the Institute for Social Research in Oslo. The Sample focused is also the 10th-grade cohorts in 1994 and 1998, and income is also measured ten years later. Reisel implements a revised version of the Mincer wage equation where the education levels are used as explanatory variables rather than years. Education levels are categorised from no high school graduation to high school, college attendance, bachelor’s degree, and master’s degree and higher. The reference group is high school level. Estimation results for the rest of the levels are -17.5%, 26.1%, 50.7% and 72.1% for the US, from low to high education level. In addition, for Norway, the returns are estimated to be -52.9%, 27.4%, 28.5% and 35.6%, also from low to high education levels.

Montenegro and Patrinos (2013) Study the return to education around the World using the Mincer wage equation. The reported results are based on the study of a large database constructed from existing national household surveys, which is prepared for the World Bank’s World Development Report Unit. The study covers 131 economies. Using the most recent available data from 2000 to 2011, Montenegro and Patrinos examine the return to education by region and income group. The return to East Asia and the Pacific is 10.3%, and South Asia is 7.0%, whereas, for the developed economies such as the UK and the US, the return is about 10%. Regarding the income group, the returns are estimated to be 10.5%, 8.9%, 10.7% and 10.0%, respectively, for low, lower-middle, upper-middle- and high-income groups.

Recently, analyses on the return to education are also conducted in developing countries. For example, Rani (2014) studies the return to education in India using the Mincer wage equation. Data comes from the India Human Development Survey, made available by the National Council of Applied Economic Research. The most important advantage of Rani’s research is that it is nationally representative and covers nearly all states and union territories of India. The Return is estimated to be 14.1% if only controlling for experience variables. After controlling for English skills, family, social and regional characteristics, the return decreases to 8.6% but remains highly significant. Dutta (2006) also focuses on the return to education in India but with time variations. Three survey years in National Study Survey are used, which are 1983, 1993 and 1999. Different education levels are used as explanatory variables, and the reference group is no schooling. In addition, Dutta (2006) specifically focuses on the difference in return to education between regular and casual workers in the analysis. It is reported that the return shows a decreasing pattern for regular workers across the years. In 1983, the returns are estimated to be 6.58%, 13.61%, 34.86% and 61.92% for primary school, lower middle school, upper middle school and tertiary education, respectively. However, in 1999, these education levels' returns are 4.85%, 10.90%, 29.45% and 60.25%, respectively. For casual workers, no wage disparities are found between education levels in 1983. In addition, in 1993, only significant returns to primary and lower middle schools are found, with 22.7% and 16.5%, respectively, in India's labour market. Warunsiri and McNown (2010) study the return to education in Thailand. Data is collected by the National Statistical Office of Thailand, Statistical Forecasting Bureau, as part of the National Labour Force Surveys (LFS) for 1986–2005. In the pooled analysis of 20 years, the return to education is estimated to be 11.5%. The gender difference is also analysed, where the return to male workers is 10.7% and female workers is 12.9%, showing a higher return for females in Thailand. Some researchers in developing countries specifically focus on rural areas. For example, Maluccio (1998) studies the return to education, specifically in rural areas of the Philippines. Using data from the Bicol Multipurpose Surveys in 1994 and the methodology of the Mincer wage equation, the return to education in rural Philippines is estimated to be 7.3% after controlling for gender, age and marriage status and rural communities.

In terms of China, most of the studies focus only on urban areas. For example, Li and Ding (2013) Study the return to education in the 1990s in China by using China Household Income Project (CHIP) from 1990 to 1999 and the Mincer wage equation. A continuously increasing pattern of return to education is found. In 1990, the return is only estimated to be 2.43%. However, when it comes to 1999, the return increases to 8.10%. Similar research is conducted by Ren and Miller (2012), focusing on

Chinese urban areas and the urbanisation development between 1993 and 2004. Data comes from the China Health and Nutrition Survey (CHNS), and gender difference is also focused on. In 1993, the return to males is estimated to be insignificant after controlling for individual and employment characteristics. Return to females is 2.0%, which is statistically significant at 5% level. Regarding 2004, both returns are significant for males and females. However, female workers still have a 3.8% higher return than male workers. The higher return to females is also found in Silles (2007) in the UK and Warunsiri and McNown (2010) in Thailand. Ding et al. (2012) conduct an analysis focusing on the early 21st century, using data from the China Urban Household Survey (CUHS) of the National Bureau of Statistics (NBS). Not consistent with the finding from Li and Ding (2003), no clear increasing pattern is found from 2002 to 2009. The return is estimated to increase slightly from 9.74% in 2002 to 10.33% in 2009. Asadullah and Xiao (2020) research the return to education in China using a more recent dataset. China General Social Survey (CGSS) in 2010 and 2015. An important feature of this analysis is that it covers all wage earners, including those in urban and rural areas. The estimated return to one year of education is 7.5% and 6.9% in 2010 and 2015, respectively. Asadullah and Xiao also examine the return to education interacting with English skills, based on the arguments that education is not a perfect proxy for individuals' cognitive ability. After controlling for English skills in the specifications, return to education decrease partly, to 6.7% and 6.2% in 2010 and 2015, respectively.

In recent years, there has been a small number of researchers specifically focus on the return to education in Chinese rural areas. Zhang et al. (2008) conduct an analysis based on the data obtained from a survey of 808 households in 5 provinces, 25 counties, 50 townships and 101 villages in rural China conducted by the authors in April 2005. They only focus on those off-farm wage earners in rural areas, and the off-farm labour participation is found to be 41.7%. Return to education is estimated to be 7.0% in rural areas. In addition, they also find that one year of post-middle school education would result in 11.8% of wage growth. Liu et al. (2019) also focus on off-farm wage earners in rural areas in China. Self-employed workers who report their profits or revenues are excluded. Wages include regular monthly wages, bonuses, subsidies, and in-kinds. The mincer wage equation is used to estimate the return to education, and it is reported that education can explain 2.4% of wage growth in Chinese rural areas. Liu et al. also examine whether the return to education would be affected by including different experience variables: potential working experience and adjusted working experience with employment interruptions. However, a small and insignificant difference in return to education is found based on different experience measures.

3.2.3 Endogeneity Issue and Sample Selection Issue in Estimating Return to Education

3.2.3.1 Enodogeneity Issue and Instrument Variable (IV) Method

As mentioned in the previous part, when using the Mincer wage equation and OLS method to estimate the return to education, the estimates may suffer from the problem of endogeneity, mainly driven by the unobserved ability variable included in the error term but also correlated with explanatory variable, education[1]. As Hanushek (2015) noted, there is a long line of research studying whether omitting ability variables would lead to bias because more able individuals would choose to be better educated and, at the same time, have better performance in the labour markets. In addition, the analysis of the endogenous problem is also correlated with the debates between human capital theory and signalling theory, whether education increases individuals' human capital and therefore affects wages or just serves as a signal of innate ability.

The most preferred method to solve the endogenous problem is to add direct measurements of innate ability into the wage equation. Harmon et al. (2003) control for the direct measures of ability by using English and Math skills in ages 7, 11 and

1. Though some other factors would affect education achievements simultaneously, such as family inputs and enthusiasm, in most of the studies, the ability bias is focused, and the instruments in the IV method are also designed based on omitted innate ability.

16 as controls in the analysis of return to education. The dataset used comes from the National Child Development Survey. The children's early development was followed closely, and subsequent labour market careers have been recorded in this survey. It is found that returns to education decrease slightly after controlling ability variables in different age cohorts and remain highly significant, which confirms the human capital explanation of the return to education. Aslam et al. (2012) also cover the direct measurement of individuals' innate ability in the analysis. However, rather than focusing on cognitive skills at a young age, they include individuals' Raven Progressive Matrices test scores as control variables, which is a widely used test of abstract reasoning designed to capture "innate ability" independent of schooling. Estimation results are quite similar to Harmon et al. (2003). The effect of Raven test scores is tested to be insignificant. However, the return to schooling remains large and significant, with 4.5% for males and 8.3% for females. In fact, Aslam et al. also support the human capital assumption.

The direct measurements of innate ability are not often accessible in survey data, and there are arguments that the ability included should be truly correlated with labour market outcomes and not be contaminated by the effect of education (Harmon et al., 2003). Therefore, many researchers implement an Instrument variable (IV) method to solve this bias, where the connection between education and unobserved ability is cut off by instruments that correlated with education achievements but not with omitted variables[2]. For example, Aslam et al. (2012) find a decreasing return to education after using the IV method and parental education as instruments. Return to education reduces from 5.6% to 2.3% and becomes insignificant for all the waged workers. However, after dividing the sample according to gender, both return to male and female becomes larger under the IV method. A larger return to education is also found in Asadullah and Xiao (2020), who also use parental education as instruments. It is found that the return to education increases from 9.2% to 16.4% in 2010 and from 9.7 to 21.4% in 2015.

2. Detailed explanations are provided in the following section 3.3

Besides using parental education as instruments, Butcher and Case (1994) use the individuals' sibling information as an instrument to education years, which is the "presence of any sisters in the family. The rationale is that the number of children in the family would significantly affect the individuals' educational achievements. Butcher and Case use the data from the Penal Study of income dynamics in the 1985 wave, and only females between 24 to 65 years old are included in the IV analysis. It is concluded that return to education is larger after using the number of siblings as instruments, which increases from 9.1% under OLS to 18.4% under IV, but the coefficient turns out to be insignificant. Another method based on sibling information is to use the twins' reported education level as the instrument for self-reported education level. Following this method, Bonjour et al. (2003) take advantage of the data from the Twins Research Unit and focus only on females with twin pairs in the UK. It is found that the return is slightly larger after using the IV method, reaching 7.7%, compared with 7.3% under OLS, which also violates the original assumption of IV. Bonjour et al. also cover smoking habit as an instrument, based on arguments from health economics, that better-educated individuals would also have better health habits. However, IV estimators are still 50% larger than OLS, no matter using the smoking habit in individuals 16 or 18 years old. Since it is often found in the literature that the IV estimator is larger than the OLS estimator, Wang et al. (2012) summarise two explanations. Firstly, the IV estimation may only cover the Local Average Treatment Effect (LATE) or the ATE for the subpopulation influenced by the IV. The Treatment Effect here actually indicates that the individuals treated with higher education levels can have higher wages. When treatment effects are heterogeneous across units, the LATE and the ATE may take on different values, which would potentially cause complications in the comparison between IV and OLS results. Secondly, the IV method solves the possible measurement error problem in education years, which is also driven by the correlation between the explanatory variable and the error term.

In fact, besides using the instruments previously mentioned, some researchers also implement policy (institutional) changes or natural experiment variables as instruments. For example, Devereux and Fan (2011) conduct policy-based IV research. They focus on the education expansion to school cohorts from the late 1960s to the mid-1970s. It is argued that not only the higher education expanded during this period but also the proportion of people who stayed in education beyond the compulsory schooling age of 16 and the average school leaving age also increased rapidly. To examine the condition of return to education during this expansion period, Devereux and Fan (2011) use UK Quarterly Labour Force Survey (QLFS) and keep individuals born from 1958 to 1982 and who are aged between 25 and 50. They divide the sample into three parts according to the birth cohorts (school cohorts), which are:

(1) Pre-1970 cohorts who did not experience the expansion

(2) Cohorts during 1970 and 1975

(3) Post-1975 cohorts when the expansion is nearly finished.

They use these cohort dummies as instruments for the education years and conduct an IV estimation. OLS results show that the return to one year of education is 7.8% for males and much higher for females, with 9.6%. These values are considered upward biased after using the IV method, which is consistent with the original assumption of IV. The returns are 6.2% for males and 5.3% for females under IV, showing a narrower gap between gender.

A similar policy-based analysis is also conducted in China. Campos et al. (2016) focus on the Chinese return to education by using the proposal of the Compulsory Education Law and Minimum Working Age Rule as instruments. Data used is the National Health and Nutrition Survey, by pooling survey waves from 1993 to 2011. Compulsory Education Law was first proposed in 1986, requiring every young child to finish at least 9-year compulsory education in China. Minimum Working Age Rule was published in 1991, which forbids those children under 16 years old to be employed in formal jobs, further ensuring the completion of Compulsory Education. Since the immediate implementation of the law is questioned in China, Campos et al. (2016) set three benchmarks for 12 different provinces included in the analysis to be affected, which are: the year 1986 for Beijing, Chongqing, Liaoning and Heilongjiang; the year 1987 for Shandong, Jiangsu, Shanghai, Hubei and Henan; the year 1988 for

Guizhou and 1991 for Hunan and Guangxi. In China, children often finish compulsory education at the age of 15. Therefore, the law affects individuals born after 1971, 1972, 1973 and 1976 in corresponding provinces. Unlike the Compulsory Education Law, there is only one benchmark for the Minimum Working Age Rule. Since it affects children under 16 years old, those born after 1975 are affected. It is found that under OLS, the return to education is estimated to be 5% for all workers. However, the return increases to 19.9% and 18.6% when the law or the rule is separately used as instruments. When both policies serve as instruments, the estimated return under IV is 18.9%. Xie and Mo (2014) extend the analysis by implementing a more detailed method to set the benchmarks, which compares the children's schooling time and the proposal time of the law and rule to clarify those individuals who are affected or not. According to the arguments of Xie and Mo, individuals affected by the law are those born after September 1971, and those affected by the rule are those born after September 1975. Besides the implementation of conventional education policies, Huang et al. (2022) argue that the higher education expansion policy proposed more recently in 1999 would also increase the individuals' overall education achievements in the country. Data used is the 2017 wave of the China Household Finance Survey (CHFS). Those who reached 18 years old (graduated from high school at the age of 18) in 1999 were the first cohort to be affected by this policy, and the birth cohort benchmark of 1980 is used as the instrument. Alongside the instrument of tertiary education policy, the household registration ("hukou") status and the year trend in the post-expansion period are also included as instruments. Results show that the return to education increases largely from 4.9% under OLS to 16.5% under IV for men and from 6.2% under OLS to 12.4% under IV for women. In the first step of regression, the three instruments are tested to be joint significant to affect individuals' overall education achievements.

3.2.3.2 Sample Selection Issue and Heckman Two-step Method

The sample selection issue is mainly driven by the non-random selection into waged jobs. In many survey data, only the income of waged workers is available to researchers. However, the decision to be employed in a waged job is not a random draw, and individuals in waged and non-waged jobs may have different characteristics. If studies are only restricted to this non-random group of individuals, the earning distribution would be truncated, and estimates under the OLS method would be biased and not representative of the population (Comola and de Mello, 2010). The Heckman (1974) Two-step method is often used in the literature, where the bias can be corrected by introducing an inverse Mills ratio in the wage equation[3].

For example, Kingdon and Unni (2001) research the return to Education in urban districts of two states in India, Madhya Pradesh (MP) and Tamil Nadu (TN). Both OLS and Heckman Two-step methods are used, and data comes from the National Sample survey between 1987 and 1988. In the first step of the Heckman method, a probit regression is run on the factors to affect waged work participation. The inverse Mills ratio can be obtained from the first stage, and in the second stage, this ratio serves as an extra explanatory variable in the wage equation to correct the selection issue and result in an unbiased estimate of the return to education. It is found by Kingdon and Unni that in the MP state, both male and female samples suffer from significant sample selection bias. The return to education decreases from 10.04% to 9.07% for men, and from 8.61% to 7.80% for women, under the Heckman method. Sample selection bias is also found in the other state TN. However, for men, a downward bias is found that the return to education increases from 9.38% to 9.86%. For women, a similar upward bias as MP is found, that the return decrease from 8.10% to 7.80%.

Similar to Kingdon and Unni, Kanjilal-Bhaduri and Pastore (2018) also focus on the Indian case and Heckman method by using more recent data, which comes from the Employment Unemployment Survey of the National Sample Survey Office from 2011 to 2012. This analysis treats both regular salaried workers and casual wage earners as

3. Detailed explanations are provided in the following section 3.3

waged work participants. Results show that for both male and female workers, the return to education suffers from significant selection bias, consistent with the finding obtained in Kingdon and Unni. After correcting the bias, the returns to education for females and males in urban areas are quite similar, with 17.0% and 16.9%, respectively.

The Heckman method for sample selection issue is also focused on by researchers in Indonesia, such as Dumauli (2015). The fourth wave (from 2007 to 2008) of the Indonesia Family Life Survey is used, and only female samples are included in the analysis of the Sample selection issue. Results show that female workers suffer significantly from the self-selection issue. Return to education is considerably larger after using the Heckman method, from 4.5% to 11%. In terms of China, Liu et al. (2019) also examine the self-selection issue for waged workers, especially for those in Chinese rural areas. Using data from China Rural Development Survey, Liu et al. find that the rural sample suffers significantly from the non-random selection issue. The estimated return under OLS is downward biased, but the gap is quite small before and after the correction. Under OLS, the return to education is 2.1%, whereas, under Heckman, it is 2.9%. Liu et al. also focus on returns to different education levels rather than years in rural areas. It is concluded that only tertiary educated workers would enjoy a significant return, with 35.2% under OLS, compared to those with primary education or lower. After using the Heckman method to correct selection bias, the return to tertiary education increases slightly to 39.4%.

3.2.4 Return to Education with Urban/Rural Differences

Though not many researchers in advanced countries focus on comparing urban and rural areas, we still find an example from Tokila and Tervo (2011), who focus on the return to education in both urban and rural areas in Finland. The data is based on the Longitudinal Census File and the Longitudinal Employment Statistics File constructed by Statistics Finland, and the Mincer wage equation is implemented. Besides comparing different areas, Tokila and Tervo also focus on various returns to education between wage earners and entrepreneurs in their analysis. It is found that, for both wage earners and entrepreneurs, return to education is slightly higher in urban areas under the OLS method. In rural areas, the returns for wage earners and entrepreneurs are 9.8% and 10.2%, respectively. In urban areas, the returns are 9.9% and 10.7%, respectively. However, after using the Heckman method to correct the sample selection bias, the higher return for entrepreneurs in urban areas disappears. In addition, no large variations are found in the group of wage earners, and urban workers still enjoy a slightly higher return. In developing countries, Rani (2014) focuses on the urban/rural difference in return to education, besides the analysis on the aggregated sample. Education levels are categorised into four parts which are no schooling, elementary school, secondary school and tertiary, and the reference level is no schooling. It is reported that in urban areas, the returns are 27.7%, 48.7% and 72.7% for elementary school, secondary school and tertiary, respectively, after correcting the sample selection bias using the Heckman method. The return in each level is higher in urban areas compared with rural areas in India. For rural workers, the returns are 19.5%, 30.5% and 35.4%, respectively. Similar to Rani, Warunsiri and McNown (2010) study the urban/rural difference in return to education in Thailand. The third quarter data of National Labour Force Surveys is used. The return in urban areas is estimated to be 11.5% using the Mincer equation, and in rural areas, the return is 11.3%, showing a small gap. However, Warunsiri and McNown (2010) also implement a pseudo-panel approach. Though LFS is not a longitudinal dataset, a penal can be formed using the birth-year cohort in the cross-section dimension and the survey years in the time series dimension. A birth cohort dummy can be added to the specification to serve as a cohort fixed effect to solve the possible unobserved heterogeneity issue at the cohort level. Under this method, the return to education in urban areas is considerably higher than in rural areas, with 18.9% for urban and 14.2% for rural areas. Warunsiri and McNown argue that the higher return in urban areas may encourage seasonal and permanent migration of rural workers to cities.

In terms of China, Weng et al. (2016) examine the regional return to education using China Health and Nutrition data, including survey waves of 1989-2011. Individuals' urban/rural status is classified according to their residential status. In Chinese literature, two methods are often used to divide individuals into urban and rural. The first is based on individuals' current location, such as working and residential places. The second is based on household registration ("Hukou") status, and those with rural hukou are defined as rural individuals, no matter where they live and work. It is found by Weng et al. that in the year 2000, rural areas have a return to education of 3.49%, which is 0.3% slightly higher than that in urban areas. However, from 2004 to 2011, the return to the urban sample is always higher. In 2011, the return for urban workers is 6.13%, whereas for rural workers, is 2.82%, with a gap of more than two times. Asadullah and Xiao (2020) also compare the urban/rural return to education based on individuals' residential status. Data used is the China General Social Survey (CGSS), with two survey waves in 2010 and 2015. In 2010, the return in urban areas is 10.4%, which is highly significant at 1% level. However, the return in rural areas is quite small, with 0.1%, which is tested to be insignificant. Regarding 2015, there is a slight decrease in return to education in urban areas, from 10.4% to 8.3%. In rural areas, the return increases to 2.6% and is significant under 1% level. However, urban return is still more than three times higher than the return in rural areas.

Campos et al. (2016) analyse the urban/rural comparison based on individuals' registration or "Hukou" status. This method only focuses on individuals' original background rather than current living and working status. Data used is China Health and Nutrition Survey from 1993 to 2011. It is concluded that under the pooled data, the return to urban workers is 4.8%, whereas the return to rural workers is 3.8%. After implementing the IV method and using Compulsory Education Law and the Minimum Working age rule as instruments, returns in both areas increase dramatically. The return for rural workers turns out to be much higher than that for urban areas, under IV, with 29.7%. However, urban workers only have a return of 11.9%. Fu and Ren (2010) conduct an analysis that combines the different methods of defining individuals' urban and rural status. The sample is divided into three parts: urban residents, migrant workers in urban areas but with rural "hukou", and rural residents. Using data from the 1% National Population Sample Survey (NPSS) in 2005, Fu and Ren conclude that the return to years of schooling is 5.47% for all the workers and decreases to 2.93% after controlling for individuals' employment characteristics. In terms of the differences in urban/rural status, they find a descending rank of return to education, from local urban migrants to rural workers, for all of the education levels. For example, for the return premium of primary school to no schooling, the returns are 28%, 18% and 12% for local urban, migrant and rural workers, respectively. In addition, for the highest education level, tertiary education, the returns are 115.4%, 89.7% and 73.8%, respectively.

3.2.5 Hypotheses for Return to Education in China

The return to education is studied extensively in both international and Chinese literature. It is often found in the Chinese labour market that workers enjoy a significant and positive wage return to education, similar to those found in Western countries. This empirical evidence supports the arguments in human capital, signalling and social network theories that indicate higher wages for better-educated workers (Bonjour et al., 2003; Montenegro and Patrinos, 2013; Rani, 2014; Li and Ding, 2013).

An important characteristic of the Chinese labour market is the significant urban-rural segmentation driven by the strict household registration policy, and workers from different areas have low crossover capability. However, limited studies in Chinese literature focus on the urban-rural difference in return to education, especially in contemporary China. Researchers often examine the aggregated sample of workers comprising different areas or only focus on workers in urban areas. In fact, some existing theories support the idea of a different return to education in segmented labour markets, and most of them indicate a higher return for urban workers. For example, education quality may be higher in urban areas, which results in higher productivity for urban workers with the same amount of human capital achievements. Also, agglomeration theories imply a pool of skilled workers in urban areas, which increases the demand for higher-educated workers to serve the needs of innovation and productivity from key economic drivers. In addition, the urban labour market is argued to be more functional. In the rural labour market, skilled workers may suffer from the asymmetric information problem and lower wages that should be rewarded for their actual skills and productivity. Existing empirical evidence supports the theories on higher return to education in urban areas, such as Weng et al. (2016) and Asadullah and Xiao (2020).

We base the arguments in existing theories to derive the hypotheses on the returns to education between urban and rural areas. However, as shown in the previous subsections, in the empirical process of estimating the return to education, we may have problems of unobserved heterogeneity and self-selection. Firstly, it is argued in the literature that the Instrument Variable (IV) method can be used to solve the problem of unobserved heterogeneity in innate ability by using appropriate instruments. The innate ability is argued to be positively correlated with education years and wages. Therefore, the estimated return to education would be smaller after using the IV method. Secondly, the Heckman Two-step method can be used to solve the problem of selection bias. In rural areas, a considerable proportion of individuals are taking non-waged jobs. The wage information for these individuals is missing in the regression. Therefore, the estimated higher return in urban areas may be driven by the issues on econometric methods rather than the differences in labour markets. For example, Liu et al. (2019) provide evidence that the return to education in rural areas increases significantly under the Heckman two-step method.

The return to education with urban/rural differences is not studied extensively, and in many Chinese studies, the robustness of estimations is often ignored. Therefore, based on the arguments on theories and empirical methods in the literature, we propose the following hypothesis for this analysis:

(1) Wage Return to education is significant for all the waged workers in China

(2) Wage Return to education is higher in urban areas than in rural areas

(3) The estimated return to education will be smaller under the IV method

(4) The return gap between urban and rural areas will be smaller under the Heckman method

3.3 Methodologies

3.3.1 Mincer Wage Equation

To start with, we can consider the following linear regression model proposed by Mincer (1974).

$$\mathrm{lnwage_i} = \beta_0 + \beta_1 \mathrm{education_i} + \boldsymbol{\delta}\mathbf{X} + \mathrm{u_i} \qquad (1)$$

In this model, $\mathrm{wage_i}$ is the hourly wage, $\mathrm{education_i}$ indicates the years of education for each individual and vector $\mathbf{X}$ includes a series of control variables. The wage variable is in the log form because the linear relationship originally derived by Mincer is in the form of a log relationship between wage and education years. β_1 is the return to education, which can be estimated by the usual OLS method. It can be interpreted as, with one year growth of education, an individual's wage would increase β_1 percent. It needs to be emphasised that in our analysis, the dependent variable used is the individual's gross hourly wage, which includes net wage and all kinds of cash rewards, subsidies, and bonuses. Also, according to most of the measurements in the literature, the control variable $\mathbf{X}$ often includes those individual characteristics. Similarly, our analysis includes age, age square, gender, ethnicity, marriage, and registration (Hukou) status as the basic controls.

Besides the basic characteristic controls, the differences in job conditions are also effective in explaining the variation in individuals' wages. Sometimes an individual is paid more in the labour market, possibly because he lies in a specific industry, occupation, sector, etc. The positive correlation between job conditions where the workers are employed and the education levels would result in overestimating actual return to human capital. Therefore, in our analysis, we further include five different kinds of demand side controls (or employment controls) in $\mathbf{X}$, which indicates the conditions of industry, occupation, sector, contract type and firm size. The detailed definitions and measurements of all these variables, in addition to the education, wage and basic control variables, are shown in section 3.4.

3.3.2 Omitted Variable Bias and Instrument Variable (IV) Method

The omitted variable bias is often considered an important drawback of Mincer's method on estimating return to education. This bias results from the unobserved factors included in the error term that would also be correlated with the core independent variable, schooling years. Therefore, the basic assumption of OLS regression will be violated, and the independent variables will be endogenous. A widely examined issue in the literature is that omitting individual ability would generate bias in the estimated return to education. Abler students are with higher possibility to attend more years of schooling and also earn higher wages in the labour market at the same time. Therefore, the estimated return to education would be upward biased if the ability controls are omitted.

A widely accepted method to solve the omitted variable bias is to find out an instrument correlated with the endogenous variable, education years, but not correlated with unobserved traits in the error term. Then we can solve the bias with the following two steps.

For the first step, we conduct the following regression:

$$\mathrm{education_i} = \alpha_0 + \alpha_1 \mathrm{instrument_i} + \boldsymbol{\mu}\mathbf{X} + \varepsilon_i \qquad (2)$$

We can have the fitted value of education years by estimating the first step equation, which is $\widehat{\mathrm{education}}_i$. In the next step, we can represent the $\mathrm{education_i}$ with the $\widehat{\mathrm{education}}_i$ in the wage equation:

$$\mathrm{lnwage_i} = \beta_0^{'} + \beta_1^{'}\widehat{\mathrm{education}}_i + \boldsymbol{\delta}^{'}\mathbf{X} + u_i^{'} \qquad (3)$$

The $\beta_1^{'}$ is called the IV estimator of return to education. The error term $u_i^{'}$ is not correlated with the new independent variable. The previous process is called the Two-Step Least Square (2SLS) method, and $\beta_1^{'}$ is proved to be a consistent estimator.

In fact, it is not agreed in the literature that there exists the best instrument for the possible endogenous variable, schooling years. Various instruments are used, and results are also different accordingly. Therefore, to achieve higher robustness, we implement two kinds of instruments in our analysis. Firstly, parental education levels are widely accepted as a valid instrument in the literature. Parental academic achievements are believed not to be correlated with an individual's omitted, unmeasured ability born with (Bound and Solon, 1999). At the same time, family background variables such as parental education would strongly predict children's schooling years. For example, more educated families can provide an educational-friendly environment for their children, and financial resources are more willing to be invested for children to achieve higher education levels (Eccles, 2005). Secondly, we use the policy changes on education as instruments. The rationale is that a child born after the policy's implementation threshold would possibly have more years of education than those born earlier and unaffected. Following the literature such as Campos et al. (2016) and Xie and Mo (2014), we refer to the following policy changes:

(1) Minimum Working Age Rule (also known as Provisions on the Prohibition of Using Child Labour)

(2) Higher Education Expansion Policy

The Minimum working age rule was proposed in April 1991, forbidding children younger than 16 to take any full-time jobs. Since in China, an individual will reach 15 years old when finishing compulsory education, this policy significantly decreases the dropping out rate in the compulsory education period and ensures most of them would successfully complete at least secondary school. Some other researchers (e.g. La, 2014) also use the Compulsory Education Law as the instrument, but the immediate implementation of this law is often questioned. The effective enforcement year of this law was different across the nation, which makes it difficult for us to find a national consistent benchmark. In fact, there is evidence showing that this law was actually enacted in some provinces (e.g. Hunan and Guangxi) until 1991 (Campos et al., 2016), where the benchmark year coincides with the Minimum Working Age Rule. Therefore, we only include the Rule as the instrument in our analysis. It is pointed out by Xie and Mo (2014) that the Minimum working age rule would generate strong and immediate effect because it carries harsh penalties. Those caught employing child labour (under

16 years old) are fined, and sometimes, their business license can be revoked. In addition to the Rule, the Higher Education Expansion Policy was proposed in December 1998. From 1998 to 2018, the gross enrollment rate of higher education increased dramatically from 10% to 50% (World Bank, 2022). The number of annual enrollments grew by eight times, which is considered the most important policy in recent decades that helps with the highest education levels of young Chinese workers and also the average education achievements of the population. Similar arguments are also found in Huang et al. (2022). These policy changes are not considered to be correlated with individuals' unobserved heterogeneity because the government proposes them. We set two thresholds on individuals' birth years by using two dummy variables to distinguish those who are affected by the policies or not. Detailed information on the measurements is shown in the following subsection 3.4.

3.3.3 Sample Selection Issue and Heckman Two-step Method

In our analysis, only wage earners are included in the earnings equation. Other individuals in the sample are excluded, such as those temporarily unemployed, self-employed, and not in the labour market. These individuals could also have been able to gain wages if entering the labour market, but their income is unobservable to us. Therefore, in the previous OLS regression procedure, we are only estimating a sub-sample of the population. As Gronau (1973) noted, the observed distribution represents only one part of the wage offer distribution, as the other part is rejected by the job seekers as unacceptable. However, the problem is that those individuals who take paid jobs may be self-selected and not a random draw in the population. With self-selected samples, the mean value of the error term in the earnings equation may not equal zero, violating the basic assumption of the classical Ordinary Least Squares (OLS) method. Therefore, the estimation of the return to education would be biased and will generate problems when applying it to the whole population. Comola and de Mello (2010) further assert that if the information on earnings is usually available only for salaried workers, OLS estimates are inconsistent if the earning distribution is truncated.

To solve this sample selection bias, Heckman (1979) provides a two-step estimation procedure. To start with, individuals base their decisions to participate in the labour market on their evaluation of a reservation wage, say Er, which may be interpreted as the opportunity cost of working. Individuals will only enter the labour market if the wage offer E exceeds the reservation wage. Thus, working individuals (i.e. individuals for whom wages are observed) are those for whom E > Er. For non-working persons, E < = Er.

Let I^* be the net benefit of working, therefore:

$$I^* = E - E_r \qquad (4)$$

Individuals would only enter the labour market when $I^* > 0$.

The net benefit of working I^* can be correlated with some of the observed factors, such as:

$$I^* = \boldsymbol{\Upsilon W} + \varepsilon_i \qquad (5)$$

Where $\boldsymbol{\Upsilon}$ is a vector of coefficients and ε_i is a random error assumed to have a standard normal distribution. $\mathbf{W}$ is a series of variables that affect employment status. Now, we consider the following wage equation:

$$\text{lnwage}_i = \beta_0 + \beta_1 \text{education}_i + \boldsymbol{\delta X} + u_i \qquad (6)$$

Where wage_i represents the individual wages and $\mathbf{X}$ is a vector of control variables which affect individual earnings. Now wage_i is only observed for $I^* > 0$. Taking the expectation of equation (6) we have:

$$E(\text{lnwage}_i | \, I^* > 0) = \beta_0 + \beta_1 \text{education}_i + \boldsymbol{\delta X} + E(u_i | \, I^* > 0) \qquad (7)$$

According to the relationship in equation (5), we can re-write equation (7) as:

$$E(\mathrm{lnwage_i} \mid \varepsilon_i > -\boldsymbol{\Upsilon W}) = \beta_0 + \beta_1 \mathrm{education_i} + \boldsymbol{\delta X} + E(u_i \mid \varepsilon_i > -\boldsymbol{\Upsilon W}) \quad (8)$$

If there are any correlations between the unobserved effect on earnings and the unobserved effect on labour force participation, the expected value of the error term in the wage equation would not be zero, and the estimates of the coefficients may be biased. According to Heckman (1979), if assuming u and ε are jointly normal distributed with zero mean, $E(u_i \mid \varepsilon_i > -\boldsymbol{\Upsilon W}) = c * \lambda(\boldsymbol{\Upsilon W})$, where c is the correlation coefficient between u and ε times the standard deviation of u, and λ is the inverse Mill's ratio.

Therefore, the Heckman two-step method can be conducted as follow:

For the first step, though I^* is unobservable to us, we can estimate the first step regression using a binary probit model, which is shown as follow:

$$I = \boldsymbol{\Upsilon W} + \varepsilon_i \quad (9)$$

where I is a latent variable indicating whether an individual participates in the paid work or not. I = 1 for wage earners, whereas I = 0 for individuals with other employment statuses, such as self-employed, unemployed, and not in the labour market. **W** is a series of variables that affect employment choices. From this equation, we can obtain an inverse Mills ratio $\lambda_i = \frac{\phi(\boldsymbol{\Upsilon W})}{\Phi(\boldsymbol{\Upsilon W})}$ for each individual i.

Then in the second step, we insert the inverse Mill's ratio as an extra independent variable into the wage equation, shown as:

$$\mathrm{lnwage_i} = \beta_0' + \beta_1' \mathrm{education_i} + \boldsymbol{\delta}'\boldsymbol{X} + c\lambda_i + \nu_i \quad (10)$$

Now $E(\nu_i) = 0$. We can conduct the usual OLS method to estimate coefficient β_1', which is the return to education under correction of selection bias. If c is estimated to be large and significant, the original wage equation suffers from the significant bias on self-selection. To achieve better identification and avoid the possible collinearity problem (Wooldridge, 2016), the $\mathbf{W}$ used in the wage participation equation should not be the same as $\mathbf{X}$ used in the wage equation, which is called the exclusion restriction. In our analysis, two additional variables are included in the probit model, which are the numbers of young children and old people in the family. These variables are often used in the literature and considered effective factors to affect an individual's decision to enter the labour market but would not significantly affect individuals' wage offers. We will provide more detailed explanations in the following section 3.4.

3.4 Data, Sample and Variables

3.4.1 Data Description

Our analysis uses data provided by China Family Panel Studies (CFPS). CFPS is a national and comprehensive social tracking survey project designed by the research team of Peking University and funded by Peking University and the Natural Science Foundation of China. It aims to collect data from individual, family, and community levels to reflect the changes in China's society, economy, population, education and health and to provide a data basis for academic research and public policy analysis. CFPS focuses on the economic and non-economic welfare of Chinese residents and many research topics, including economic activities, educational attainments, family relations and family dynamics, population migration, and physical and mental health.

The target sample size of CFPS is 16000 households and over 50000 individuals. The respondents are household members from 30 provinces/cities/autonomous regions in China (out of 34). Till 2018, CFPS has successfully conducted five rounds, every two years since 2010. We use the most current dataset provided in 2018 in our analysis. We directly take advantage of the adult survey and focus on the self-reported answers directly from individuals themselves rather than those from individuals' family members because proxy answers lose some important information on core variables and are less convincing.

There are two important advantages to using CFPS to analyse the return to education in China. Firstly, the most important advantage is that it is a nationally representative survey, which claims to cover over 90% of the Chinese population, showing that it is well-suited for the examination of the national level return to education. Unlike CFPS, some other surveys, such as China Health and Nutrition Survey (CHNS), only provide individual observations in fewer than 12 provinces. These surveys cannot be strictly representative of the whole nation, and the estimation results concluded are also less convincing. Secondly, CFPS provides detailed weekly working hours for each worker. This makes us possible to generate the hourly wage, which is the most important dependent variable in the regression. Some of the previous studies only rely on individuals' monthly or yearly wages without considering the hours actually worked, which are argued to conclude imprecise results of the return to education.

3.4.2 Restrictions on the Sample

For selecting the samples to be included in our analysis, we propose the following restrictions:

(1)In CFPS, five big provinces are over-sampled. Therefore, to achieve a nationally representative sample, we need to use the resampled individuals in the big provinces combined with those from other provinces.

(2)We only focus on wage earners in their main jobs. We only include workers doing paid jobs in the wage equation because the income information of self-employed workers is not available in CFPS. However, individuals not doing waged jobs, such as those self-employed and not in the labour market, are not totally excluded from our analysis. As explained in the methodology part, these individuals can be included in the first step regression to help solve the self-selection bias.

(3)We only include working-age individuals in our analysis. Particularly, we include male workers aged from 16 to 60 and female workers aged from 16 to 55, which follow China's minimum working age and retirement age rule.

(4)We exclude those who are currently enrolled in full-time education.

(5)After all these measurements, we exclude those individuals with incomplete information on the core variables we use. Finally, we leave for 3642 urban and 1949 rural observations in the OLS regression for the Mincer estimation.

Detailed statistics on sample restriction are included in the following Table 3.1. In addition, we provide the employment status composition of sample individuals, including those in the wage equation and Heckman method, in Table 3.2.

Table 3.1: Sample restrictions

	Observations left	**Percentage**
Total adult self-reported observations	30143	100%
Drop over-sampling observations	19725	65.44%
Drop age > 60	14873	49.34%
Drop age > 55 female	14137	46.90%
Employment in the labour market	11339	37.61%
Drop missing job type	10987	36.45%
Keep wage earners	6352	21.07%
Drop missing values on core variables	5591	18.55%

The Original CFPS Data-set we use is from the adult survey that only with individuals older than 16

Table 3.2: Distribution of employment status for sample individuals

	Wage earners		**Non-wage earners**						**Total**	
	Employed by others		Unemployed		Self-employed		Not in the labour market			
All	5591	50.92%	134	1.22%	4278	38.96%	977	8.90%	10980	100%
Male	3184	54.84%	66	1.14%	2297	39.56%	259	4.46%	5806	100%
Female	2407	46.52%	68	1.31%	1981	38.29%	718	13.88%	5174	100%
Urban	3642	62.85%	82	1.42%	1494	25.78%	577	9.96%	5795	100%
Rural	1949	37.59%	52	1.00%	2784	53.69%	400	7.71%	5185	100%

3.4.3 Classification of Individuals' Urban and Rural Status

To analyse the return to education with urban/rural differences, it is important to clearly define the individuals' status of urban and rural. In our analysis, we implement a method based on individuals' residential status, which is a geographic classification method. China National Bureau of Statistics (2010) proposed a formal rule on classifying urban and rural areas in China. By comparing the residential locations and the areas defined by the rule, CFPS provides a variable indicating the urban and rural status of each individual covered in the survey, and this variable is directly used in our analysis. Some other researchers (e.g. Campos et al., 2016) also base individuals' household registration status on the classification. Those who are originally born (registered) in rural areas are also considered rural workers, even if they migrate to the city areas. However, in this study, we would like to focus on the returns in different geographical labour markets based on individuals' current working and living status rather than individuals' original backgrounds. However, the second classification relying on the registration status is not totally excluded. In the following empirical process, we also use it as a robustness check.

In fact, there is a small proportion of researchers also using working locations to divide individuals' urban and rural status, such as Fu and Ren (2010). The difference between working and residential locations may rely on commuting between different areas, which may generate possible variations in the estimated returns to education. However, in CFPS, working locations for workers are unavailable to us. Therefore, we are not able to check the difference between these two methods. Nevertheless, it can be considered that the difference in the inconsistency between residential and working locations would be minor, compared with that between residential places and social backgrounds.

3.4.4 Variables

As mentioned previously, our analysis uses individuals' gross hourly wages and education years as the core dependent and independent variables. Besides these, we include some basic controls: ethnicity, gender, age, marriage status, "Hukou" (national registration system) status and province. In addition, we also add five kinds of demand-side controls in different specifications alongside those basic ones. In this part, we provide detailed explanations of these variables, and the summary statistics are also provided in the last part of this subsection.

3.4.4.1 Individuals' Wages

Using hourly wages is considered the most precise measurement when estimating the return to education. Sometimes, individuals would have higher monthly or yearly wages due to their longer working hours rather than higher productivity. For the first step, we acquire the information on the "average monthly wage income of last 12 months" in the dataset. Then we can generate the hourly wage by dividing the monthly wage by a worker's total hours worked in a month. However, unfortunately, we only have the total working hours in a week but do not know how many weeks individuals work in a month. Therefore, we assume that all the individuals work every week in a month, and the hourly wage can be generated by the following formula:

hourly wage = monthly wage*12/52/hours worked in a week

It needs to be emphasised that in our analysis, the monthly wage is the gross one, which includes net wage and different kinds of cash rewards and subsidies. All these incomes are measured after tax and deduction of necessary payments, such as insurance and pensions. The net wage in China is the basic wage obtained regularly each month without considering other extras. In Chinese literature, both gross and net wage are commonly used, and our measurement is similar to scholars such as Ren and Miller (2012) and Li et al. (2008). The rewards are categorised into two parts. The first is the normal monthly reward, and the second is the annual one provided at the end of the year. We divide the annual reward by 12 to make it on a monthly basis. Besides the rewards, there are also five kinds of subsidies, which are shown as follows:

(1)Transportation subsidies

(2)Meal subsidies

(3)Housing subsidies

(4)Festival expenses

(5)Others

All of these subsidies are also on a monthly basis. In fact, rewards and subsidies are important components of individuals' wages. According to the data, more than 30% of the waged income is from rewards and bonuses.

3.4.4.2 Education Years

CFPS provides information on the highest achieved education levels for each individual in the survey. In our analysis, we transfer these levels of education into years and obtain the highest achieved education years for each individual. Some researchers also focus on actual education years taken, even if some of the years are at unfinished levels. Years of education in unfinished levels are also covered in CFPS, but this measurement suffers from considerable missing values. In addition, students and teachers would put more effort into the final year of each level because students will face graduation or entrance examinations. Therefore, this would generate a considerable gap between those early leavers and students who successfully finish the level (Dickson and Smith, 2011).

To measure education years, we first acquire individuals' highest education levels in the CFPS dataset. Then we transfer them into years according to the instructions officially provided in the CFPS manuals. These years of education can be used to create the variable of "education years" in our analysis. There are in total eight levels of formal education in China, and the following Table 3.3 illustrates the relevant years for each level.

Table 3.3: Education years for each finished education level

Education level	Education years
No formal qualification	0
Primary school	6
Secondary high	9
Senior high	12
3-year college	15
4-year college	16
Postgraduate (master's degree)	19
Postgraduate (PhD)	22

Source: CFPS users' manual

3.4.4.3 Basic Individual Characteristics Controls

(1) Age

Other than the schooling years, individuals' working experience is also an important factor affecting wages. However, in practical terms, economists often face difficulties calculating actual years of experience and often rely on a proxy indicator (age - years of education - 6) if education starts at age 6. This can be unreliable, particularly for those who take periods of inactivity, such as rearing children. In addition, as Lemieux and Card (2001) and Wang (2012) noted, in the case that schooling years may suffer from the endogeneity problem, the experience constructed in the proxy way would also be biased estimated, and the individual's age would be a better option. Similar measurements are accepted by Campos et al. (2016) and Xie and Mo (2014). Therefore, in our analysis, since the actual working experience is not available in CFPS, we use individuals' age to proxy experience.

(2) Gender

Gender equality is long focused on by many labour economists, and the pay gap between males and females is also extensively studied in the literature using statistical methods. Significant pay gaps are found in many developing countries, including India (Rani, 2014) and Indonesia (Dumauli, 2015). In our analysis, we also would like to examine whether male and female workers would be treated the same in the Chinese labour market. In addition, the estimates on return to education would also be affected because of the correlation between gender and education. For example, male workers may have higher wages than female workers in the labour market and, at the same time, they are also better educated. Therefore, the return to education would partly reflect the advantages of the payoff to male workers if the gender differences are not controlled.

(3) Ethnicity

China is a country with 56 different ethnicities. The main ethnicity is "Han", which accounts for more than 95 per cent of the Chinese population, and the other 55 ethnicities are considered minorities. It is often focused on in the international literature that minorities may suffer from unequal treatment in the labour market, especially in a country like China still experiencing economic reform. Therefore, in our analysis, we specifically examine whether there are wage differences between

"Han" and other ethnicities. We define a dummy variable to divide them, where the dummy equals 0 if an individual is from the majority "Han" and 1 for others.

(4) "Hukou" and Residential Status

"Hukou" status is also called the national registration status. Every person in China needs to be registered as an "urban" or "rural" resident according to their birthplace, and the free flow of rural residents to city areas is restricted to some extent. The direct influence of the registration system is that it generates barriers in the social and economic development between urban and rural areas, and the labour markets in different areas are forced to be separated. However, in recent years, the Chinese government has been trying to eliminate the barriers, and there is an increasing number of workers who comes originally from rural areas but successfully find a job in urban areas. These workers are considered rural-urban migrants. Economic studies are also focused on this special category of workers, and some scholars (e.g. Zhu, 2015) argue that migrants can only be employed in some specific occupations and would suffer from lower wages than local urban workers. Therefore, in our analysis, we conduct some brief comparisons between different "Hukou" statuses. Similar to ethnicity, we define a dummy variable to divide individuals with different registration statuses, and the dummy equals 1 if an individual has urban "Hukou".

The migration of workers between urban and rural areas would result in an inconsistency between "Hukou" and residential status. Some migrants already reside in urban areas but do not receive urban "Hukou". Therefore, in our analysis, we also add controls of residence status in the specifications. We follow the formal demographic classification of rural and urban for individuals' residential locations provided by the Bureau of Statistics of China. The correlation coefficient between "Hukou" and residence status is only about 40%; therefore, we do not need to worry about the collinearity problem.

(5) Province Level Regional Controls

It is mentioned in the previous subsection that individuals in our analysis come from more than 30 provinces/cities/autonomous regions in China. However, economic development could vary between regions, and the wage levels would also vary in different provinces. This difference is not correlated with individual-level characteristics because some provinces originally had better economic development and provided higher wages than other places. For example, from the aggregate level statistics introduced in the second chapter, the average wage in Shanghai is 40% higher than that in Xinjiang province, showing a considerable gap in average income. Therefore, our analysis divides the 30 provinces into four different economic regions: East, Central, West and Northeast. This classification follows the method officially provided by China Statistics Bureau (2011) in order to scientifically reflect the social and economic development of different regions in China and provide the basis for the Party Central Committee and the State Council to formulate regional development policies. We set three dummies for the four categories and use the Western region as the reference group. Provinces included in different regions are illustrated in the following table 3.4.

Table 3.4: Provinces in different regions

Northeast	Heilongjiang , Jilin, Liaoning
North	Beijing, Tianjing, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong , Hainan
Central	Shanxi, Anhui, Henan, Hubei, Hunan
West (reference group)	Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang, Neimenggu

Source: China Statistics Bureau

3.4.4.4 Employment Variables

(1) Contract

According to the Chinese Law of Labour, if an individual is officially employed by an enterprise (full-time job), the employer should sign a formal contract with him to guarantee the basic rights of employees. However, this law is violated in some small companies, especially in those not public-owned. Individuals are forced to accept oral or no contracts to keep their jobs. Therefore, their wages may be quite volatile according to the company's operation conditions because there is no guarantee for their basic wages. In our analysis, we define a dummy variable indicating whether individuals sign formal contracts with their employers, and the variable equals 1 for those individuals with contracts.

(2) Sector

The coexistence of public and non-public sectors is an important feature of the current Chinese economy. Before the economic reform in 1978, there were limited private-owned enterprises in China. The differences in labour market outcomes for individuals in public and non-public sectors have been more focused in recent years. Researchers often study whether the individuals employed in public-owned enterprises still enjoy significant advantages in the labour market. Therefore, our analysis categorises individuals in different sectors using a dummy variable, where individuals in the public sector = 1, and others = 0.

(3) Occupations and Industries

Occupations can be used as important control variables affecting individuals' wages. In CFPS, there is a question on the occupation: "Please describe the occupation you are doing now". According to the answers, the staff of CFPS will do some initial classifications of the occupations and then match them with the code book of "National standard occupational classification of the People's Republic of China". There are three levels of classification on the occupation in this code book, and in the third level, the classification is very detailed. For example, the first level is "Professional and Technical Personnel". The second level could be "Engineering Technical Personnel", and the third level could be "Petroleum Engineering Technicians". CFPS totally follows the classification method and structure of the national code book. The only variation is that CFPS re-categorises and renames the occupations in the first level, which results in 6 normal occupations and 3 extra occupations that include "military personnel", "unemployed", and "other employees not elsewhere classified". In total, there are over 100 third-level occupations contained in CFPS. In our analysis, we control for the 6 first-level occupation groups and combine the last three groups into "others".

The coding of industries is more direct and convenient. In CFPS, there are 21 categories of industries which are totally the same as those in the national codebook (industry). Similar to the occupation, each individual will provide information on the industries they belong to, and the staff will help classify them into 21 categories. We include all the industries except the International Organisations because there are no observations in this category. Because of the limitation of observations, in some industries, there are only individuals fewer than 10. Therefore, we re-categorise these 21 industries into different sector groups, following the three-sector classification method. Those sectors are raw materials, manufacturing and services. We further classify the service sector into two parts. The first part is closely correlated with sales of products, including retailing and wholesaling. The second part includes other services such as administrative, public and entertainment services, etc.

(4) Firm Size

Literature often finds a higher wage for workers employed in larger firms. It is possible that larger firms could guarantee profits, and the workers' wages would not experience large variations. Another explanation could be that larger-scale firms would provide more rewards and benefits to the employees. These incomes are important components of gross wages, just as we measure in the analysis. Therefore, to check the theory on the advantages of larger firms in China, we add firm size variables to the wage equation. In this analysis, we follow the literature in developing countries to use 100 and 200 employees as benchmarks for the firm size, such as Dutta (2006) and Huang et al. (2022). However, it is worth mentioning that there is another criterion that is often used in the UK and European countries, where a medium sized enterprise is defined as between 50 and 249 employees and a small enterprise as less than 50 (Ward and Rhodes, 2014). This criterion is also accepted by the International Labour Organisation and is widely used in international analyses.

3.4.4.5 Variables Used in the IV Method

In the methodology section, we mentioned that two instruments would be used in the IV method, which are parental education and policy changes. However, besides the original information provided in CFPS, these variables require further specific measurements. Therefore, in this subsection, we detail how we define these variables.

(1) Parental Education

Parental education levels are the most commonly used instruments in the literature. The measurements of these variables are also easier than policy changes. In CFPS, there is a direct question regarding the parental education for those who take participate in the individual survey:

"What are your parents' education levels when you are 14 years old?"

We directly use the answer to this question to measure individuals' parental education, and this method is consistent with those in Chinese literature such as Asadullah and Xiao (2020). Some other researchers also use parents' highest education levels achieved as instruments. However, in most cases, parents' educational achievements would not vary largely when their children are already 14 years old. In addition, in China, most individuals would finish compulsory education at 15. Family backgrounds at 14 years old would greatly help them finish compulsory education and decide whether to take further non-compulsory education. Similar to the measurement of individuals' education years, we transfer parental education levels into years, also using the criteria in Table 3.3. Parental education would also be a continuous variable which would be convenient for our analysis. However, because some proportions of individuals in the survey do not successfully answer the question of parental education, we may suffer from a missing value of 14% of the whole sample.

(2) Policy Changes

In the previous subsection, we introduced that we use two kinds of policy (institutional) changes as alternatives to the conventional IV: the release of the Minimum Working Age Rule and the Higher Education Expansion Policy. Each rule/policy has a clear starting time agreed upon in the literature. Therefore, we set thresholds on individuals' birth years according to the time that the changes first took effect to divide who is affected or not. In China, the term period usually starts in September. Individuals who reach age 6 can attend primary school, and the registration deadline for primary school is 1st September each year. If a child reaches 6 years old before September, he can successfully attend school in that year. Otherwise, he needs to wait until next September. In addition, in China, it usually takes 9 and 12 years for an individual to finish compulsory education (primary and lower middle school) and upper middle school. With this information, we can introduce how we define the thresholds. Firstly, the Minimum working age rule officially came into effect in April 1991, forbidding children under 16 to take any official jobs. Therefore, individuals affected are those who did not reach 16 years old in April 1991, that is, those born after April 1975. The first cohort affected are those born from September 1974 to September 1975. Some of the students in this cohort did not reach 16 years old, and this rule would help them decide whether to finish that year of education in 1991. The instrument is generated using a dummy variable, where individuals born after April 1975 equals 1, and 0 otherwise. This measurement is consistent with Xie and Mo (2014).

Secondly, similar to the law, the expansion policy on higher education was initially proposed in December 1998 and took effect in the summer of 1999 when the enrollment of the new academic year started. Individuals normally reach 18 years old when they graduate from high school. Therefore, those born between September 1980 and September 1981 are the first cohort affected because they just caught the chance of the first year of expansion when they graduated from high school in the summer of 1999. Based on this, we set the threshold dummy to be 1 for those born after September 1980 and 1 for others. Similar measurements are shown in Huang et al. (2022).

Our measurements on policy changes are also quite similar to those used in Chinese literature, such as Campos et al. (2016), Xie and Mo (2014) and Huang et al. (2022). In the IV specifications, we implement both dummies for the Minimum Working Age

Rule and the Higher Education Expansion Policy as instruments. Results are compared to those obtained by using parental education as instruments.

3.4.4.6 Variables Used in the Heckman Method

To satisfy the exclusion restriction, we need to add an instrument in the first step of the Heckman method, which is correlated with waged job participation but does not affect the wage offer. Normally in the literature, the number of elderly and children in families are used as instruments. The rationale for choosing these variables is that some workers may need more time to care for family members. They will choose a job with more flexible time arrangements or even decide not to participate in the labour market. Specifically, we choose the number of children smaller than 14 years old and the number of old people greater than 65 years old as instruments, consistent with Kingdon and Uni (2001) and Kanjilal-Bhaduri and Pastore (2018).

Under the conventional instrumental strategy, taking care of family members, such as raising children, would inhibit only women's participation in waged jobs given the typical gender division. However, many researchers find a "puzzling" result that the number of children or old people in the family will also significantly affect men's waged work participation choices. As Kanjilal- Bhaduri and Pastore (2018) argued, it is possible that not only women but also men would take the responsibility of taking care of family members and the instrumental strategy, in fact, is suitable for both genders. Kanjilal- Bhaduri and Pastore (2018) find a significant negative effect of childhood care on the probability of doing waged jobs for men in their study. It is also argued in their paper that the negative effect is not unique in the case of India, and other studies can be referred to, such as Divakaran (1996), Kingdon (1998) and Kingdon and Unni (2001). In fact, in the international literature, it is common that researchers have used the family care variables as instruments for both males and females, such as Nieto and Ramos (2017), Tokila and Tervo (2011) and Liu et al. (2019). The idea proposed by Kanjilal- Bhaduri and Pastore (2018) could also be supported in the Chinese labour market. Since the one-child policy was abandoned in 2013, it is harder for only women in a family to take care of more than one child as well as old people. Though it is argued that men may take more economic responsibilities, in our analysis, we are not using family care as instruments to selection into non-participation in the labour market. Self-employed individuals are also included in the reference group. Men could choose to take part in self-employed jobs to keep a balance between economic income and family. Actually, empirical results in the following subsection 3.5.4 confirm that the instruments are not gendered. There are some other variables also often used as instruments, such as household assets (Kingdon and Uni, 2001) and regional (provincial) unemployment rate (Dumauli, 2015). A household asset is used as the proxy for unlaboured income because it reduces the possibility of participating in waged work. The provincial unemployment rate is included since the high unemployment rate increases the probability for females to participate in waged work. However, information on these instruments is not available in the CFPS. Therefore, we only rely on the number of family members (young and old) in our analysis.

3.4.4.7 Summary Statistics

Table 3.5 illustrate the brief notations and summary statistics on all the variables used, with an urban/rural difference. To better show the differences between rural and urban areas, we also estimate the significance of the mean gap between variables using a t-test. Firstly, we can clearly find the difference in the labour market across urban/ rural areas from the two important variables: education years and hourly wage. Urban workers have about two more years of education in mean compared with rural workers. It can be seen that, on average, rural workers have already finished the compulsory education levels (9 years), whereas urban workers have achieved high school education. This would be attributed to the policies such as “compulsory education” and “minimum working age” starting in the 1980s, which confirms that young rural workers finish at least compulsory education before entering the labour market.

Besides education, urban workers also earn higher hourly wages than rural workers, and the gap is confirmed to be highly significant by the t-test. The gap in mean earnings provides evidence that China suffers from a significant unequal development between regions. For the basic characteristic controls, we find out that there are 55 per cent of male workers in urban areas, which is slightly higher than the proportion of female workers. However, it is clear that the majority of waged workers are men in the rural labour market. Male workers take account for around 61%, significantly higher than that in urban areas. This can be explained by the fact that physical condition is more required in rural areas. Fewer occupations are suitable for female workers, and a larger proportion of females choose to take more responsibilities to care for their families. Besides gender, we also focus on individuals' "Hukou" status in our analysis. It is quite interesting that we find there are over 50% of waged workers in urban areas do not have urban "Hukou". Most owners of rural "Hukou" in urban areas come from the countryside, showing that internal labour force migration is quite common in contemporary China. However, for rural areas, despite the small proportion of workers from cities, it is clear that the waged workers mainly consist of rural individuals that are locally born.

In terms of the demand side control, some differences are also found. The proportion of individuals signing official contracts is 15% higher in urban areas. In addition, there is a higher proportion of workers in urban areas employed in public sectors compared with rural areas. Only around 18% of individuals in rural areas can find a job in publicly owned enterprises, while in urban areas, the number is about 33%. The difference in the sector can sort of explain why fewer rural workers sign contracts. Jobs in the public sector often provide formal contracts to each worker employed, strictly following the Law of Labour. However, considerable amount workers in privately owned enterprises are forced to accept oral or no contracts in order to keep their jobs. This would make their wages volatile, and their rights would not be guaranteed when they have disputes with employers.

In Table 3.5, we also show summary statistics on the variables we use in the robustness checks. Firstly, we find that parents of urban workers have significantly more schooling years than those of rural workers. Further, parents' schooling years are quietly low in both urban and rural areas. Only fathers of urban workers finish the

Table 3.5: Summary statistics on variables with urban/rural differences

Variables	Urban		Rural		Urban-rural Gap
	Mean	Sd.	Mean	Sd.	Difference in mean
Lnwage Log hourly gross wage	2.841	0.692	2.670	0.654	0.171***
Education years Highest achieved education years	11.502	3.915	9.352	4.149	2.150***
Male Male = 1, female = 0	0.551		0.605		-0.054***
Age Individual's age	37.626	10.599	36.112	10.934	1.514***
Age square Age square	1528.043	828.260	1423.559	834.643	104.484***
Minority Minorities = 1, "Han" = 0	0.049		0.124		-0.075***
Marriage Currently married with living spouse = 1, others = 0	0.782		0.747		0.035***
Urban "Hukou" Registration status of urban = 1, others = 0	0.491		0.104		0.388***
Northeast Living in Northeast China = 1, others = 0	0.128	0.334	0.042	0.201	0.086***
East Living in East China = 1, others = 0	0.403	0.491	0.381	0.486	0.022
Middle Living in Middle China = 1, others = 0	0.258	0.437	0.253	0.435	0.005
West Living in West China = 1, others = 0	0.211	0.412	0.324	0.435	0.113***
Signing contract Signing contract = 1, others = 0	0.575		0.423		0.152***
Public sector Public sector = 1, others = 0	0.327		0.177		0.150***
Raw materials Raw materials = 1, others = 0	0.020	0.099	0.080	0.140	-0.060***
Manufacturing Manufacturing = 1, others = 0	0.401	0.490	0.522	0.500	-0.121***
Retailing and wholesaling Retailing and Wholesaling = 1, others = 0	0.335	0.472	0.267	0.443	0.068***
Other services Other services = 1, others = 0	0.244	0.323	0.131	0.345	0.113***
Small firm Number of employees smaller than 100 = 1, others = 0	0.477	0.500	0.578	0.494	-0.101***
Medium firm Number of employees smaller than 200 but greater than 100 = 1, others = 0	0.216	0.412	0.177	0.382	0.039***
Large firm Number of employees greater than 200 = 1, others = 0	0.307	0.486	0.245	0.598	0.062***
Occupation 1 Leaders and managers of enterprises = 1, others = 0	0.070	0.256	0.044	0.205	0.026***
Occupation 2 Professionals & technicians = 0, others = 0	0.191	0.393	0.118	0.323	0.073***
Occupation 3 Office workers and related staff = 1, others = 0	0.131	0.337	0.083	0.275	0.048***
Occupation 4 Commercial staff and Service workers = 1, others = 0	0.253	0.435	0.234	0.423	0.019
Occupation 5 Agricultural, Forestry, Animal husbandry, Fishery = 1, others = 0	0.014	0.118	0.026	0.158	-0.012***
Occupation 6 Production workers, transport equipment operators and other labourers = 1, others = 0	0.338	0.473	0.490	0.500	-0.152***
Father education Farther's education years	7.108	4.252	5.730	4.186	1.377***
Mother education Mother's education years	5.246	4.443	3.538	3.987	1.711***
Rule Born after April 1975 = 1, others = 0	0.655		0.675		-0.020

Table 3.5: Continued

Variables	Urban		Rural		Urban-rural Gap
	Mean	Sd.	Mean	Sd.	Difference in mean
Policy Born after September 1980 = 1, others = 0	0.534		0.551		-0.016
Young children Number of children younger than 14 years old in the family	0.597	0.573	0.571	0.545	0.028
Old people Number of elderly greater than 65 years old in the family	0.139	0.387	0.188	0.521	-0.049***

Samples for the descriptive statistics are for wage earners, except the numbers of young children and old people in the family are based on samples from different employment statuses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

primary school level of education on average. Compared with their children's education levels, it can be clearly seen that Chinese education develops rapidly across generations. Unlike the parents' education, limited differences have been found in the variables indicating the policy changes. Since these policies were published nationwide, rural and urban workers have been consistently affected. The mean value on the proportion of individuals affected by the rule and tertiary are quite similar across urban and rural areas, and the small variation may only capture the difference in age distribution. Secondly, we find small gaps in the average number of children younger than 14 years old in the families between different areas. However, in the rural areas, there are significantly larger numbers of older people over 65 years old than in urban areas.

In Table 3.6, we further provide statistics on the composition of individuals' highest education achievements for wage earners to show a more detailed education distribution besides the average level. It can be seen that in current China, there are still 3.24% and 8.41% wage earners who have not finished any formal levels of schooling in urban and rural areas, respectively. The lower middle school education is the leading education level in both areas. About 90% and 74% of individuals finish at least compulsory education in urban and rural areas, respectively. In addition, it is found that in urban areas, the proportion of workers achieving tertiary education is 35.94%, which exceeds the proportion of upper middle education. In rural areas, the proportion of upper middle education is slightly higher, but there are still 16.98% of tertiary-educated individuals working in rural areas.

Regarding the gender gap, we find that the proportion of no formal qualification for females is 6.69%, which is considerably larger than for males. The leading education level for males is lower middle school, which accounts for 34.64%. However, in the female group, the leading education level is tertiary education, where 34.5% of workers are graduates from colleges and universities. This finding may imply that in current China, females are more promoted to achieve tertiary level education compared with males. In fact, the compulsory education finishing rate is also quite similar between genders, with about 83%.

Table 3.6: Composition of individuals' education achievements

	Urban	Rural	Male	Female
No formal qualification	118 3.24%	164 8.41%	121 3.80%	161 6.69%
Primary school	335 9.20%	353 18.11%	441 13.58%	247 10.26%
Lower middle	1047 28.75%	742 38.07%	1103 34.64%	686 28.50%
Upper middle	833 22.87%	359 18.42%	708 22.24%	484 20.11%
Tertiary	1309 35.94%	331 16.98%	811 25.47%	829 34.50%
Total	3642	1949	3184	2407

3.5 Empirical Results

3.5.1 OLS Regression Results on Return to Education

In this part, we show the empirical results obtained in OLS regression based on the empirical model of the Mincer wage equation introduced in the methodology part. We divide the sample according to individuals' residential status to examine the urban/rural difference in return to education. We include two specifications in regression. The first only includes basic individual characteristic controls, and the second further considers employment controls. From Table 3.7, It can be seen in column 1 that for urban workers, with the one-year growth of education, an individual's hourly wage would increase by 6.3%, and the coefficient is tested to be highly significantly different from zero. If further controlling for the employment

Table 3.7: Return to education in urban and rural areas

	Urban		Rural	
	(1)	(2)	(3)	(4)
Education years	0.063***	0.046***	0.037***	0.025***
	(0.003)	(0.004)	(0.004)	(0.004)
Male	0.307***	0.311***	0.327***	0.321***
	(0.021)	(0.022)	(0.028)	(0.031)
Age	0.035***	0.033***	0.038***	0.031***
	(0.009)	(0.009)	(0.010)	(0.010)
Age square/100	-0.047***	-0.042***	-0.053***	-0.048***
	(0.016)	(0.017)	(0.015)	(0.015)
Minority	0.119**	0.106**	0.006	0.005
	(0.049)	(0.049)	(0.043)	(0.042)
Marriage	0.023	0.033	0.002	0.012
	(0.031)	(0.030)	(0.037)	(0.036)
Urban "Hukou"	0.055**	0.032	0.231***	0.198***
	(0.025)	(0.025)	(0.050)	(0.049)
Northeast	-0.149***	-0.133***	-0.056	-0.062
	(0.037)	(0.036)	(0.068)	(0.065)
East	0.171***	0.166***	0.092***	0.083**
	(0.028)	(0.027)	(0.033)	(0.032)
Middle	0.026	0.034	-0.007	-0.009
	(0.031)	(0.030)	(0.039)	(0.038)
Signing contract		0.098***		0.199***
		(0.024)		(0.030)
Public sector		-0.001		0.022
		(0.027)		(0.043)
Raw materials		0.105		-0.020
		(0.093)		(0.122)
Manufacturing		-0.013		0.165***
		(0.035)		(0.053)
Retailing and wholesaling		0.002		0.151***
		(0.031)		(0.051)
Small firm		-0.117***		-0.071*
		(0.026)		(0.037)
Medium firm		0.012		-0.000
		(0.029)		(0.043)
Constant	1.248***	1.378***	1.498***	1.816***
	(0.161)	(0.201)	(0.191)	(0.331)
Occupations	No	Yes	No	Yes
N	3642	3642	1949	1949
Adj. R^2	0.206	0.236	0.157	0.197

Robust Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

variables in the second column, urban workers' return to one year of education decreases to 4.6%. This result reflects that part of the return to education can be explained by the correlation between education and employment controls. In terms of the rural workers, in column 3, we find that if education achievements increase one year, an individual's hourly wage will increase by 3.7%. After controlling the employment variables, the return decreases to 2.5% but remains highly significant under the 1% significance level.

It is clear that urban workers enjoy a higher return to education, no matter the category of controls included. Two different methods are used to test the significance level of the return gap between urban and rural areas: the t-test and the SUR test. Results are shown in Table A.1 in Appendix A, and it can be seen that the gaps in return are highly significant under 1% significance level under both tests. This finding is consistent with most studies in Chinese literature, such as Campos et al. (2016) and Asadullah and Xiao (2020).

Some possible explanations exist for the considerable gap in return to education between urban and rural areas. Firstly, Yang et al. (2010) argue that there would be a significant gap in the supply side of education between urban and rural areas. Students in rural areas may suffer from worse education qualities which would affect the quality of human capital accumulated and the future productivity of rural workers, resulting in a lower return to education than those in urban areas. Secondly, Li et al. (2005) point out that the rural labour market may suffer from lower functionality than urban markets. The rural labour market may reward less human capital, but other non-market factors (such as social relationships and backgrounds) are used in assigning jobs and wages, which largely hinder the degree of return to education. Similar arguments are shown in Tokila and Tervo (2011) that individuals may accept a lower income in exchange for other regional amenities, such as scenery.

For other variables, in both urban and rural areas, male workers enjoy 30% higher wages than female workers, showing a considerable gender wage gap in the Chinese labour market. Minority groups do not suffer from lower wages, and in urban areas, individuals from minority groups even enjoy significantly higher wages of more than 10% than those from the majority group, “Han”. Urban “hukou” also provides workers with higher labour market earnings in both urban and rural areas. However, when the employment controls are added, the higher wages for registration status become insignificant in urban areas. According to the results on different provinces, it is clear that workers in Chinese eastern areas earn significantly higher wages than the reference group, western areas. This finding is consistent with those in the aggregate level that eastern areas have the highest GDP per capita in China, showing an unbalanced development between different areas.

The estimated effects of employment controls on wages are shown in columns 2 and 4. The inclusion of these variables would not largely affect the estimated coefficients on other basic characteristic controls. We find individuals signing formal contracts with employers enjoy higher payoffs, but the significant effect of the sector is not concluded by empirical models. Also, lower wages are found for workers employed in enterprises with small scale in both urban and rural areas. In addition, in rural areas, individuals in manufacturing and sales-related services sectors would have higher earnings. However, no significant earnings disparities between different industry groups are found in urban areas.

In the Mincer equation, returns for each year of education are assumed to be equal. However, this may drive the concern that different levels of education would provide individuals with various amounts of human capital accumulated. For example, one year of education in tertiary education would have a different effect on wages compared to one year of education in primary school. Therefore, in this part, we follow the literature to estimate the return to education by substituting the independent variable, education years, with different category dummies of education levels. The reference group includes those individuals who have no formal qualifications. Estimated results are shown in Table B1 in Appendix B. It can be found in urban areas that wage returns continuously increase with the growth of education levels. The highest return is shown in the tertiary education group, where graduates earn 73.2% more than those with no formal qualifications, and the return remains large with 66.8%, even considering the employment characteristics. However, we find an insignificant return to primary school in rural areas compared to those without formal qualifications. This may imply that in rural areas, the requirements of education in jobs are not very detailed, and individuals with primary school education and lower are doing very similar jobs. Nevertheless, the returns also show an increasing pattern for other education categories. Tertiary education still enjoys the highest wage payoffs, with 61.2% and 45.9%, in the specifications with and without employment controls, respectively. Comparing the returns to education categories in different areas, we find for each level of education, the return in urban areas is higher than that in rural areas. This finding is consistent with those concluded previously when a continuous variable of education years is used.

As mentioned in the previous subsection 3.4.3, the literature often uses two different measurements of individuals' urban and rural status. In recent years, a number of rural individuals have migrated to urban areas to find waged jobs but do not successfully obtain the urban "hukou" (registration status). As shown in the descriptive statistics in subsection 3.4.4, these migrants account for around 50% of all the individuals in the urban areas. Under the classification based on residential status, they are defined as urban workers. However, under the classification according to the social background ("Hukou"), they are still defined as rural workers. Some researchers argue that though individuals with urban or rural "Hukou" live and work together in the urban areas, they stay in distinct labour markets (e.g. Zhu, 2015). This assumption is focused on by researchers such as Messinis (2013). They find that the return to education for migrants would be significantly lower than for local urban workers. Therefore, in our analysis, we further divide the urban samples into two categories: locally born workers and migrants, corresponding to the arguments in different classification methods. Results are shown in Table C.1 in Appendix C. It is found that local urban workers have a return to years of education of 6.3%, which is 3.1% higher than that for migrant workers. The return gap between these two groups is tested to be significant at the 1% level under the t-test and SUR test[4]. However, the return to rural workers still ranks the lowest, but very close to that for migrants. This result is consistent with those findings in Chinese literature, such as (Zhu, 2015). The gap between local urban workers and migrants shows they are not treated equally in the urban labour market. Possible explanations would be that migrant workers are often accepted for doing jobs with low skill requirements.

4. P-values for the two test statistics are both 0.000.

3.5.2 Return to Education in Subgroups

In this subsection, we further examine the heterogeneous returns to education in different subgroups, specifically the returns in different genders and sectors. The analyses on return to education for these subgroups often focus on the aggregated level of samples. However, in our analysis, we further disaggregate the samples according to urban and rural areas to see the returns gap in gender and sector in geographic labour markets in China. Limited studies conduct similar analyses in the literature.

The return to education with gender differences would provide suggestions to both males and females on the decision of education investments. Some researchers (e.g. Kanjilal-Bhaduri and Pastore, 2018) argue that the lower female participation rate in higher levels of education in the country may result from the lower return to education in the labour market compared with males. In our analysis, we could further provide suggestions to males and females on education according to segmented labour market conditions. In addition, sector development attracts the attention of an increasing number of researchers in current China. When the People's Republic of China was first established, only public sector and nation-owned companies were allowed for business. However, recent decades have witnessed fast development in the private sector. According to the statistics in Chapter 2, till 2020, about 95% of institutions in China are privately owned, and about 70% of workers are employed in the private sector. The differentiated estimation on return to education between sectors would provide evidence on how the human capital can be rewarded in institutions with various ownership, which could reflect the difference in features in various economies. Also, better-educated individuals often want to be employed in a sector that can make better use of and payoff for their educational achievements and skills. Empirical evidence on the return gap between sectors would help them decide on employment choices.

Table 3.8 provides empirical results by adding interaction terms between subject groups and education years. Firstly, for gender, it can be seen that the return to females' one year of education is 5.5% in urban areas. The coefficient obtained on the

Table 3.8: Return to education in urban and rural areas with heterogeneity in subgroups

	Gender		Sector	
	Urban	Rural	Urban	Rural
Education years	0.055***	0.036***	0.041***	0.025***
	(0.004)	(0.006)	(0.004)	(0.005)
Education years*male	-0.017***	-0.020***		
	(0.005)	(0.007)		
Education years*public sector			0.019***	0.004
			(0.006)	(0.009)
Male	0.509***	0.508***	0.314***	0.321***
	(0.064)	(0.072)	(0.022)	(0.031)
Age	0.034***	0.032***	0.030***	0.030***
	(0.009)	(0.010)	(0.009)	(0.010)
Age square/100	-0.042***	-0.048***	-0.043***	-0.046***
	(0.014)	(0.016)	(0.018)	(0.017)
Minority	0.110**	0.003	0.105**	0.005
	(0.049)	(0.043)	(0.048)	(0.042)
Marriage	0.033	0.006	0.035	0.012
	(0.030)	(0.036)	(0.030)	(0.036)
Urban "Hukou"	0.035	0.198***	0.031	0.196***
	(0.025)	(0.049)	(0.025)	(0.050)
Northeast	-0.136***	-0.063	-0.129***	-0.061
	(0.036)	(0.064)	(0.036)	(0.065)
East	0.166***	0.085***	0.167***	0.083**
	(0.027)	(0.032)	(0.027)	(0.032)
Middle	0.035	-0.008	0.032	-0.009
	(0.030)	(0.038)	(0.030)	(0.038)
Signing contract	0.096***	0.198***	0.108***	0.200***
	(0.024)	(0.030)	(0.024)	(0.030)
Public sector	-0.001	0.027	-0.238***	-0.016
	(0.027)	(0.043)	(0.086)	(0.100)
Raw materials	0.117	-0.022	0.111	-0.022
	(0.092)	(0.122)	(0.093)	(0.122)
Manufacturing	-0.012	0.166***	-0.008	0.166***
	(0.035)	(0.053)	(0.035)	(0.053)
Retailing and wholesaling	0.003	0.150***	0.008	0.153***
	(0.031)	(0.051)	(0.031)	(0.052)
Small firm	-0.121***	-0.075**	-0.116***	-0.071*
	(0.026)	(0.037)	(0.026)	(0.038)
Medium firm	0.012	-0.000	0.013	-0.000
	(0.029)	(0.043)	(0.029)	(0.044)
Constant	1.266***	1.687***	1.467***	1.828***
	(0.205)	(0.328)	(0.201)	(0.332)
Occupations	Yes	Yes	Yes	Yes
N	3642	1949	3642	1949
Adj. R^2	0.238	0.201	0.238	0.197

Robust Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

interaction term is highly significant, showing a significant gap between males and females in return to education. Male workers in urban areas suffer from a lower return of 1.7%, and their return is only 3.8%. Similarly, in rural areas, the return for male workers is 2% lower than that for female workers. The return for females is 3.6%, whereas for males, it is only 1.6%. The estimated returns also show that for both subgroups of males and females, returns to education are higher in urban areas.

Dougherty (2005) proposes some ideas to explain the gender gap in return to education. For example, due to the quality of schooling investment, females tend to be more motivated students than males and extract more from their time in school, which leads to higher productivity of female workers at the same education level compared to male workers. In addition, it is also argued that schooling has two effects on earnings for females. The first is the direct human capital effect, and the second is the anti-discrimination effect. Better-educated females are less likely to tolerate discrimination and can seek an offer that fully values their characteristics. Ren and Miller (2012) also provide some explanations that the gender gap in return may occur due to the limited supply of female skilled workers in the labour market and different skill requirements between female-dominated and male-dominated jobs.

Secondly, in Table 3.8, we can see that the return to education for the private sector is 4.1% in urban areas. The return to the public sector is significantly higher by 1.9%, which reaches 6.0%. However, there is no significant gap between sectors in rural areas, and returns to both sectors are around 2.5%. In addition, similar to the subgroup in gender, we find for both sectors, the return to education is higher in urban areas than in rural areas. Possible explanations for the return gap between sectors is that the public sector is responsible for a number of skill- and technology-oriented industries that are essential to the country, such as energy, education and scientific research and development. These jobs have a higher demand for skills; therefore, educated workers or professions would be rewarded with higher payoffs. In addition, wage rigidity is often shown in publicly owned institutions where the earnings would be stable for a specific education level. However, in private institutions, wages would also be determined by the performances and achievements in jobs, which is considered more efficient and reduce the explanatory ability of education to wages (Rao, 2015). Similar arguments are also raised by Psacharopoulos (1979) that the lack of competition in the public sector may result in a higher return to education. Besides these, it needs to be mentioned that in our analysis, we use gross wage to measure individuals' earnings, and it is possible that in the public sector, regular benefits and rewards are important components of wages, and better-educated individuals would significantly benefit more from these extra payments.

3.5.3 Robustness Check I: Omitted Variable Bias and IV Method

In the previous subsections, the return to education is estimated according to the OLS method. This method is widely used in the literature but still suffers from important shortcomings. As explained in the methodology part, one of the most important problems is the omitted variable bias, that driven by the correlation between omitted innate ability in the error term and education years. We conduct the Instrument Variable (IV) method to solve this problem. In this subsection, we propose the empirical results using two instrument categories: parental education years and policy changes in China.

To make sure the efficiency of the IV method, we also show results on three kinds of diagnostic tests, besides illustrating the empirical results on IV estimators, which are the Stock and Yogo (SY) weak instrument test, the Sargan-Hanson over-identification test and the Durbin-Wu-Hausman (DWH) endogeneity test. These tests are used to test the basic assumptions of strong instruments, over-identification restriction and endogenous regressors, respectively.

Firstly, a weak instrument test is used to examine whether the instruments included strongly correlate with the endogenous variable in the first step regression. The rationale is to conduct an F test on the joint significance of estimated coefficients on external instruments. However, the normal benchmark, such as rejecting the null at the 5% significance level, is insufficient. Stock and Yogo (2005) provide a rule of thumb that the strong instrument assumption would be satisfied if the F statistic is greater than 10. This rule of thumb is accepted by a number of researchers in the literature and also implemented in our analysis.

Secondly, the over-identification test aims to determine whether the instruments included are truly exogenous. The idea is that if all the instruments are exogenous, the 2SLS residuals should be uncorrelated with the instruments. The number of over-identifying restrictions equals the number of external instruments minus the number of endogenous variables. The Sargan-Hansen over-identification test statistics follow the chi-square distribution. However, one of the limitations of the over-identification test is that it must satisfy a pre-condition that at least one valid instrument exists. In addition, if there is only one external instrument, the model is said to be just identified, and an over-identification test cannot be used. The null hypothesis of the over-identification test is that all instruments are exogenous.

Thirdly, the traditional Hausman (1978) test holds the idea that if there are no significant statistical differences between the coefficients on OLS and IV regression, both estimates are consistent, and the endogeneity assumption is not confirmed. The IV method would not be necessary since the 2SLS estimator is less efficient than OLS and can have very large standard errors (Wooldridge, 2016). Hausman test statistics also follow the chi-square distribution, and if the statistic exceeds the critical value at, say 5% significance level, the null hypothesis of no differences between coefficients is rejected. However, the traditional Hausman test is not applicable under heteroskedasticity, therefore in this subsection, we implement the regression-based Durbin-Wu-Hausman (DWH) test, which can easily be formed by including the residuals of each endogenous right-hand side variable, as a function of all exogenous variables, in a regression of the original model (Davidson and MacKinnon, 1993). F statistics are computed with the same null hypothesis as the Hausman test.

In the following table 3.9, we show IV estimation results under the 2SLS procedure by using parental education as instruments. Since we lose about 14% of observations because of missing information on parental education, we provide OLS estimates on return to education under the restricted sample for comparison. It is found that after using the IV method, the return to education is considerably larger than that in OLS, showing that one-year growth of education years would result in a 9.0% and 4.4% increase in an individual's hourly wage in urban and rural areas, respectively. Both estimators are still significant, but the coefficient for rural workers is only weakly significant at the 10% level. Under IV, we find a consistent result compared with the OLS method that urban workers enjoy a higher return to education than rural workers.

Table 3.9: IV regression results on return to education in rural and urban areas
Instruments: parents' education years

	Urban		Rural	
	OLS	IV	OLS	IV
Second stage				
Education years	0.044***	0.090***	0.025***	0.044*
	(0.004)	(0.013)	(0.005)	(0.025)
First stage				
Father education years		0.089***		0.101***
		(0.014)		(0.022)
Mother education years		0.103***		0.089***
		(0.013)		(0.022)
Male		0.399***		0.896***
		(0.110)		(0.181)
Age		-0.001		-0.182***
		(0.043)		(0.065)
Age square/100		-0.124**		0.082
		(0.058)		(0.059)
Minority		-0.545**		-0.654**
		(0.272)		(0.260)
Marriage		-0.045		0.098
		(0.146)		(0.230)
Urban "Hukou"		1.579***		1.265***
		(0.123)		(0.265)
Northeast		0.084		0.630*
		(0.182)		(0.370)
East		0.436***		0.669***
		(0.139)		(0.205)
Middle		0.222		0.239
		(0.151)		(0.236)
Weak instrument test with Stock-Yogo critical value				
F statistic		72.936***		28.725***
p-value		0.000		0.000
Sargan-Hanson over-identification test				
Chi2(1) statistic		2.443		0.670
p-value		0.118		0.404
Durbin - Wu - Hausman (DWH) endogeneity test				
F statistic		8.171***		0.553
p-value		0.004		0.457
N	3642	3118	1949	1659
R^2	0.243	0.221	0.199	0.189

Robust standard errors in parentheses: * p < 0.1 , ** p < 0.05, *** p < 0.01

R^2 value is for the second stage regression

Other variables in both stages include: gender, age, age square, marriage status, Hukou status and province controls, contract type, sector, firm size, industry controls and occupation controls

In terms of the diagnostic test results for IV, we find in both areas, the IV estimators pass the strong instrument test and over-identification test, showing that the instruments are strongly correlated with the endogenous variable and are truly exogenous. However, it needs to be mentioned that the null hypothesis of no endogenous regressor cannot be rejected among the rural samples. The Chi-square statistic is only 0.553, with quite a small p-value. It is argued by Wooldridge (2016) that the IV estimator is less efficient than OLS when explanatory variables are exogenous, which means the OLS result in column 3 is actually more reliable. However, even if our test results support more on OLS estimator for the return to education among rural workers, the previous finding on a higher return to education in urban areas still exists.

Under the IV method, we find the estimated returns to education are larger than that under the OLS method, including urban and rural areas. In fact, this result does not support the original assumption that return to education would be reduced after the omitted variable bias problem solved. Normally, there are three possible explanations. Firstly, some researchers such as Imbens and Angrist (1994) and Aronow and Carnegie (2013) point out that the IV estimation only covers the local average treatment effect (LATE) or the ATE for the subpopulation that is influenced by the IV. When treatment effects are heterogeneous across units, the LATE and the ATE may take on different values, which would potentially cause complications in the comparison between IV and OLS results. Secondly, Wang (2012) points out that the IV method solves the possible measurement error problem in education years, also driven by the correlation between the explanatory variable and the error term. However, Card and Lemieux (2001) argue that measurement error may only account for 10 to 20% of the growth of estimators. Thirdly, it is also possible that omitted variable bias is not restricted to the innate ability though we propose a specific assumption. Bias driven by other factors that are not observable to us may also be resolved by the IV method, and some of the factors may not be positively correlated with the education years, which could result in a larger IV estimator on return to education. For example, it is known that technical skills, rather than academic skills or smartness, would also benefit individuals' income. However, it could be the case that technical skills and educational achievements are negatively correlated.

In Table 3.9, we also illustrate the factors that could affect the individuals' education achievements obtained in the first step of the 2SLS procedure. It is clear that parental education, including fathers' and mothers' education, would have significant and positive effects on their children's education levels in both urban and rural areas. In addition, individuals with urban "hukou" have more years of education, whereas minorities in China suffer from lower education achievements. Regarding employment controls, in both urban areas, individuals who sign formal contracts with their employers have higher education achievements, and the public sector tends to employ workers with higher education levels. In addition, in rural areas, individuals in the raw materials and manufacturing sectors have lower years of obtained education on average.

The estimators under the IV method would also be sensitive to the instruments used. Therefore, to achieve higher robustness, we further include the policy changes as instruments to make a comparison. Empirical results are shown in Table 3.10. It is found that in both urban and rural areas, returns to education under IV are still considerably higher, to a larger extent than that shown in Table 3.9. In fact, many studies in the literature conclude a higher return to education under IV, such as Wang (2012) and Dickson and Smith (2011), by using different kinds of instruments. Therefore, our results are not rarely seen in the literature. In addition, the return to education in urban areas under IV is still higher, about two times than that in rural areas. However, similar to the results in Table 3.9, the explanatory variable does not satisfy the endogenous assumption for the rural sample, which means we should also rely more on the OLS estimation. From the first step results, both the Minimum Working Age Rule and the Tertiary Education Expansion Policy would help with the growth of individuals' education achievements all over China. Especially before and after the tertiary expansion policy proposed, there is a gap of 1.1 and 1.8 years of education on average for urban and rural workers, respectively.

Table 3.10: IV regression results on return to education in rural and urban areas
Instruments: Policy changes

	Urban		Rural	
	OLS	IV	OLS	IV
Second stage				
Education years	0.046***	0.139***	0.025***	0.066**
	(0.004)	(0.013)	(0.004)	(0.021)
First stage				
Rule		0.498**		0.954***
		(0.215)		(0.369)
Policy		1.117***		1.819***
		(0.185)		(0.319)
Male		0.331***		0.753***
		(0.103)		(0.168)
Age		0.039		-0.162***
		(0.043)		(0.063)
Age square/100		-0.135**		0.213**
		(0.061)		(0.096)
Minority		-0.584**		-1.101***
		(0.245)		(0.251)
Marriage		-0.115		0.033
		(0.139)		(0.218)
Urban "Hukou"		1.979***		1.499***
		(0.112)		(0.234)
Northeast		0.251		0.659**
		(0.175)		(0.335)
East		0.505***		0.636***
		(0.128)		(0.190)
Middle		0.396***		0.415*
		(0.140)		(0.212)
Weak instrument test with Stock-Yogo critical value				
F statistic		24.762***		24.351***
p-value		0.000		0.000
Sargan-Hanson over-identification test				
Chi2(1) statistic		1.077		0.597
p-value		0.299		0.440
Durbin - Wu - Hausman (DWH) endogeneity test				
F statistic		8.415***		2.673
p-value		0.004		0.102
N	3642	3642	1949	1949
R^2	0.236	0.184	0.197	0.136

Robust standard errors in parentheses: * p < 0.1 , ** p < 0.05, *** p < 0.01
R^2 value is for the second stage regression
Other variables in both stages include: gender, age, age square, marriage status, Hukou status and province controls, contract type, sector, industry controls and occupation controls

3.5.4 Robustness Check II: Self-selection Bias and Heckman Two-step Method

Besides the omitted variable bias, in the methodology part, we also introduce that samples used in the OLS regression may suffer from non-random selection. Possible bias may be generated when only the income of wage earners is included in the regression. This problem can be solved by using the procedure of Heckman two-step method. In the first step, we conduct a regression on the waged work participation and obtain an inverse Mills ratio, which is the Lambda in Table 3.11. In the second step, we include this ratio into the basic model and estimate the return to education again, which is the return robust to the selection bias. The two-step results are shown in the following table 3.11. Similar to the tables on IV results, in columns 1 and 3, we provide results under the OLS method for comparison, though we do not have missing values on observations under the Heckman method. Firstly, from the second stage regression results, we find the coefficient on Mills ratio (Lambda) is only significant in rural areas, showing that only rural samples in the original OLS regression suffer from the significant self-selection bias. The returns to education in urban areas are quite similar under the two methods. However, the return to education in rural areas increases considerably, from 2.5% under the OLS method to 4.2% under the Heckman method, showing that the estimated return under OLS suffers from a downward bias if not considering the self-selection issue. The downward bias for return to education in rural areas is also concluded by Liu et al. (2019), who also focus on the self-selection issue of Chinese rural workers. The return increases from 2.1% under OLS to 2.9% under Heckman, to a smaller extent than that found in our analysis.

The direct effect of correcting self-selection bias is that the gap in return to education between urban and rural areas is largely moderated. Comparing results under Heckman, urban areas only have 0.7% higher return to rural areas, which is tested to be insignificant under both the t-test and SUR test (shown in table A.2 in Appendix A). This result on the relationship between returns in different areas is concluded by limited studies in Chinese literature. Possible explanations could be that the Heckman method is rarely used in disaggregated samples with urban/rural differences, and many of the previous studies are not nationally representative.

Table 3.11: Heckman two-step regression results on return to education in rural and urban areas

	Urban		Rural	
	OLS	Heckman	OLS	Heckman
Second stage				
Education years	0.046***	0.049***	0.025***	0.042***
	(0.004)	(0.007)	(0.004)	(0.008)
Lambda		0.053		0.387**
		(0.133)		(0.161)
Constant		1.328***		1.472***
		(0.266)		(0.301)
N	3642	3642	1949	1949
First stage				
Education years		0.082***		0.064***
		(0.005)		(0.005)
Male		0.147***		0.313***
		(0.037)		(0.040)
Age		-0.005		-0.012
		(0.015)		(0.015)
Age square/100		-0.021		-0.036
		(0.045)		(0.048)
Minority		-0.245***		-0.198***
		(0.076)		(0.059)
Marriage		-0.262***		-0.329***
		(0.061)		(0.063)
Urban “Hukou”		0.382***		0.560***
		(0.043)		(0.082)
Northeast		0.144**		-0.267***
		(0.069)		(0.094)
East		0.226***		0.306***
		(0.047)		(0.049)
Middle		0.091*		0.199***
		(0.051)		(0.054)
Young children		-0.127***		-0.114***
		(0.020)		(0.018)
Old people		-0.003		0.034
		(0.028)		(0.030)
Constant		0.002		0.210
		(0.290)		(0.290)
N		5795		5185
Pseudo R^2		0.304		0.258

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Lambda is the inverse Mills ratio for the correction of self-selection

Other variables in the second stage include: gender, age, age square, marriage status, Hukou status, province controls, contract type, sector, firm size, industry controls and occupation controls

Regarding the first-step results, we find education years, gender of male and urban “Hukou” status would positively affect an individual’s choice to participate in waged work in both rural and urban areas. However, in contrast, individuals who are married and minorities in ethnicity would be less likely to attend waged jobs, no matter their residential status. For the instruments used for the exclusion restriction, we find that having old people over 65 years old would have an insignificant effect on individuals doing waged jobs in both urban and rural areas. However, individuals who have children under 14 years old in families would be less likely to be wage earners than those who do not have children in families. From the first stage results, we only include basic characteristics controls because we do not have information on employment controls for those who are self-employed, unemployed and not in the labour market. This measurement is acceptable in the literature and is consistent with that used by Nieto and Ramos (2017).

In Table 3.12, we further disaggregate the samples in both urban and rural areas according to gender differences. In the literature, some researchers still argue that the sample selection issue is more driven by females because they would take more responsibilities in taking care of family members and would concern more on the choice of employment status (Wang, 2012). From the first stage results in the table, it can be seen that the number of children in the family would significantly affect the choices to be waged workers for both males and females, showing that our instruments are not gendered. However, from the coefficients on Lambda in the table, we find only for females in rural areas, the Lambda is significant, showing that only female workers suffer significantly from self-selection bias. After correcting for the bias, female return in rural areas increases from 3.1% to 4.9%, which is very close to that in urban areas. In addition, female workers enjoy a higher return in different areas than male workers, consistent with the finding in subsection section 3.5.2. The return to rural men still increases by 1.4% under the Heckman method. This is driven by the fact that though insignificant, the coefficient of Lambda for rural male samples is not very small, and the significance level just exceeds the 10% benchmark.

In fact, besides the previous analysis of subgroups, we still need to illustrate the Heckman results for different sectors. However, the disaggregation on samples is not applicable for sectors because we do not know the sector information for self-employed individuals, unemployed and not in the labour market, which would restrict us from dividing them into separate groups. Therefore, in this part, we only focus on the gender difference.

Table 3.12: Heckman two-step results on return to education with gender and urban/rural differences

	Urban Male		Urban Female		Rural Male		Rural Female	
	OLS	Heckman	OLS	Heckman	OLS	Heckman	OLS	Heckman
Second stage								
Education years	0.039***	0.040***	0.051***	0.056***	0.016***	0.030***	0.031***	0.049***
	(0.005)	(0.010)	(0.006)	(0.010)	(0.006)	(0.011)	(0.007)	(0.011)
Lambda		0.017		0.134		0.386		0.447**
		(0.193)		(0.154)		(0.242)		(0.202)
Constant		1.641***		1.296***		2.039***		1.101**
		(0.337)		(0.424)		(0.364)		(0.514)
N	2005	2005	1637	1637	1179	1179	770	770
First stage								
Education years		0.072***		0.090***		0.060***		0.060***
		(0.008)		(0.008)		(0.007)		(0.008)
Age		-0.043**		0.074***		-0.018		0.034
		(0.020)		(0.025)		(0.019)		(0.027)
Age square/100		0.012		-0.023***		-0.031		-0.063***
		(0.011)		(0.008)		(0.032)		(0.040)
Minority		-0.364***		-0.146		-0.139*		-0.312***
		(0.110)		(0.105)		(0.077)		(0.094)
Marriage		-0.155*		-0.457***		-0.169**		-0.733***
		(0.084)		(0.094)		(0.080)		(0.109)
Urban "Hukou"		0.394***		0.364***		0.538***		0.568***
		(0.059)		(0.063)		(0.111)		(0.123)
Northeast		0.264***		0.008		-0.284**		-0.257*
		(0.097)		(0.099)		(0.124)		(0.147)
East		0.188***		0.276***		0.295***		0.341***
		(0.064)		(0.070)		(0.066)		(0.075)
Middle		0.062		0.136*		0.245***		0.145*
		(0.070)		(0.076)		(0.073)		(0.083)
Young children		-0.109***		-0.166***		-0.098***		-0.152***
		(0.027)		(0.031)		(0.024)		(0.029)
Old people		-0.030		0.045		0.003		0.068
		(0.038)		(0.042)		(0.040)		(0.046)
Constant		0.887**		-1.310***		0.466		-0.037
		(0.390)		(0.460)		(0.366)		(0.494)
N		3063		2732		2743		2442
Pseudo R^2		0.224		0.256		0.221		0.218

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Lambda is the inverse Mills ratio for the correction of self-selection

Other variables in the second stage include: gender, age, age square, marriage status, Hukou status, province controls, contract type, sector, firm size, industry controls and occupation controls

3.5.5 Robustness Check III: Further Regression Results by Using Larger Samples

In the previous section 3.4, we introduced that to conduct a nationally representative analysis, we implement the "resampling" method on the original data. In CFPS, five provinces are over-sampled to make them self-representative. Therefore, the resampling method is required officially by the CFPS for conducting the national level empirical analysis. However, the limitation is that this method results in an over 30% loss on the whole sample. This may drive the concern that the empirical results obtained previously, such as the higher return to education in urban areas and the self-selection bias for rural samples, can only be achieved under the restricted data. In addition, for the disaggregated analysis between urban and rural areas, we find waged workers in rural areas suffer from a significantly smaller sample size than that in urban areas. Since the low waged job participation and the self-selection bias for rural workers are essential findings in our analysis, we should be more cautious with the sample size. Therefore, in this subsection, we include further regression results as additional robustness checks, which use the larger samples available from not adopting the "resampling" method. We provide updated results on return to education with the comparison between urban and rural areas under OLS and Heckman method in Table E.1 and E.2 in Appendix E.

Comparing results from data before and after resampling (Table 3.7 and Table E.1), we find the estimated returns to education are quite similar. It is clear that the return to education is still higher in urban areas than in rural areas under the larger sample size. In addition, from the results of Heckman two-step method in Table E.2, we find that rural workers also suffer significantly from the self-selection bias, reflected by the fact that the coefficient on Lambda is significantly different from zero. After correcting self-selection bias in the OLS regression, we find that the return gap between urban and rural areas is eliminated. This finding is also consistent with that obtained by using resampled data. Therefore, in general, the robustness of the most important findings in this chapter is confirmed to be robust under a larger sample size.

3.6 Conclusion

The main research aim of this chapter is to estimate the return to education in both urban and rural areas in China. From the Mincer wage equation, we find that the returns to one year of education are both significant in urban and rural areas, with

6.4% and 3.7%, respectively. After controlling for the employment characteristics, the returns in both areas decrease, to 4.6% and 2.5%, respectively, but remain significant. These results support the first hypothesis in section 3.2.5 that workers in both urban and rural areas enjoy significant education wage premiums. The return gap between urban and rural areas is also estimated to be highly significant under the t-test and SUR test method, supporting the second hypothesis that urban areas enjoy a significantly higher return to education. Despite education years, the returns to education categories are also examined in the analysis. It is found that all education levels in urban areas enjoy premiums to the reference group of no schooling, where the tertiary level enjoys the highest return of 56.8%. However, in rural areas, the wage gap between primary education and no schooling is insignificant, but workers with tertiary education still enjoy the highest return, with 45.9%.

The returns to education in subgroups are also examined in both urban and rural areas. We find that female workers have significantly higher returns than male workers in both areas. Returns to female workers are 5.5% and 3.6%, and for male workers are 3.8% and 1.6% in urban and rural areas, respectively. The gap between gender can be explained by the low supply of skilled female workers and the difference in skill requirements between male- and female-oriented jobs. In addition to gender, we also find in urban areas, the return to education in the public sector is much higher than that in the private sector. The estimated return in the public sector is 6%, whereas in the private sector, it is only 4.1%. Possible explanations for the gap between sectors could be wage rigidity in public-owned institutions and the lower competition among workers in the public sector.

The Mincer equation is often estimated by using the OLS method. However, arguments in the literature point out that the OLS estimators on return to education may suffer from biases generated by omitted variables or individuals' self-selection into waged jobs. Corresponding to these concerns, in our analysis, we conduct the IV and Heckman two-step method to solve these problems. Firstly, for IV, we use parental education and policy changes as instruments, but the results show that the estimated returns to education under both IVs are larger, which is inconsistent with the initial hypothesis that the return to education under OLS is upward biased. Possible explanations could rely on the local average treatment effect or the measurement error in education achievements. Secondly, regarding the Heckman method, we find individuals in rural areas suffer from significant self-selection issues in waged work. After correcting the self-selection bias in the regression, the return to education in rural areas increases from 2.5% to 4.2%. The return gap between urban and rural areas is largely moderated and is tested to be insignificant, supporting the fourth hypothesis in section 3.2.5. We further disaggregate the samples according to gender in both urban and rural areas. It is found that the self-selection bias among rural workers is mainly driven by females rather than males.

Based on the existing empirical results, this analysis also has some implications. Firstly, the positive return to education in both urban and rural areas in China would encourage individuals and families to continue investing in education, which would also explain why, in current China, education is always focused on and treated seriously in Chinese families. However, the considerable gap may imply that individuals in different areas would have various motivations to invest in education. Also, based on the different labour market conditions, there may be restrictions on the proposal of education policies consistent at the country level. For example, in recent years Chinese government wants to propose a 12-year compulsory education policy to decrease the dropout rate in high schools. However, based on the lower return, this policy would be less supported by residents in rural areas, and policymakers need to consider whether it is worthwhile to promote this policy to rural areas in terms of the payoff, considering the limited education expenditure each year.

The higher return in urban areas may also drive the outflow of labourers from rural to urban areas. In recent years, the education expansion in China significantly decreases the illiteracy rate and increases the average education levels of the population, especially in rural areas. Therefore, workers, especially those with higher education achievements, would migrate to a labour market that provides higher returns to their human capital, which can be considered an explanation for the increasing urbanisation rate in recent China.

However, the previous implications are based on the OLS estimation results. The self-selection results imply that ignoring the sample selection issue may lead to significant bias in estimating return to education, especially in rural areas. There are about 54% of individuals in rural areas are not waged workers, and after correcting for the self-selection bias among rural workers, the return gap between urban and rural areas is largely moderated. Therefore, we need to be very cautious about the results consistently shown in the previous literature that urban areas enjoy the advantage of higher payoff to education, especially for those analyses not considering the self-selection issue.

The analysis in this chapter is clearly not out of limitations. Firstly, when measuring the urban/rural status of individuals, we refer to the residence locations and social backgrounds (registration status) and make a comparison between them. However, another method is also used in the literature, which refers to the working location as the benchmark to divide urban/rural workers. The difference between working and residence locations is mainly driven by commuting between areas. However, in CFPS, individuals' working locations are not available to us. Therefore, we are not able to compare different returns between working and residence locations to achieve more robust results. Secondly, CFPS only provides information on wage income for employees. Therefore, we cannot compare the return to education between self-employed workers and those employed by others. In recent years the comparison between the two groups of workers is more focused, and evidence shows that there would be significant differences in the return to education between them (e.g. Tokila and Tervo, 2010). In addition, it also argued that the estimation of return to education for self-employed workers may not suffer from the omitted variable bias because, in the self-employment market, education does not need to play the role of signal (Harmon et al., 2003). However, we are not able to check this assumption in the analysis. This limitation can be solved by using better data that provide income information for self-employed workers in future research. Thirdly, we use the IV method to solve the possible omitted variable bias in this chapter. However, the returns under the IV method are considerably larger, which is inconsistent with the original assumption that returns would decrease if considering the unobserved heterogeneity. Several explanations are provided in the literature. Firstly, some researchers such as Imbens and Angrist (1994) and Aronow and Carnegie (2013) point out that the IV estimation only covers the local average treatment effect (LATE) or the ATE for the subpopulation that is influenced by the IV. When treatment effects are heterogeneous across units, the LATE and the ATE may take on different values, which would potentially cause complications in the comparison between IV and OLS results. Also, Wang (2012) points out that the IV method solves the possible measurement error problem in education years, which is also driven by the correlation between the explanatory variable and the error term. In addition, it is also possible that omitted variable bias is not restricted to innate abilities, though we propose a specific assumption. Bias driven by other factors that are not observable to us may also be resolved by the IV method, and some of the factors may not be positively correlated with the education years, which could result in a larger IV estimator on return to education. In our analysis, we are not able to test these hypotheses, and we leave them for examination in future research. Further, it is better to use some direct measures to represent omitted abilities, such as the IQ test (Aslam et al., 2012). However, in CFPS, we do not have such information that is related to individuals' innate abilities.

Chapter 4 Return to Over-education for Graduate Workers in China: The Role of Skills Heterogeneity

4.1 Introduction

China has experienced a rapid, large-scale expansion of higher education since the turn of the 21st century (Hu and Hibel, 2015; Dai et al., 2022). The gross enrolment rate increases dramatically from 5.9% to 50.6% within a very short period between 1998 and 2018 (World Bank, 2022). On the one hand, higher education expansion would help largely with the fast economic growth in recent China (Kang et al., 2021; Dai et al., 2022). However, on the other hand, the substantial change in the supply side of education may lead to a disequilibrium in the labour market. Employers' demand may have failed to increase in the same proportion as the supply (Freeman 1976; Chevalier and Lindley, 2009). This drives the concern about whether the labour market can appropriately use the growing number of highly educated workers. A similar pattern of expansion in higher education is found in the UK from the 1980s to the 2000s. Evidence from Dolton and Vignoles (2000) points out that up to 40% of graduates in the UK market have "too much" education than their job requirements. Green and Zhu (2010) focus on the over-education incidence of graduates in the expansion period from 1992 to 2006 and find an increasing pattern from 21.7% to 33.2%. However, unlike the UK and other advanced countries, the over-education condition and its consequences are still not largely focused on by Chinese researchers. In previous studies in China, many researchers have devoted efforts to estimating the return to education or college wage premium, which assumes a homogeneous wage payoff in the same level of education, mainly based on the arguments from Mincer (1974). However, there is also an increasing concern about whether there are wage differences between individuals when the education obtained cannot be fully utilised. According to work carried out in recent decades, a number of empirical evidence point out the fact that over-educated workers would be paid less than other workers in the same education level who match the graduate job requirements but earn more than their co-workers whose education levels match the requirements of non-graduate jobs. In this analysis, we try to extend the current literature on over-education to Chinese graduates to discover the incidence of over-education and its effect on individuals' labour market outcomes. In fact, the research on over-education in China is mainly restricted by the in-availability of datasets. Some surveys only cover a few provinces, which are not nationally representative and do not provide enough information on occupations to help researchers define over-education. For example, Ren and Miller (2012) successfully estimate the wage effect of over-education. However, only nine provinces (out of 34) in China are considered, and the number of occupations defining over-education is limited. In our analysis, we take advantage of the newly formed CFPS (China Family Panel Studies) dataset that covers 30 provinces all around China and provides three alternatives to measure the over-education. Subjective, objective and statistical methods are used, where reference (required) education levels rely on the job analysts' suggestion, self-assessment and statistical mean/mode, respectively. In fact, in the literature, all the measurements are argued to have pros and cons, and there is no agreement on the most preferred method. Therefore, the comparison between them would be of high value. In section 4.3, we will cover more detailed information on the three measurements.

Another significant advantage of using CFPS is that it provides information on individuals' skills proficiency, which enables us to test alternative theories explaining the wage effect of over-education by disentangling skills from education. In recent years, an increasing number of researchers are dissatisfied with the skills homogeneity assumption. Arguments state that even if in the same level of educational achievements, individuals would also have heterogeneity in skills levels and utilisation.

Two main lines of research on explaining the wage effect of over-education address the assumption of skills heterogeneity. Firstly, some studies try to eliminate the impact of unobserved skills in the wage equation, such as using fixed effect and longitudinal analysis (Bauer 2002; Frenette 2004; Thai 2010; Marvromaras et al. 2013). Secondly, observed skills proficiency serve as controls to explain the wage penalty generated by over-education. Assignment theory indicates a high correlation between education mismatch and under-utilizing skills, meaning over-education implies over-skill. Another theory uses skills levels rather than utilisation to explain over-education, assuming over-educated individuals are more possible to have lower skills, therefore, suffer from lower wages. If the skill levels were controlled, there would be no wage differences.

In our analysis, we follow the second line of research. Both the effects of the utilisation of skills and skills levels are considered. Thanks to the CFPS dataset, tested scores of skills proficiency in numeracy and literacy are both available to us. Besides the cognitive skills, we also have information on non-cognitive skills, which can be used as a robustness check. In general, this analysis has the following specific aims which would contribute to the current literature:

(1) Provide evidence on the over-education incidence and the wage difference between matched and over-educated workers, filling the gap in Chinese literature.

(2) Implement three methods to measure over-education corresponding to the arguments in the literature.

(3) Incorporate the skills heterogeneity assumption into the analysis to determine whether the effect of over-education on wages still exists after controlling for skills variations.

The most important contribution of this analysis is that we could compare returns between different measurements of over-education, which is the first attempt in the Chinese literature to our current knowledge. In addition, very limited papers examine the relationship between skills heterogeneity and the over-education wage penalty in China. The only paper in China we can refer to is from Wu and Wang (2018), but their study only focuses on one province in China, which is not nationally representative.

The chapter is structured as follows. In the first part, we introduce the backgrounds and specific research aims. In the second part, we provide a review of the literature, including different theories we may use in the analysis. In the third part, we explain the data and sample selection and provide detailed introductions to our chosen variables. In the fourth part, we illustrate the methodologies. In the fifth and sixth parts, we provide empirical results, including over-education incidence and estimation results on the over-education effect on wages from empirical models. In the last part we conclude.

4.2 Literature Review and Hypotheses

4.2.1 Return to Over-education Methods and Wage Penalty to Over-education

The research on the wage consequences of over-education has extensively used a modified version of the Mincer wage equation, first introduced by Duncan and Hoffman (1981). The so-called ORU model divides actual years of education into over-, required- and under-education. The ORU is the abbreviation of over-education, required-education, and under-education. Individuals are compared with those doing jobs with the same years of the required education. The results of empirical studies on the effects of education mismatch on wages have been consistent across nations and the periods analysed. It is often found that over-educated individuals would earn higher wages than well-matched workers in the same type of job, whereas under-educated workers would have lower income than well-matched workers even if they are doing the same jobs (Duncan and Hoffman, 1981; Groot, 1996; McGuinness, 2006; Chiswick and Miller, 2008; Wu, 2008).

Another approach other than the ORU method is to estimate the wage penalty for over-education by comparing workers with the same level of education using a dummy variable, which is the so-called V&V method proposed by Verdugo and Verdugo (1989). In their research considering the case of the US, over-educated individuals suffer from a significant wage penalty compared with those matched in the same level of education, whereas under-educated individuals enjoy higher wages if they do jobs that require higher education achievements. This result is also supported by several empirical studies in the international literature (Kiker et al., 1997; Alisjahbana and Manning, 2006; Iriondo and Pérez-Amaral, 2013). In addition, some Chinese studies using the V&V method also conclude a negative wage return to over-education. For example, Wu and Wang (2018) point out that for both high school and higher education graduates, over-educated individuals suffer from significant wage penalties. Zhu (2014) finds that the effect of field of discipline mismatch is around -6% under OLS. However, this effect declines -1.3% when using a nonparametric estimation method but remains significant.

In recent decades, many researchers have examined the effect of over-education on graduates based on the V&V method. This method has a unique advantage when studying the over-education impact on a specific education level. In this method, there is no need to measure the reference education achievements. The variable indicating the education years can be directly eliminated from the model because all individuals hold the same level of education. Since most graduates suffer from over-education rather than a deficit in human capital in jobs, the examination of mismatch can be restricted to over-education. Therefore, only one dummy variable indicating the over-education status remains in the V&V model. Chevalier (2003) focuses on the case of the UK by including an over-education dummy in the wage equation using data from a postal survey organised by the University of Birmingham in the winter of 1996. Over-educated graduates suffer from 14.4% lower wages than those having matched jobs, and the wage penalty decreases slightly to 10.1% after controlling for the unobserved skills. Green and Zhu (2010) also examine the return to over-education in the UK, but with a time trend across the expansion period of higher education in the UK from 1992 to 2006, with the help of the UK Skills Survey. A significant wage penalty for over-education is also found, but the wage gap fluctuates across the years. McGuinness and Bennett (2007) focus specifically on graduates in Northern Ireland using a quantile regression method and data from a cohort study of all Northern Ireland-domiciled students entering higher education in 1991/1992. It is concluded that on the mean level, over-educated male and female workers suffer from 11.3% and 22.8% lower wages, respectively. Also, the wage penalties are larger for the workers in the lower wage quartile. Regarding the studies in China, Liu et al. (2021) consider graduates from 25 universities in China and estimate the over-education wage penalty to be 6.8% using the data from Talent Cultivation and Employment Survey in Chinese

Local Universities. The over-education coefficient remains significant, even further controlling for different education quality factors. Zhang and Zhu (2021) develop a novel approach to studying over-education by taking advantage of online recruitment platforms and using word segmentation and dictionary-building techniques via Python. However, consistent with most of the studies in China, the wage penalty for over-education under the novel approach is still found to be significant, with 5.1%.

4.2.2 Different Measurements on Over-education

In fact, in the analyses on the effect of over-education on wages, there are always arguments in the literature on how to measure individuals' reference education, or in other words, how to define the status of over-education. Usually there are three methods often used in the literature, which are subjective, objective and statistical methods where the reference education level is defined according to individuals' self-assessment, job analysts' suggestions in the form of an occupational dictionary and realised matches using mean/mode in specific occupations, respectively.

All the methods have their pros and cons. For example, firstly, the statistical method is favoured because the occupation information is often available in individual-level surveys (Verhaest and Omey, 2006). However, Chevalier (2003) points out that the statistical definition would be affected largely by the cohort effect and be sensitive to the aggregation level necessary to obtain a reliable distribution of education. Secondly, for the objective method, the advantage is clear that the reference education level is provided formally by analysts' suggestions, which is more reliable. However, individuals under the same job titles would do very different jobs according to their heterogeneity in skills and knowledge; therefore, the classification only based on job titles may not be of high precision (Flisi et al., 2017). In addition, for the objective method, the Dictionary of Occupation is normally lengthy and needs time to be renewed. It may not be up to date when used and requires the upgrade of the classification scheme, especially in an environment where the reference education level changes rapidly (Hartog, 2000). Thirdly, the subjective method could be considered the most precise method because individuals will assess their job demands according to the work they are currently doing, which is more detailed and accurate than the measurement of aggregation level of occupations or job titles. However, it is also evident that the subjective method still suffers from some critical drawbacks. For example, workers in smaller or less structured organisations may lack sufficient benchmarks against which they can assess their job requirements. Further, even where benchmarks are available, respondents may apply different criteria when determining their job requirements (Chevalier, 2003).

In fact, there are still no agreements in the literature on which method is most preferred. Therefore, the direct comparison between different measurements is considered valuable since a limited number of datasets can simultaneously provide information to measure different required education levels. Hartog (2000) reviews all of these methods in detail, suggesting that data availability should dictate the choice. Kiker (1997) focuses on the Portugal case using Personnel Records data collected by the Portuguese Ministry of Labour. It is reported that the wage penalty for over-education is higher under the objective method (6.8%) than that under the statistical method (2.8%), confirming the importance of the choice of measurements. Kler (2005) also compares the objective and statistical methods based on Australian graduates. However, the reference level of education in an occupation comes from the mean value rather than the mode value used by Kiker (1997). Data comes from the Australian Bureau of Statistics 1996 Households Sample File. Wage penalties under the objective method are also larger for both male and female graduates. Verhaest and Omey (2006) consider three different measurements of over-education, further including the individuals' self-assessment method. The wage penalty under the subjective method is lowest with 1.3%, three times lower than that under the statistical method. However, contrary findings are concluded by Mateos-Romero and Salinas-Jiménez (2017) when focusing on Spain's case, using the Programme of International Assessment of Adult Competencies (PIAAC) data provided by OECD. The wage penalty under the subjective method is estimated to be the highest among all the three measurements. At the same time, objective and statistical methods lead to very similar results on the over-education effect. Therefore, in summary, most of the empirical findings report a significant return to over-education under different measurements, but the variations in coefficients exist across methods used. There are no agreements on which method would generate the highest wage penalty. In China, to our current knowledge, no analysis includes the comparison between three measurements in one paper. Therefore, in our study, we try to fill this gap in the literature.

4.2.3 Return to Over-education and Skills Heterogeneity

With increasing empirical evidence pointing out the wage gap between matched and over-educated individuals, some researchers argue that the penalty does not simply come from the difference in job characteristics and try to use the variations in individuals' human capital to explain it.

In studies without information on individuals' skills, researchers often rely on the longitudinal feature of the data to eliminate the possible effects of unobserved skills heterogeneity by using the fixed effect method. It is usually found that the over-education penalty would decrease or even becomes insignificantly different from zero after controlling for the unobserved factors (Santis et al., 2022; Mavromaras et al., 2013; Tsai, 2010). Yin (2016) conduct a longitudinal analysis on the return to over-education in China using data from China Health and Nutrition Survey (CHNS). It is found that the over-education wage penalty declines dramatically after using the fixed effect method, which is consistent with the findings in developed countries. However, using longitudinal data and fixed effects would also have some clear limitations. For example, since some individuals do not change their over-education status across periods, the return to over-education is only estimated for a small group of samples, which can be argued to be not representative. In addition, Palczyńska (2021) also emphasises that the strict exogeneity assumption may not hold because there would be time-varying heterogeneity that changes with the over-education status, which is not captured in the fixed effect.

Besides the fixed effect method, another group of researchers try to use direct measures of individuals' skills. Thanks to the data available in recent years that provide information on skills-related questions, skills heterogeneity can be directly controlled in empirical models. Firstly, the conventional wisdom on assignment theory points out that the human capital used in the job depends not only on workers' achievements but also on the match to the job. Job characteristics would restrict the human capital of over-educated individuals. They may under-utilize their skills, consequently providing lower productivity and suffering from lower wages (Pietro and Urwin, 2006). This implies that over-education and over-skill are closely correlated, and the penalty for over-education reflects the penalty for over-skill. However, the assignment theory does not seem supported by Nieto and Ramos (2017) using Programme for the International Assessment of Adult Competencies (PIAAC) data. They find a minimal correlation between skill and education mismatch. The person chi-square test cannot reject the hypothesis of no correlation between the two factors. Green and McIntosh (2007) find the correlation coefficient is only 0.2 between over-education and over-skill, using the 2001 wave of the British Skills Survey. The return to over-education decreases by 15% after controlling for the over-skill variable, which is tested as an insignificant change. Similar results are obtained by Sanchez and McGuinness (2015), focusing on the EU's 2001/2002 graduate cohort. A larger correlation is found with a correlation coefficient of 0.38, but in the wage equation, coefficients on over-education and over-skill are both highly significant, showing that the penalty for over-education cannot be totally explained by over-skill. Unlike many studies, Pietro and Urwin (2006) find a high correlation between over-education and over-skill using data from National Statistical Italian Centre on Italian graduates in 2001. About 78% of over-educated individuals are also over-skilled at the same time, supporting the assignment theory at the descriptive level. However, despite the high correlation between the two factors, the over-education wage penalty still does not reduce largely after including the over-skill control. The estimated effect drops from 5.9% to 4.7%. Similar to the results obtained from Sanchez and McGuinness, both over-education and over-skill can determine individuals' wages to a significant extent. Therefore, in general, the assignment theory is not largely supported in the literature. To our existing knowledge, no study argues that skill mismatch can totally explain the effect of over-education.

Secondly, some other researchers rely more on a theory of using variations in skills levels to explain the over-education wage penalty rather than the utilisation of skills. They assume that even in the same level of education, there would be differences in human capital achievements. Individuals with lower skills would be less productive and earn lower wages. At the same time, individuals with lower skills are more likely to be over-educated. Consequently, the wage penalty for over-education only reflects the lower wages for skills rather than the job characteristics imposing restrictions. Nieto and Ramos (2017) focus on the case of Spain and control for individuals' cognitive proficiency in the wage equation using the Programme for the International Assessment of Adult Competencies (PIAAC) data. It is found that coefficients on over-education decrease by 18% after controlling for the variations in literacy skills, showing that skill levels only partly explain the wage effect of over-education. Similar results are concluded using Chinese data. Wu and Wang (2018) provide evidence using Yunnan province as an example, and the data come from Skills Towards Employability and Productivity (STEP). Unlike Nieto and Ramos, they control three different kinds of skills, which are cognitive, non-cognitive and technical skills. Results show that the effect of over-education on graduates decreases by 20% but remains significant after controlling for different categories of skills. In addition, coefficients on all the skill variables are also estimated to be positively significant, showing a determinant role of skills proficiency in individuals' economic outcomes. Sohn (2010) finds out that in the United States, the over-education penalty decreases from 5.6% to 4.5% after controlling for different dimensions of skills of cognitive and non-cognitive abilities, similar to Wu and Wang (2018). Data comes from the National Education Longitudinal Study. However, some researchers argue that individuals' skill proficiency would have a minor effect on the over-education wage gap. Palczyńska (2021) report that in Poland, the return to over-education only decreases from 14.1% to 13.4%, showing that skills proficiency only explains about 5 per cent of all the wage penalty. In addition, the return to over-education for young graduates remains nearly unchanged after including skills variables. Data used also comes from the Programme for the International Assessment of Adult Competencies (PIAAC) provided by OECD, similar to Nieto and Ramos (2017). Palczyńska (2021) also controls for cognitive and non-cognitive skills in his analysis, similar to Sohn (2010). However, regardless of all workers or only graduates, cognitive skills are tested not able to affect individuals' wages. Only some non-cognitive skills would show determinant effects, including conscientiousness, agreeableness and neuroticism. In summary, studies in the literature provide consistent findings that though skills utilisation or skills levels would partly explain the wage effect of over-education, no empirical evidence supports the idea that assignment theory or heterogeneity theory in skills levels would totally explain the wage penalty generated by over-education. The correlation between skills and over-education is poorly examined in China. Therefore, in our analysis, we would like to find out which theory is more supported in the Chinese labour market.

4.2.4 Hypotheses for Return to Over-education and Skills in China

Over-education may arise when the demand for skilled workers cannot increase at the same speed as the supply. In fact, some existing theories can be used to explain the over-education condition circumstance in the labour market and its effect on individuals' wages. For example, the career mobility model (Sicherman & Galor, 1990) suggests that workers might choose a position for which they are over-educated if the position offers them a higher probability of being promoted by providing on-the-job training and experience. This theory implies that over-education is a temporary phenomenon. Matching theory (Jovanovic, 1979) also predicts that over-education is temporary. This model posits that the mismatch arises because of imperfect information about the quality of the match. With increasing tenure, the mismatch between a worker and an employer is detected, and the worker is able to improve the match through a job search.

Thurow's job competition theory (Thurow, 1972) assumes that wages are determined solely by the characteristics of jobs and that a worker's education only determines his or her position in the queue for the best jobs. The model suggests that job characteristics may be the only factor determining wages. Therefore, the labour market is not a bidding market for selling existing skills but a training market where training slots must be allocated to different workers. However, the empirical regularities are not explained by Thurow's job competition theory. Assignment models (e.g. Sattinger, 1993, 2012) are often seen as better explaining the wage consequences of educational mismatch. These models assume that wages are determined by the characteristics of both the job and the worker and are a solution to the problem of allocating heterogeneous workers to heterogeneous jobs.

The over-education condition and its consequences on wages are examined widely in the literature in advanced counties. The findings often comprise two parts. Firstly, a considerable amount of individuals in the labour market, especially graduates, are suffering from the over-education issue. For example, from the recent literature, Nieto and Ramos (2017) find a 35.6% of graduates are over-educated in the case of Spain, and Palczyńska (2021) finds 40% of all waged workers who are doing jobs requiring a lower education level than their achievements in Poland. Secondly, over-education would generate a wage penalty for workers. Mateos-Romero and Salinas-Jiménez (2017) use three different methods to measure the wage difference between matched and unmatched graduates and find consistent results on the lower wages for over-educated workers. Similar results are found in the UK (Chevalier, 2003; Walker and Zhu, 2010), Poland (Palczyńska,2021) and China (Wu and Wang, 2018).

In addition, in current literature, an increasing number of researchers have tried to use the heterogeneity in individuals' human capital to explain the wage penalty of over-education. Two distinct theories can be referred to. Firstly, assignment theory points out that individuals' human capital is restricted by job characteristics, and over-education implies over-skill. Secondly, some other researchers rely more on a theory of using variations in skills achievements to explain the over-education wage penalty. It is argued that some individuals have lower skills than others, even at the same education level. These individuals would suffer from lower productivity and wages and, at the same time, are more likely to be over-educated. Though both theories look rationale, most of the empirical results in the literature indicate that skills heterogeneity can only partly explain the over-education wage penalty, even if both utilisation and skills levels are considered (Chuang and Liang, 2020).

The existing analyses on the Chinese return to education are still limited, especially the studies on the relationship between over-education and skills heterogeneity. Our analysis would like to fill this gap based on the contributions of the existing theories and empirical evidence in the literature. In summary, we propose the following hypotheses for this analysis:

(1) Graduates in the Chinese labour suffer significantly from the over-education problem

(2) Over-educated graduates have lower wages on average than those who are matched

(3) Individuals' skills heterogeneity can partly explain the over-education wage penalty

4.3 Data, Sample and Variables

4.3.1 Data Description and Sample Restrictions

In this chapter, we also use data provided by China Family Panel Studies (CFPS), which is a national and comprehensive social tracking survey project designed by the research team of Peking University and funded by Peking University and the Natural Science Foundation of China. CFPS focuses on Chinese residents' economic and non-economic welfare and many research topics, including economic activities, educational attainment, family relations and family dynamics, population migration, and physical and mental health. It aims to collect data from individual, family and community levels to reflect the changes in China's society, economy, population, education and health and to provide data basis for academic research and public policy analysis. The target sample size of CFPS is 16000 households and over 50000 individuals. The respondents are household members from 30 provinces /cities / autonomous regions in China (out of 34). Till 2018, CFPS has successfully conducted five rounds, every two years since 2010.

The most important advantage of the CFPS survey is that it provides information on individuals' cognitive proficiency at a national level, which is not shown in any other surveys in China to our knowledge. CFPS assesses two dimensions of cognitive skills: numeracy and literacy. Respondents who take the face-to-face interview are tested formally on both math and word questions, and the answers are scored by the interviewers on a scale of 0 to 34 points. In our analysis, the correlation between numeracy and literacy skills is relatively low (correlation coefficient only around 0.5), making it possible to compare the results under different skills domains. The following empirical tests will focus on literacy skills and use numeracy skills as a robustness check.

Besides the observed cognitive skills, we also consider the effect of non-cognitive skills in this analysis. Measuring and quantifying skills is much more complex than education levels because it has different dimensions. Some of them are often unobserved to us, different from the cognitive skills that can be formally tested. However, arguments are often raised on the robustness of the effect of skills when only a single skill domain is considered and ignoring other unobserved traits (see Chevalier, 2003 and Mateos-Romero and Salinas-Jiménez, 2017). Therefore, our analysis tries to avoid this critical drawback by covering non-cognitive skills often ignored in other studies. In CFPS, information on the "Big Five" personality traits (conscientiousness, extroversion, agreeableness, openness, neuroticism) and locus of control are available to us. These factors are often used in the previous literature as proxies of non-cognitive skills rather than just reflecting individuals' innate psychological traits (Wu and Wang, 2018; Palczyńska, 2021; Sohn, 2010). The information on non-cognitive skills comes from respondents' self-assessments.

Besides the skills, we consider three sets of independent variables in each specification. The first set is education-related variables, including the over-education status dummy with education quality controls. The second is the ordinary individual characteristic controls, including ethnicity, gender, age, marriage status, registration status, urban/rural and provinces. For the last, we still control for job characteristics in each specification. However, according to the arguments proposed by researchers such as Palczyńska (2021), most of the job characteristics would be intermediate outcomes and would generate a downward bias on the effect of over-education. Therefore, our analysis includes some basic job-related controls, including firm size, contract type, sector and industry. The dependent variable included in our study is the individual's hourly wage. It needs to be emphasised that in our analysis, the wage used is the gross one, including different kinds of cash rewards, subsidies and bonuses. In our analysis, we choose the data from the survey year 2014. This is the most recent year we can acquire cognitive skills with non-missing values. The survey year 2018 also provides information on numeracy and literacy skills, but over 40% of wage earners are missing because only those who take the face-to-face interview rather than telephone interview are formally tested on cognitive skills. The large number of missing values would result in an unavoidable selection bias problem. For the samples included, as mentioned before, we directly take advantage of the adult survey and focus on the self-reported answers from individuals rather than those proxies by others. We focus on individuals in working ages (16-60 years old male and 16-55 years old female). Only graduates are included because we directly focus on the consequence of the fast higher education expansion condition in contemporary China. Individuals from other levels of education may also suffer from over-education, but it has been a long time since the policies of secondary and high school expansion were proposed. The labour market has enough time to react to the shock in the supply side, and it is less likely that over-education in these education levels would lead to severe consequences for the contemporary Chinese labour market. Another reason is that one of the research aims of this analysis is to compare different measurements of over-education. The objective method, as introduced to follow the job analysts' suggestions, is only available for graduates. In addition, if all the education levels are included, we must consider the under-education problem. Under-educated individuals cannot be treated simply as matched workers, which will complicate our analytic method and change the initial research ideas. Therefore, combining these reasons, choosing graduates is the best choice for examining over-education in this analysis.

In the wage equations, we only include wage earners in working ages and not currently enrolled in education. However, other individuals who do not participate in the labour market or undertake self-employed jobs are also included in the statistical method to control for possible selection bias (Heckman, 1979). After excluding all the missing observations for core variables, the final sample is 1265 graduates and 995 among them are waged workers. In the following Table 4.1, we detail the steps of sample restriction. In addition, we show the comprise of all the sample individuals with different employment statuses and illustrate the heterogeneity with subgroups in Table 4.2.

Table 4.1: Sample restrictions

Actions	**Observations left**	**Percentage**
Total adult self-reported observations	32376	100%
Drop over-sampling observations	21356	65.96%
Drop age > 60	16717	51.63%
Drop age > 55 female	15651	48.34%
Employment in labour market	12223	37.75%
Drop missing job types	11987	37.02%
Keep wage earners	5843	18.05%
Keep tertiary education level	1228	3.88%
Drop missing values on core variables	995	3.07%

The original CFPS dataset we use is from the adult survey that only with individuals older than 16

Table 4.2: Distribution of employment status for sample graduates

	Wage earners	**Non-wage earners**			**Total**
	Employed by others	Unemployed	Self-employed	Not in the labour market	
All	995 78.66%	34 2.69%	141 11.15%	95 7.51%	1265 100%
Male	526 80.80%	15 2.30%	85 13.06%	25 3.84%	651 100%
Female	469 76.38%	19 3.09%	56 9.12%	70 11.40%	614 100%
Urban	834 81.76%	26 2.55%	90 8.82%	70 6.86%	1020 100%
Rural	161 65.71%	8 3.27%	51 20.82%	25 10.20%	245 100%

4.3.2 Definitions of Education and Skills Mismatch

4.3.2.1 Education Mismatch

The key research aim of our analysis is to define over-education using CFPS. As mentioned before, since we focus on the group of graduates, we can use three measurements to categorise them into over-educated or matched following the statistical, objective and subjective methods. We try to compare the results obtained from these three methods, including the over-education incidence and wage returns, in order to find out any possible differences.

(1) Objective Method

The objective method relies on the job analysts' suggestions, where the reference education of each occupation is provided by some analysts, such as the Standard Occupational Classification System in the UK or the Dictionary of Occupational Titles in the US. Unfortunately, the job analysts' definition of reference education level is unavailable in China. However, it is possible for us to link each occupation in CFPS to the International Standard Classification of Occupations (ISCO) with the help of information provided initially in CFPS. Following the suggestions by Mateos-Romero and Salinas-Jiménez (2017), individuals with tertiary education (including colleges and universities) would be expected to be in skilled occupations (ISCO 1–3) if they were adequately educated for their jobs, while those in semi-skilled occupations (ISCO 4-9) are classified as over-educated.

(2) Subjective Method

The subjective measurement of mismatch is comparatively more direct and efficiently conducted but requires individuals' self-assessments. Usually, a respondent in a survey would be asked a question whether the schooling years obtained is lower or higher than the requirement of the current job (direct method) or asked to provide a reference qualification for doing the current job to be compared with individuals' obtained education level (indirect method). In CFPS, there is a survey question: "What is the reference education level to be qualified to do the job regarding knowledge and skills?" Individuals who answer that the reference level of education is non-tertiary (high school and lower education levels) are classified as over-educated, which is an indirect subjective method similar to that used in Sánchez-Sánchez and McGuinness (2015) and Green and Zhu (2010).

(3) Statistical Method

The statistical method is also called the realised matches method based on the information on individuals' occupations provided in the dataset. Required education level can be achieved in each occupation according to the statistical mean. Individuals whose education years differ from the mean by some ad hoc value (such as one standard deviation) are defined as mismatched (Sicherman, 1991). Besides the mean, the mode value can also be used as the reference, but it does not rely on the standard deviation. If using the mode, over-educated individuals are those who have education years higher than the mode level in their occupations.

The realised matches method is feasible for our analysis because the occupations are classified in detail in CFPS. In most surveys, interviewers would provide some occupation titles for respondents to choose from, such as CHNS providing 11 occupation categories. However, this is not the case in CFPS. Respondents are asked to describe what kind of occupation they are currently doing, for example, "English teacher in high school". After this information is collected, the aggregation and coding process is completed by the CFPS team, according to the "National standard occupational classification and Code of the People's Republic of China (GB /t6565-2009)", which is the formal code book published by China Standards Press in August 2009. CFPS codes implement a three-level classification of occupations consistent with the code book. For example, the first level is "Professional and technical personnel", the second level is "Engineering technical personnel", and the third level is "Petroleum engineering technicians". In 2014, CFPS codes ended up with 9 occupations in the first level (including military personnel, unemployed and other workers not elsewhere classified), 63 in the second level and more than 300 in the third level.

Due to the sample size limitation, we can't use the 3-digit occupations in the analysis. Otherwise, we would have many occupations with only 1 or 2 observations, or even 0. However, using the first-level classification is also not preferred. This measurement would result in a considerable heterogeneity of the jobs under the same occupation title, and the variance of the schooling years would be pretty large, leading to non-robust results. Therefore, in our analysis, we decide to use the second-level classification. We combine some occupations with a small number of observations and finally end up with 43 occupations for our study. We do not simply re-classify the occupations with few observations into "others". We merge them into those occupations that already exist in the survey and require doing similar jobs. For example, the occupation of religion personnel has only three observations; therefore, we merge it with the occupation of literature and art personnel and end up with an occupation called "religion, literature and art", which contains 148 observations. Our analysis ensures that every occupation (including the newly formed ones) has more than ten observations. This measurement is consistent with that used in Battu and Sloane (2002), where a 2-digit classification is also used, and occupations with fewer than ten observations merge with the other appropriate and adjacent occupations. Detailed classifications of Occupations and summary statistics on education achievements in each occupation are shown in Appendix L.

In our analysis, we prefer to use the mode of schooling years in each occupation as the reference level of education, based on the arguments regarding that mode is a better choice than mean (e.g. Kiker 1997; Battu and Sloane 2002). Individuals are classified as over-educated if they work in occupations with the mode education level lower than tertiary. However, in the process of empirical analysis, we provide evidence on both mean and mode for comparison.

4.3.2.2 Measurements of Over-skill

Unlike over-education, there are mainly two ways to define over-skill, which are subjective and statistical methods. The objective method is unavailable because, usually, analysts would not provide detailed skills requirements for each occupation.

The subjective method relies on the individuals' self-reported skills utilisation in their jobs. Normally, they are asked to what extent the skills achieved have been utilised in their current jobs, and the over-skill would be formed from the answers by comparing the actual and required ones. It is clear that the subjective method is convenient to measure, but arguments are often raised on the answers from self-awareness. For example, the criteria used to define the over-skill differ among respondents. Individuals with a lower level of skills may be unaware of the extent of their skills mismatch, while those with higher skills may assess it more accurately (Mateos-Romero and Salinas-Jiménez, 2017). Therefore, another method based on formally and objectively tested cognitive skills is also accepted by the literature, which is the statistical or realised method. The measurement is quite similar to the statistical method on education, where the reference level of the skill is obtained from the mean/mode level in each occupation.

In our analysis, we follow the statistical method to define over-skill. The mean value is used, and over-skilled individuals have cognitive skills that exceed one standard deviation of the mean of skills in their occupations. Unlike the measurements on dealing with over-education, the mode method is not used because the scores of cognitive skills range from 0 to 34 and have a significantly larger variance than education levels. It is possible that individuals with mode (required) skill levels only account for a tiny proportion of all the individuals in one occupation, and the majority of individuals are classified as over- or under-skilled, which will result in an over-statement of the skill-mismatch condition. In fact, the mean method is usually used in the literature by many researchers in the analysis of over-skill, such as Fsili et al. (2017) and Nieto and Ramos (2017). To our current knowledge, there has yet to be an existing study using the mode to measure over-skill under the realised matches method.

A combination method on subjective and statistical is also used by researchers such as Neito and Ramos (2017). However, in our analysis, the information on self-assessment on skills utilisation is not available. Therefore, the only choice is to use the statistical method directly.

4.3.3 Variables

Despite the definitions of education and skill mismatch, in this part, we further introduce in detail other variables used in the analysis that are mentioned before. In fact, most of the variables have the same definitions as those in 3.4 in Chapter 3, including individuals' wages, basic characteristic controls and most employment controls. In this part, we only cover the definitions of those new variables or those with different definitions. However, we provide a summation of notations and descriptive statistics on all the variables used in this chapter, illustrated in Table 4.4 at the end of this part.

4.3.3.1 Higher Education Types

As is known in China, there are two kinds of education systems at the tertiary education level: vocational colleges and academic universities. Academic education aims to teach fundamental and advanced knowledge, whereas vocational education focuses more on specific skills directly used in the labour markets. However, both education systems are formally categorised into tertiary-level education by the government. Students would achieve formal certificates or qualifications from tertiary education institutions. In our analysis, we divide the graduates from two systems with a dummy variable, "uni-type", where university students are equal to 1 and try to determine whether there would be significantly different payoffs between them.

4.3.3.2 Cognitive Skills

CFPS assesses two dimensions of cognitive skills: numeracy and literacy. Respondents who take the face-to-face interview are tested formally on both math and word questions, and the answers are scored by the interviewers on a scale of 0 to 34 points. They can get one point after correctly answering one question. The test will stop if they continuously provide wrong answers to three questions. The final score equals the question number of the last question they could achieve in the test. It can be seen in the summary statistics in subsection 4.4 that individuals' literacy scores are much higher than numeracy skills. In fact, the number of questions and the scale of the points are the same, but literacy questions may be easier to answer than numeracy ones. In our analysis, the correlation between numeracy and literacy skills is relatively low (correlation coefficient only around 50%), which seems abnormal in the literature. In the cases of Spain and Poland, the correlation between the two dimensions of skills is relatively high, with a correlation coefficient higher than 0.9 (Nieto and Ramos, 2017; Mateos-Romero and Salinas-Jiménez, 2017; Palczynska, 2021). One reason could be that in China, education results are closely correlated with promotion ability to higher levels. Starting from secondary school, in order to get higher scores in entrance examinations, students are forced to choose to either focus on Science or Arts in their studies, which may lead to a more significant difference between their numeracy and literacy skills. This characteristic among workers allows us to compare the results under different skill domains. Therefore, in the empirical parts, we first focus on numeracy skills and then use literacy skills as a robustness check.

4.3.3.3 Non-cognitive Skills

It is mentioned in the previous part that an increasing number of evidence in the literature shows that better non-cognitive skills would also help with the growth of individuals' wages. However, some studies only focus on one or two kinds of non-cognitive skills, and the evidence is less convincing. Our analysis includes a more comprehensive range of non-cognitive skills comprising the locus of control and five personality traits.

Firstly, the theory of locus of control is initially raised by Rotter (1964), which mainly reflects an individual's attitudes to life and enthusiasm. Individuals with the characteristics of external control consider that their behaviour results are controlled by external forces such as opportunity, luck, fate and authority, and they are powerless and lack self-belief. In contrast, individuals with the characteristics of internal control believe that their activities and results are determined by their own internal factors and their own abilities and efforts can control the development of the situation. In our analysis, the locus of control is based on the following six questions in Table 4.3.

Individuals will be scored from 1 to 5 according to their answers to the question, and we take their average as the final locus of control score. At the same time, we make sure all the answers are in the same direction so that higher scores on the question indicate more external control[1].

The CFPS also include inventories of the Big Five personality factors: openness, conscientiousness, extroversion, agreeableness and neuroticism (Costa and McCrae, 1992). These five characteristics comprehensively could reflect an individual's non-cognitive abilities and are considered important determinants of an individual's performance and success in the career. For each personality factor, three questions are proposed in the survey, also shown in Table 4.3.

Table 4.3: Skills and questions related

Skills	Related questions
Locus of control	Wealth reflects personal achievement
	Hard work pays off
	Intelligence pays off
	The social relationship is more important than hard word
	There are great opportunities for me to improve my living standards
	I am confident in the future
Openness	Having originality and creativity
	Pay attention to the experience of art and aesthetics
	Be imaginative
Conscientiousness	Be rigorous and serious
	Often be very lazy
	Do jobs efficiently
Extroversion	Love to talk
	Be cheerful and sociable
	Be reserved and conservative
Agreeableness	Be tolerant of nature
	Sometimes be rude to others
	Be considerate of others and kind to almost everyone
Neuroticism	Often be worried
	Easy to be nervous
	Often be relaxed and able to deal with pressure

Source: CFPS survey

1. The score ranges from 1 to 5, indicating the answer of totally disagree, disagree, neutral, agree and strongly agree.

We add all of the factors as controls in the regression, and the score of each element comes from the average score of the three related questions. Similarly, we also ensure that higher scores indicate higher levels of specific personalities in each question for the simplicity of our analysis[2].

4.3.3.4 Summary Statistics

In the following Table 4.4, we provide notations on brief descriptions for all of the variables used in our analysis. In addition, we provide the summary statistics for each variable with the difference in education mismatch status. Though previously we used three different methods to define over-education, in this subsection, we use the subjective method as a representative, which is the most often used method in the literature.

It can be seen from the table that matched graduate workers have higher log hourly earnings with a gap of 0.258, which is estimated to be highly significant under the t-test. In addition, over 50% of graduates in the matched group are from universities. However, in the over-educated group, university graduates only account for 38.9%, showing that college graduates are more likely to suffer from the over-education problem. For other basic characteristic controls, we cannot find significant differences between over-educated and matched workers. The distributions of workers in different provinces and urban/rural areas are quite similar, and we find an insignificant gender difference based on the education mismatch status.

Regarding the employment characteristics controls, we find a larger proportion of individuals signing formal contracts and employed in the public sector within the matched group. In addition, there is a significantly higher proportion of individuals doing Manufacturing jobs in the over-educated group. Over-educated individuals also tend to be more employed by firms with a smaller scale.

2. Similar to the locus of control, scores from 1 to 5 indicate the answers of totally fit, fit, neutral, not fit and totally not fit. However, not all the questions are in the same direction. For example, in the question "Are you reserved and conservative?", the scores should be reversed in the order from 5 to 1 according to the answers to make sure the consistency that higher scores indicate better extroversion. For instance, in this question, answering totally not fit means that you have the highest level of extroversion. Therefore, this individual's score should be 5.

Table 4.4: Descriptive table of variables

Variables	Matched		Over-educated		Match-Over Gap
	Mean	Sd.	Mean	Sd.	Difference in mean
Lnwage Log hourly gross wage	2.962	0.685	2.704	0.663	0.258***
University Institution types, university = 1, college = 0	0.511		0.389		0.222***
Male Male = 1, female = 0	0.514		0.562		-0.048
Age Individual's age	33.199	9.060	33.393	8.611	-0.193
Age square Age square	1184.169	683.085	1188.990	625.536	-4.821
Minority Minorities = 1, "Han" = 0	0.064		0.071		-0.007
Marriage Currently married with living spouse = 1, others = 0	0.715		0.718		-0.003
Urban "Hukou" Registration status of urban = 1, others = 0	0.735		0.695		0.040
Urban residence Living in urban areas = 1, living in rural areas = 0	0.841		0.831		0.010
Northeast Living in Northeast China = 1, others = 0	0.144	0.351	0.120	0.326	0.024
East Living in East China = 1, others = 0	0.396	0.489	0.438	0.497	-0.042
Middle Living in Middle China = 1, others = 0	0.266	0.442	0.250	0.434	0.016
West Living in West China = 1, others = 0	0.194	0.395	0.192	0.394	0.002
Contract Singing contract = 1, others = 0	0.732		0.656		0.076**
Public sector Public sector = 1, others = 0	0.572		0.396		0.176***
Raw materials Raw materials = 1, others = 0	0.018	0.076	0.024	0.119	-0.008
Manufacturing Manufacturing = 1, others = 0	0.229	0.420	0.380	0.486	-0.151***
Retailing and wholesaling Retailing and wholesaling = 1, others = 0	0.277	0.448	0.308	0.463	-0.032
Other services Other services = 1, others = 0	0.489	0.050	0.289	0.454	0.200***
Small firm Number of employees smaller than 100 = 1, Others = 0	0.489	0.500	0.549	0.498	-0.060*
Medium firm Number of employees smaller than 200 but greater than 100 = 1, Others = 0	0.154	0.361	0.065	0.247	0.089***
Large firm Number of employees larger than 200, Others = 0	0.357	0.488	0.386	0.479	-0.029
Literacy Test scores on literacy	29.311	5.227	27.990	6.026	1.321***
Numeracy Test scores on numeracy	16.099	5.482	14.769	5.814	1.330***
Conscientiousness Self-reported scores of Conscientiousness	3.823	0.560	3.741	0.575	0.082*
Extroversion Self-reported scores of Extroversion	3.281	0.720	3.172	0.713	0.109*
Agreeableness Self-reported scores of Agreeableness	3.489	0.466	3.429	0.445	0.060
Openness Self-reported scores of Openness	3.345	0.739	3.099	0.776	0.246***
Neuroticism Self-reported scores of Neuroticism	3.200	0.741	3.186	0.754	0.014
Locus of control Self-reported scores of Locus of control	3.538	0.493	3.438	0.496	0.101**
Young children Number of children younger than 14 years old in the family	0.504	0.676	0.565	0.698	-0.061
Old people Number of elderly greater than 14 years old in the family	0.195	0.501	0.279	0.588	-0.084**

Samples for the descriptive statistics are for wage earners, except the amounts of young children and old people in the family are based on samples from different employment statuses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Considering the skills variables, it is clear that matched graduates have higher levels of cognition on both literacy and numeracy. The gaps between these two skills are about 1.3 points out of the total points of 34, which are both tested to be significant. For other non-cognitive skills, matched individuals enjoy the advantage of higher scores of Conscientiousness, Extroversion, Openness and Locus of Control.

4.4 Methodologies

4.4.1 Verdugo and Verdugo (V&V) Model for Return to Over-education

To examine the return to over-education, we start from the model developed by Verdugo and Verdugo (1989), which is shown as follow:

$$\mathrm{lnwage}_i = \alpha + \beta_O \mathrm{over}_i + \beta_S S_i + \beta_U \mathrm{under}_i + \boldsymbol{\delta X} + u_i \qquad (1)$$

In the specification, over and under are dummy variables indicating the mismatch status, where over = 1 if an individual is over-educated and otherwise 0, and under = 1 if an individual is under-educated and otherwise 0. S is the education years, and **X** is a series of controls. Normally, **X** would include variables of individual characteristics such as gender, ethnicity, age, etc. In some studies, employment characteristics are also considered. In the Verdugo and Verdgo (V&V) method, over- or under-educated individuals are compared with those with the same education level but match the job requirements. According to the usual findings in the literature, in the same education level, over-educated workers would suffer from a wage penalty, whereas under-educated would enjoy a premium compared with matched ones. Therefore, usually, β_U shows a positive sign and β_O shows a negative sign.

As mentioned before, one of the advantages of the V&V method is that it is convenient for the analysis in the same education level because we do not need to add the required levels of education for each individual in the specification. In our analysis, since we only consider the graduates at the same education level, the variable S in equation (1) can be dropped. Also, if we restrict the education mismatch to over-education, we have the following simplified specification:

$$\mathrm{lnwage_i} = \alpha + \beta_0 \mathrm{over_i} + \boldsymbol{\delta}\mathbf{X} + \mathrm{u_i} \qquad (2)$$

This is the base specification we would use in the analysis. As mentioned before, we can use three measurements to define over-education, which are subjective, objective and statistical methods. We compare the coefficients β_0 in three methods to see the differences in the wage gap between over-educated and matched individuals. For the controls, specifically, we contain three groups listed as follows:

(1) Individual characteristics, including gender, ethnicity, age, marriage status, province, urban/rural area and registration status.

(2) Education control, including university type (short-term college/long-term university).

(3) Employment controls, including public/private sector, industry, contract type and firm size.

The OLS estimation of the previous specification may suffer from the problem of selection bias because wages observed are only for employees, which would result in the expected value of the error term not being equal to zero, which violates the basic assumption of OLS. Therefore, we follow the Heckman (1979) two-step here to solve the selection bias, which is also a widely accepted method in the literature. In the first step, we run a probit model on paid job participation and obtain an inverse Mills ratio. In this model, the dependent variable of paid job participation is a dummy where wage earners = 1 and non-wage earners (including those self-employed, unemployed and not in the labour market) = 0. In the second step, we add the inverse Mills ratio as an extra explanatory variable into the wage equation to eliminate the possible selection bias. To satisfy the exclusion restriction and achieve higher identification, we need to add an instrument variable not included in the wage equation in the first step. We follow the literature to use the number of elderly and young persons in families as instruments. Though in our analysis, we only include those individuals with higher education, the rationale of the choosing instrument variables is still consistent that we can assume workers who need more time to take care of family members would choose a job with more flexible time arrangements or even decide not to participate in the labour market. Inverse Mills ratios are included in all the specifications, including the following with skills heterogeneity.

To achieve higher robustness, we also implement the Propensity Score Matching method to compare with OLS. Estimators on the over-education effect in PSM come from the average treatment effect. However, individuals in the observed treated and untreated groups may not be randomised. Matching techniques are used to control the impact of covariates that may lead to different probabilities of being treated. In the first step, we run a logit regression on the selection into over-education to obtain propensity scores. In the second step, we match the treated and untreated groups according to propensity scores with different algorithms to get the average treatment effect. Detailed explanations are shown in the following subsection 4.6.6.

4.4.2 Using Skills Heterogeneity to Explain Over-education

In this subsection, we focus on using skills as controls to explain the wage gap generated by over-education. As mentioned in the introduction section, theories that address skills heterogeneity in explaining the effect of over-education are divided into two parts. Firstly, assignment theory argues that over-education implies that individuals' skills are under-utilised in those mismatched jobs. The wage gap from over-education can be explained by the lower productivity because of not fully utilising the skills. Therefore, in the following model, we further control for the over-skill based on equation (2), which is:

$$\mathrm{lnwage}_i = \alpha + \beta_0 \mathrm{over}_i + \gamma_0 \mathrm{overskill}_i + \boldsymbol{\delta}\mathbf{X} + u_i \qquad (3)$$

If it is the over-skill that generates the wage penalty rather than over-education itself, the γ_0 would be negative and the coefficient on over_i would be largely reduced or even becomes 0 if the over-skill can totally explain the effect of over-education. Other variables included in **X** are consistent with the base specification. However, it needs to be emphasised that we would have the problem of *under-skill* when using the realised matches (by statistical mean) method to define skill mismatch. Some graduates may have skills lower than the mean minus one standard deviation of the skills in their occupations. We first implement the method of treating the under-skilled individuals as if they were matched. Then in the robustness check, we try a different way by excluding the under-skilled observations to check whether there would be large differences in estimation results.

Another method to explain the over-education wage penalty is based on variations of skill levels rather than utilisation. As mentioned before, there would also be heterogeneity in human capital achievements at the same level of education. Individuals with lower skills would earn lower wages but reflected on the wage penalty of over-education. Therefore, we further add the control of individuals' skill proficiency into the base specification, shown as follow:

$$\mathrm{lnwage_i} = \alpha + \beta_0 \mathrm{over_i} + \gamma_s \mathrm{skills_i} + \boldsymbol{\delta}\mathbf{X} + \mathrm{u_i} \qquad (4)$$

If the heterogeneity theory on skill levels holds, γ_s would be positive, and after we control for the skills proficiency, the coefficient on over-education would be largely moderated or become 0 if skills levels can completely explain the over-education wage penalty.

The matching techniques are also implemented in the specifications with skills heterogeneity. We would like to see how the results would change if skills heterogeneity served as additional covariates in matching.

4.5 Incidence of Over-education and the Correlation between Over-education and Skills Heterogeneity

4.5.1 Over-education Incidence

In this part, we first propose the evidence of over-education incidence with variations in three different measurements. It is evident in Table 4.5 that most of the individuals are doing jobs that match their education level. However, it can also be found that considerable proportions of individuals are over-educated, with the highest percentage of 42.2% under the objective method and the lowest percentage of 30.14% under the subjective approach, showing that there would be variations in the incidence of over-education using different measurements. The variations in different measurements are also found in Mateos-Romero and Salinas-Jiménez (2017), who also use three different measurements on over-education, and the proportion ranges from 17.6% to 43.2%. However, the number of over-educated workers is much higher than those observed in Chinese Yun Nan province (18.2%) by Wu and Wang (2018), showing a clear gap between regional and national level data. From Table 4.6 to 4.8, we compare the three measurements in detail and show their overlap. It is found that though the proportions of individuals defined as over-educated do not have large differences between different measurements, there are considerable variations in the overlap. The largest gap shows between the subjective and objective methods, where only 66.6% of individuals who are defined as over-educated under the subjective method are also classified to be mismatched under the objective method.

Table 4.5: Incidence of over-education

	Subjective	Objective	Statistical
Education match	687 69.05%	582 58.49%	679 68.24%
Over-education	308 30.95%	413 41.51%	316 31.76%
Total	995 100%	995 100%	995 100%

Table 4.6: Overlap between different measurements: Subjective and Objective

	Objective		**Total**
Subjective	Match	Over	
Match	470 68.41%	217 31.59%	687 100%
Over	112 36.25%	196 63.75%	308 100%

Table 4.7: Overlap between different measurements: Objective and Statistical

	Statistical		**Total**
Objective	Match	Over	
Match	540 92.78%	42 7.22%	582 100%
Over	139 33.66%	274 66.34%	413 100%

Table 4.8: Overlap between different measurements: Statistical and Subjective

	Subjective		**Total**
Statistical	Match	Over	
Match	542 79.82%	137 20.18%	679 100%
Over	145 45.88%	171 54.12%	316 100%

4.5.2 Over-education Incidence with Skills Heterogeneity

In this part, we show the incidence of over-education incorporated with skills heterogeneity. We consider two dimensions of skills, which are numeracy and literacy. Firstly, in Table 4.9, we illustrate the incidence of over-skill. It can be seen that only 14.07% of individuals are classified as over-skilled under the statistical method on literacy. A larger proportion is found under numeracy, that over-skilled individuals account for over 30% of all graduates.

Secondly, in Tables 4.10 and 4.11, we further show the distribution of over-education by individuals' skills utilisation status. It is clear that for both literacy and numeracy skills, the majority of education-matched workers also fully utilise their skills in their jobs, especially under the objective and statistical method. This result is consistent with the arguments in Chevalier's (2003) research that matched individuals are homogeneous in skill utilisation. Larger proportions of over-skill are found in the over-educated group. We even find that under the statistical method, more than 50% of over-educated individuals are also over-skilled with respect to numeracy ability. The Pearson Chi-square test rejects the null hypothesis of no correlation between over-education and over-skill for all the measurements under literacy and numeracy[3,4]. This result is inconsistent with that found by Nieto and Ramos (2017) in the case of Spain. Therefore, our analysis could not easily ignore the correlation between over-education and over-skill. This evidence suggests that the over-education wage penalty

3. Under literacy skill, p-values for the Chi-square test on no correlation between over-skill and over-education are 0.035, 0.000 and 0.000 for subjective, objective and statistical methods, respectively.
4. Under numeracy skill, p-values for the Chi-square test on no correlation between over-skill and over-education are 0.032, 0.000 and 0.000 for subjective, objective and statistical methods, respectively.

can be explained by skills utilisation, though we may expect higher correlations between over-education and skills heterogeneity to satisfy the assignment theory, especially for literacy skills. In the following section 4.6, we will further check the assumption using empirical models.

Thirdly, in Figures 4.1 and 4.2, we illustrate the distribution of over-education with skills levels rather than skills utilisation statuses, according to different over-education measurements and skills dimensions, to provide evidence on individuals' skills heterogeneity in the same education level. It is found from the figures that over-educated individuals have lower skills in mean for both literacy and numeracy[5][6]. This result is also consistent with different measurements of over-education. As mentioned in the previous methodology section, evidence of the heterogeneity in skills levels in the same education level could be used to explain the wage gap generated by over-education. In Table F.1 of Appendix F, we further provide the correlation coefficients and their significance levels between over-education and skills levels. It is found that the coefficients are all significantly different from 0 at 1% level. However, most correlations are tested to be small, with the coefficients around -0.1.

Table 4.9: Incidence of over-skill

	Literacy		Numeracy	
Skill match	855	85.93%	688	69.15%
Over-skill	140	14.07%	307	30.85%
Total	995	100%	995	100%

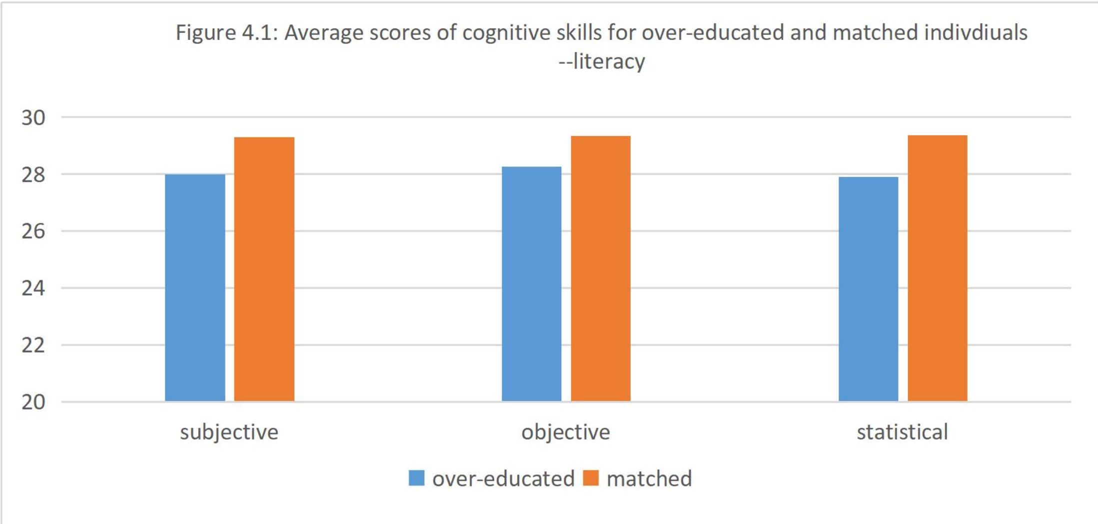
Table 4.10: Incidence of over-education with skills utilisation (literacy)

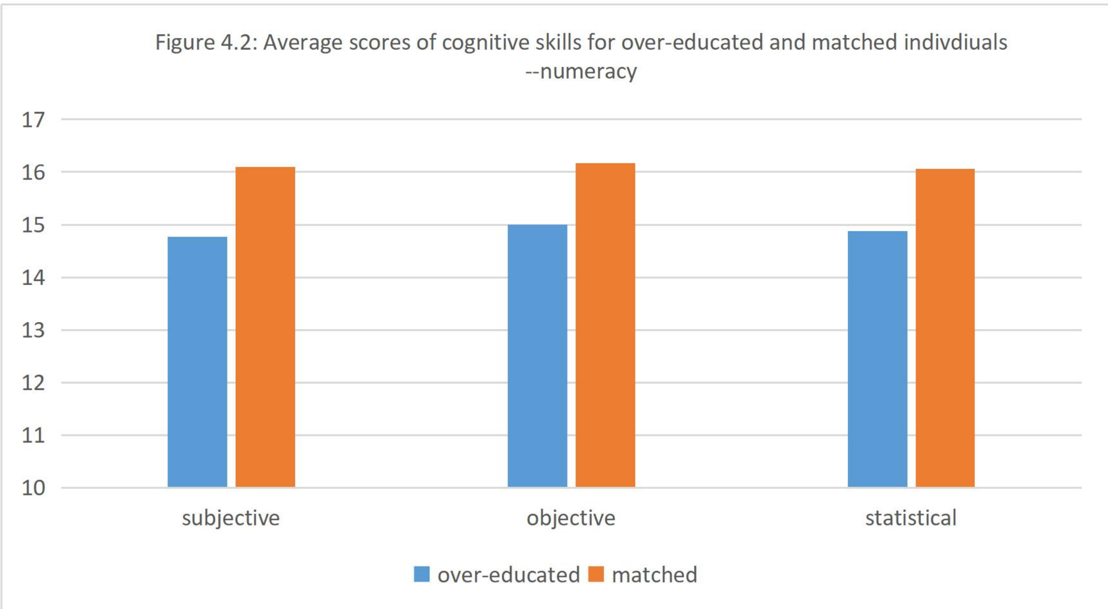
	Subjective				Objective				Statistical			
	Education match		Over-education		Education match		Over-education		Education match		Over-education	
Skill match	601	87.48%	254	82.47%	553	95.02%	302	73.12%	645	94.99%	210	66.46%
Over-skill	86	12.52%	54	17.53%	29	4.98%	111	26.88%	34	5.01%	106	33.54%
Total	687	100%	308	100%	582	100%	413	100%	679	100%	316	100%

5. Under literacy skill, p-values for the t-test on equal mean between over- and reference-educated groups are 0.002, 0.001 and 0.000 for subjective, objective and statistical methods, respectively.
6. Under numeracy skill, p-values for the t-test on equal mean between over- and reference-educated groups are 0.001, 0.001 and 0.002 for subjective, objective and statistical methods, respectively.

Table 4.11: Incidence of over-education with skills utilisation (numeracy)

	Subjective		Objective		Statistical	
	Education match	Over-education	Education match	Over-education	Education match	Over-education
Skill match	486 70.74%	202 65.58%	447 76.72%	241 58.35%	536 78.94%	152 48.10%
Over-skill	201 29.26%	106 34.42%	135 23.28%	172 41.65%	143 21.06%	164 51.90%
Total	687 100%	308 100%	582 100%	413 100%	679 100%	316 100%





4.6 Empirical Results

4.6.1 Main Results on Return to Education

In this part, we propose the results obtained from the base specification without consideration of skills heterogeneity. The estimation results on full variables are shown in Table 4.12. It is clear that in all three measurements, over-educated individuals suffer from wage penalties compared with education-matched individuals, which are estimated to be significantly different from zero. The wage differences are similar under subjective and statistical methods, with 26.7% and 22.8%, respectively. However, under the objective method based on the job analysts' definition of over-education, the wage penalty is only estimated to be 17.9%, which is smaller than those found in the other two methods. In the previous part, we see that the overlap rates between different methods are not relatively high, which may be a possible explanation for the gaps in estimated coefficients. However, in general, we find that being employed in a job with education mismatch would make individuals suffer from lower wages. Our finding on the significant over-education wage penalty is consistent with previous studies in Chinese literature, such as Wang (2018) and Liu et al. (2021). For other control variables, we find individuals graduated from universities would earn significantly higher wages than those graduated from colleges. In addition, graduates in rural areas suffer from lower income on average than those in urban areas. Some employment controls also show determinant effects on wages. We find significantly higher wages on average for those who sign formal contracts with employers and significantly lower wages on average for individuals working in small firms.

Regarding selection bias, the inverse Mills ratios are estimated to be insignificantly different from zero under three methods, showing that the over-education results on graduates do not suffer from the selection bias. We provide the first step results on probit regression in Appendix I. We find graduates with older age and who are urban residents would be more likely to attend the waged jobs. In addition, the presence of young children in the family would also significantly affect the choice of the parents

Table 4.12: Return to over-education with three measurements

	Subjective	Objective	Statistical
Over	-0.267***	-0.179***	-0.228***
	(0.046)	(0.044)	(0.047)
University	0.168***	0.185***	0.176***
	(0.049)	(0.049)	(0.049)
Male	0.041	0.047	0.053
	(0.045)	(0.046)	(0.046)
Age	0.043	0.032	0.031
	(0.030)	(0.030)	(0.030)
Age square/100	-0.040	-0.028	-0.026
	(0.037)	(0.037)	(0.037)
Minorities	-0.045	-0.042	-0.055
	(0.087)	(0.088)	(0.088)
Marriage status	-0.027	-0.016	-0.015
	(0.059)	(0.060)	(0.060)
Urban "Hukou"	-0.016	-0.010	-0.013
	(0.064)	(0.065)	(0.065)
Urban residence	0.182**	0.193**	0.186**
	(0.085)	(0.086)	(0.086)
Northeast	-0.055	-0.035	-0.037
	(0.084)	(0.085)	(0.085)
East	0.048	0.037	0.038
	(0.060)	(0.061)	(0.061)
Middle	-0.093	-0.080	-0.082
	(0.089)	(0.090)	(0.090)
Signing Contract	0.190***	0.200***	0.194***
	(0.047)	(0.047)	(0.047)
Public sector	-0.032	0.007	-0.009
	(0.049)	(0.049)	(0.049)
Raw materials	0.278	0.225	0.261
	(0.195)	(0.196)	(0.196)
Manufacturing	0.191***	0.198***	0.221***
	(0.059)	(0.060)	(0.060)
Retailing and wholesaling	0.235***	0.262***	0.270***
	(0.056)	(0.057)	(0.057)
Small firm	-0.112**	-0.117**	-0.123***
	(0.047)	(0.047)	(0.047)
Medium firm	-0.069	-0.048	-0.048
	(0.067)	(0.067)	(0.067)
Lambda	-0.080	-0.127	-0.156
	(0.413)	(0.417)	(0.417)
Constant	0.889	0.983	1.063
	(0.807)	(0.817)	(0.817)
N	995	995	995

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

taking non-waged jobs. This finding is consistent with Chapter 3 on workers at all education levels. However, it is clear that skill levels would not significantly affect the choice of graduates being waged workers. In addition, adding skill levels would not largely affect the coefficients on other variables estimated in the Heckman first-step regression. Usually, we should add all the variables included in the wage equation into the probit model. However, some variables, such as over-education and job characteristics, are only available for wage earners. Therefore, we include other controls, such as educational and individual characteristics, consistent with the method used by Nieto and Ramos (2017).

The third method we use to define over-education is the statistical method which relies on the observed distribution of education in occupations. However, there would always be arguments in the literature about whether we should use mean or mode education level as the required level. In fact, some researchers do find large differences in estimated over-education wage penalties between differently defined reference education. Therefore, in our analysis, we also provide a robustness check by comparing mode and mean in Table G.1 in Appendix G. It is found that over-education wage differences are quite similar under the two measurements, where the penalty is only 0.4% higher using mode as the reference level. This result supports the idea that we do not need to worry further about measuring reference education under the statistical method for the Chinese labour market.

4.6.2 Return to Over-education in Subgroups

In this part, we further examine the heterogeneous returns to over-education in different subgroups, specifically the returns for urban and rural workers. In Chapter 3, we find heterogeneous returns to years of education between rural and urban areas. In this chapter, we also study whether over-educated individuals would be treated differently on wages in different labour markets. In most of the previous studies, the analyses on over-education are not extended to the rural labour market, mainly because of the limited number of observations of graduates in rural areas. However, according to the 2014 wave of CFPS, about 17% of graduates are still rural workers. Therefore, the return to over-education in rural areas and the comparison of the returns between urban and rural should not be ignored.

In fact, China suffers from unbalanced economic development and labour market segmentation between urban and rural areas due to the restrictions on registration regularities. In the segmented markets, the wage penalties for over-education would also differ based on different supply and demand conditions. Actually, it is hard to assume how the wage penalties would vary across urban/rural areas. It is possible that with the limited supply of skilled workers, employers would pay over-educated graduates with similar wages compared with matched ones, even if they are currently unable to utilise their education outcomes fully. However, contrary to this, De Santis et al. (2022) propose a theory that defines different levels of over-education based on the distance between the required and obtained education. It is possible that because of limited vacancies in rural areas, graduates are able to find jobs where the required education has large gaps to the tertiary level, which would result in a significantly larger penalty in earnings than those in urban areas, as De Santis et al. (2022) concluded.

It is often considered that the return to education, such as the college wage premium, would imply a migration of labourers from a low-return market to a high-return one. In fact, the return to over-education, which shows the penalty when an individual cannot find suitable jobs, would also be a supplement reason to explain the labour flow. Skilled workers may prefer to migrate to a market where they would suffer from lower or no penalties when facing the risk of education mismatch.

In Table 4.13, we form interaction terms between over-education and individuals' urban/rural residence status to see the gap between the return to over-education in different areas. It can be seen that all the returns to over-education in rural areas are significant, with 25.7%, 23.7% and 27.6% under subjective, objective and statistical methods, respectively. From the coefficients on interaction terms, we find the returns to over-education in urban areas are estimated to have tiny and insignificant gaps with those in rural areas, according to the insignificant coefficients estimated on interaction terms. Therefore, from the estimation of subgroups, though China suffers from a segmentation between urban and rural labour markets, individuals do not suffer from various penalties for over-education. Possible explanations may rely on arguments in Bennett (1995) that for individuals with high educational qualifications, wage rates in peripheral regions are more comparable with those in central areas.

Table 4.13: Return to over-education by urban/rural

	Subjective	Objective	Statistical
Over	-0.257***	-0.237**	-0.276**
	(0.090)	(0.105)	(0.110)
Over*Urban residence	-0.028	0.080	0.067
	(0.115)	(0.113)	(0.119)
Urban residence	0.202**	0.158*	0.165*
	(0.094)	(0.095)	(0.092)
Lambda	-0.366	-0.669	-0.607
	(0.656)	(0.704)	(0.690)
Constant	1.493	1.978*	1.892
	(1.106)	(1.198)	(1.171)
N	995	995	995

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Lambda is the inverse Mills ratio for correction of self-selection.
Other controls include: university type, sex, age, age square, ethnicity, marriage, region dummies, registration status, urban status, firm size, contract type, sector and industry.

4.6.3 Using Skills Heterogeneity to Explain Wage Effect of Over-education

In Table 4.14, we show the results of wage effect on over-education after controlling the skills heterogeneity. In the first column of each method, we illustrate the estimates after the inclusion of skills utilisation and in the second column, the results after adding skills levels are shown. In this part, we first focus on literacy skills.

When the assignment theory and skills utilisation is considered, we find that in all of the measurements, coefficients on over-education are still significantly different from zero. Compared with the estimation results in Table 4.12, the estimated returns to over-education only decrease from 26.7% to 26.2%, from 17.9% to 16.7% and from 22.8% to 21.8%, under three different measurements, respectively, which shows that the over-skill only accounts for a small proportion of wage penalty. The most significant reduction is found under the objective method, that 9 per cent of the over-education wage penalty is explained by skills utilisation. Assignment theory initially assumes that over-education implies over-skill, however, it is clearly not supported by

Table 4.14: Return to over-education with skills heterogeneity (literacy)

	Subjective		Objective		Statistical		No-over	
	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)
Over	-0.262***	-0.270***	-0.163***	-0.181***	-0.218***	-0.231***		
	(0.046)	(0.046)	(0.046)	(0.044)	(0.051)	(0.048)		
Over-skill	-0.118**		-0.071		-0.034		-0.136**	
	(0.059)		(0.062)		(0.064)		(0.059)	
Skill level		-0.003		-0.003		-0.003		-0.002
		(0.004)		(0.004)		(0.004)		(0.004)
Lambda	-0.129	-0.134	-0.149	-0.173	-0.159	-0.211	-0.149	-0.117
	(0.412)	(0.420)	(0.416)	(0.424)	(0.416)	(0.425)	(0.419)	(0.426)
Constant	1.000	1.031	1.025	1.104	1.069	1.208	0.889	0.826
	(0.807)	(0.831)	(0.817)	(0.842)	(0.815)	(0.844)	(0.821)	(0.843)
N	995	995	995	995	995	995	995	995

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Lambda is the inverse Mills ratio for correction of self-selection.

Other controls include: university type, subjects, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

our empirical results. Similar to the utilisation of skills, after adding skill levels as controls into the specifications, the return to over-education remains significant and nearly unchanged, showing that the penalty generated by over-education cannot be explained by the variations in individuals' skill proficiency in the same level of education, which means that the heterogeneity theory on skill levels is also not supported[7].

Regarding the coefficients on skill variables, we first find a significant negative effect on over-skill alongside over-education in the subjective method. This result is consistent with most of the findings in the literature (Allen and Velden, 2001; Pietro and Urwin, 2006). However, under the objective and statistical method, the return to over-skill becomes insignificant but still negative. In the final two columns, we add skill variables solely into the wage equations without the inclusion of over-education.

7. Chuang and Liang (2022) argue that the effect of over-skill and skills levels may co-exist in return to education. Following this idea, in our analysis, we also control for the variables of over-skill and skill proficiency in one specification but do not find large variations in the over-education coefficients compared to those in Table 4.12. The result remains that skills heterogeneity would not largely explain the over-education wage penalty.

It is found that over-skilled individuals would suffer from 13.6% lower wages than matched, and the coefficient is estimated to be significant at 5% level. Therefore, it can be seen that over-skill affects individuals' wages directly through over-education under objective and statistical measurements. This result could be explained by the high collinearity between the two mismatch variables, illustrated in the previous section. Our finding on the effect of over-skill is very similar to that of Chuang and Liang (2022) based on the Taiwan case, where the coefficient on skill mismatch also turns out to be insignificant when the over-education variable is added. Full results on other variables are shown in Table H.1 in Appendix H.

Besides the effect of skills utilisation, we also find that coefficients estimated for skill levels are quite small and insignificant in different specifications, even if the education mismatch status is not considered. This implies that employers may only observe individuals' human capital by using education achievements as signals rather than further consider skill variations in the same education level. The insignificant effect of cognitive skill levels is also found among young graduates in Poland (Palczyńska, 2021), but not consistent with that proposed by Wu and Wang (2018), who also focus on the Chinese case. The possible reason could be that our analysis is nationwide, but Wu and Wang only include observations in one province of Yunnan. Also, the measurements of cognitive skills are different between the two studies. In our analysis, skills levels come from formal tests, and the scores range from 0 to 34. However, in Wu and Wang's analysis, skills proficiency are based on individuals' self-assessment and are only valued by four scores from 0 to 3, which may drive the concern that individuals' heterogeneity in this measurement is hidden.

It is mentioned in the variables section that we may have the problem of under-skilled individuals when we define the skills mismatch using realised matches method. Though with a small amount, the under-skilled individuals would still affect the robustness of results. In the previous measurements, we treat those under-skilled as if they were matched, but in Table G.2 in Appendix G, we provide empirical results by excluding under-skilled observations. However, we find tiny variations in coefficients.

In this section, we only focus on individuals' literacy proficiency. However, arguments are often raised in the literature that literacy may only capture one aspect of cognitive skills and could not serve as a perfect proxy (Sohn, 2010). Therefore, in the following subsection 4.6.4, we further consider numeracy proficiency and determine whether the heterogeneity in numeracy utilisation and levels would better explain the over-education penalty. In fact, it needs to be mentioned that quantifying individuals' skills is much more complicated than education achievements. Even if the cognitive skills are successfully measured, there are other dimensions of skills, including but not limited to, technical skills and non-cognitive skills[8]. In subsection 4.6.5, we further control for the non-cognitive skills alongside cognitive skills to achieve higher robustness.

4.6.4 Robustness Check I: Literacy and Numeracy Skills

As mentioned in part 4.3, the correlation between numeracy and literacy is only around 50%, which is quite abnormal in the literature. In the cases of Spain and Poland, the correlation between the two dimensions of skills is relatively high, with a correlation coefficient higher than 0.9 (Nieto and Ramos, 2017; Mateos-Romero and Salinas-Jiménez, 2017; Palczyńska, 2021). One reason could be that in China, education results are closely correlated with promotion ability to higher levels. Starting from secondary school, in order to get higher scores in entrance examinations, students are forced to choose to either focus on Science or Arts in their studies, which may lead to a more significant difference between their numeracy and literacy skills. The considerable difference makes us possible to compare results from various skill categories. The following Table 4.15 shows results controlling for skills utilisation and levels using test scores from numeracy questions. From the empirical results, we can conclude the following. Firstly, the wage penalties for over-education still remain significant, showing that the penalty comes directly from the difference in job characteristics rather than the variations in human capital had, regardless of the skills

8. For Information on technical skills, see the Skills Towards Employability and Productivity (STEP) Survey on Yunnan province, provided by World Bank at https://microdata.worldbank.org/index.php/catalog/2019.

categories included. Secondly, the significant effect of over-skill on wages does not exist anymore, even if in the specification that the over-education variable is not included. Thirdly, heterogeneity in skills levels cannot explain individuals' wages. In general, though the correlation between literacy and numeracy scores is quite low, we conclude consistent results that skills heterogeneity plays a minor role in explaining the wage penalty from over-education[9].

Table 4.15: Return to over-education controlling skills heterogeneity (numeracy)

	Subjective		Objective		Statistical		No-over	
	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe(4)
Over	-0.265***	-0.270***	-0.175***	-0.182***	-0.233***	-0.232***		
	(0.046)	(0.046)	(0.045)	(0.044)	(0.050)	(0.048)		
Over-skill	-0.041		-0.020		0.018		-0.057	
	(0.047)		(0.048)		(0.050)		(0.048)	
Skill level		-0.003		-0.003		-0.004		-0.002
		(0.005)		(0.005)		(0.005)		(0.005)
Lambda	0.008	-0.062	0.016	-0.112	0.098	-0.141	-0.093	-0.043
	(0.373)	(0.423)	(0.377)	(0.428)	(0.377)	(0.427)	(0.379)	(0.430)
Constant	0.760	0.883	0.747	0.985	0.627	1.068	0.789	0.685
	(0.757)	(0.841)	(0.764)	(0.852)	(0.764)	(0.851)	(0.771)	(0.854)
N	995	995	995	995	995	995	995	995

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Lambda is the inverse Mills ratio for correction of self-selection.

Other controls include: university type, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry

4.6.5 Robustness Check II: Controlling for Non-cognitive Skills

In this subsection, we further control for the non-cognitive skills to capture individuals' unobserved heterogeneity besides cognitive skills to achieve higher robustness. The inclusion of non-cognitive skills directly corresponds to the arguments on the muti-dimension of individuals' skills, which is considered an essential drawback in some studies when only one skill category is considered. In this subsection, we add controls of individuals' non-cognitive skills levels into specifications, including the "Big Five" personality traits and locus of control.

9. In fact, we conduct an analysis that both skills are added into the specifications at the same time, but results remain similar, that coefficients for return to over-education are still large and significant

Information on non-cognitive skills comes from the survey year 2018, and we assume that these skills are stable for adults, at least for a short period (Fossen and Büttner, 2013). Due to the follow-up rate and missing values in 2018, only 70% of the total observations remain for the current analysis[10].

It can be seen in the following Table 4.16 that openness has a significant positive effect on wages, whereas individuals with higher agreeableness would be penalised. Therefore, we have an important finding that in China, though cognitive skills have minor impacts on wages, some of the non-cognitive skills are estimated to be critical to individuals' economic outcomes. This finding is consistent with Wu and Wang (2018) using data from one province, which emphasises the condition that in China, if we want to examine the relationship between skills and wages, we need to consider different types of skills.

However, though significant effects of skills levels are found, the coefficients on over-education are still large and significant, showing that the inclusion of different dimensions of skills still cannot largely explain the wage penalty, which is consistent with the results obtained from previous specifications. The estimated returns to over-education using restricted observations are shown in the first column under each measurement, which are found to be very similar to those obtained in the previous subsection 4.6.1. Including all the cognitive and non-cognitive skills would decrease the return to education by 2.1%, 2.3% and 1.8%, according to subjective, objective and statistical measurements, respectively. Therefore, the skills proficiency would only explain up to 12 per cent of the over-education wage penalty (under the objective method) when different dimensions of skills are considered.

In this part, we only propose the estimation results on return to over-education by controlling for skills levels. To check the assignment theory, we still need to include the utilisation of all the non-cognitive skills as controls, which requires implementing realised matches method on all the personality traits and the locus of control. This

10. Possible selection bias would be generated by the fact that only part of the individuals is included across years. However, in this analysis, we consider the existing follow-up rate is acceptable and assumes the missing observations are random. In fact, we find no large differences in the return to over-education between original and restricted samples, comparing Table 4.12 and 4.16

idea is similar to that of Sánchez-Sánchez & McGuinness (2015), who also add detailed skills utilisation components to explain over-education, including non-cognitive related skills such as creativity, open mind, communication, negotiation and pressure dealing. We propose the results in Table G.3 in Appendix G. Estimation results show that coefficients on the over-education variables under different measurements are still significant, and the inclusion of utilisation of non-cognitive skills shows a smaller effect on explaining the over-education wage penalty compared to skills levels.

Table 4.16: Return to over-education controlling for non-cognitive skills

	Subjective		Objective		Statistical	
	Spe (2)	Spe (4)	Spe (2)	Spe (4)	Spe (2)	Spe (4)
Over	-0.304***	-0.283***	-0.180***	-0.157***	-0.224***	-0.206***
	(0.055)	(0.056)	(0.054)	(0.054)	(0.060)	(0.060)
Skill level (literacy)		0.004		0.005		0.004
		(0.005)		(0.005)		(0.005)
Conscientiousness		0.007		0.008		0.006
		(0.050)		(0.051)		(0.050)
Extroversion		0.040		0.044		0.048
		(0.038)		(0.038)		(0.038)
Agreeableness		-0.138**		-0.129**		-0.126**
		(0.058)		(0.058)		(0.058)
Openness		0.082**		0.090**		0.091**
		(0.037)		(0.038)		(0.038)
Neuroticism		0.014		0.020		0.019
		(0.042)		(0.043)		(0.043)
Locus of control		-0.018		-0.008		0.001
		(0.063)		(0.064)		(0.064)
Lambda	0.219	-0.007	0.255	0.063	0.250	0.066
	(0.436)	(0.434)	(0.443)	(0.440)	(0.442)	(0.439)
Constant	0.149	0.401	0.044	0.062	0.083	0.038
	(1.004)	(0.974)	(1.022)	(0.984)	(1.019)	(0.980)
N	661	661	661	661	661	661

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Lambda is the inverse Mills ratio for correction of self-selection.

Other controls include: university type, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

4.6.6 Robustness Check III: Propensity Score Matching (PSM) Method

4.6.6.1 Non-parametric Method

Empirical results obtained from the previous sections are mainly based on linear regression and OLS methods. We have conducted some robustness checks on the results by adding additional skills controls in the regressions and changing the measurements of over-education and skills. However, we have not directly checked the robustness of the methodologies. In fact, another method often used in the literature is the matching technician, which can be treated as an important comparison with the OLS method. The estimates from the matching method are normally obtained from the average treatment effect. The treated group include individuals who are over-educated and the control group include those who have matched education levels. This method can help solve the problem generated by the functional form misspecification (FFM), that the estimated causal effects of over-education to wages from linear regression are largely a result of the functional form of the statistical model rather than the data.

In our analysis, we implement the propensity score matching (PSM) method (Rosenbaum and Rubin, 1983). The propensity score is the conditional probability of receiving the treatment given a vector of pre-treatment covariates. The identifying assumption of this estimation method is the unconfoundedness or conditional independence assumption (CIA), which states that conditional on observable variables that influence selection into treatment, the treatment status is assumed to be randomised (Palczyńska, 2021). The parameter of interest in the analysis is the average treatment effect on the treated (ATT). After matching according to the propensity score, the effect is assumed totally come from the treatment rather than the covariates. Usually, the estimation of PSM can follow the undying steps:

(1) Obtain the propensity score from the logit or probit regression on selection to over-education.

(2) Match the observations in treated and untreated groups according to the propensity score. The matching algorithms may include Kernel, Nearest Neighborhood, Caliper, etc., based on individuals' propensity scores.

(3) Estimate the effect of over-education using the average treatment effect (ATT).

The previous steps can be used to obtain the estimates, but we still need to check the matching qualities by using tests on common support and covariates balance. Firstly, in the matching process, common support is often introduced to increase the matching quality. Only observations within the range of overlapping propensity scores among treated and untreated groups would be retained. However, if the range of the common support is small, we would lose a considerable amount of observations, and the remaining sample would not be representative anymore. Secondly, the covariates balance test is to check whether there would still be a large variance among covariates between treated and untreated groups after matching. We compare the mean absolute standard bias (MSB) and Pseudo R-squared on raw and matched samples. Standard bias for each covariate is defined as the difference of sample means among the treated and control groups as a percentage of the square root of the average sample variances in both groups. The formula is presented as follow:

$$\mathrm{SB(x)} = \frac{(\overline{\mathrm{x}}_{\mathrm{c}} - \overline{\mathrm{x}}_{\mathrm{t}})}{\sqrt{(\mathrm{s}_{\mathrm{xc}}^2 + \mathrm{s}_{\mathrm{xt}}^2)/2}}$$

We generate the mean standardised bias (MSB) for all the covariates to show the overall matching quality, and a lower MSB indicates a higher matching quality. Pseudo R-squared is obtained from the logistic regression on the selection into over-education. Similar to MSB, we compare the R-squared before and after matching and a lower Pseudo R-squared reflecting a higher matching quality.

4.6.6.2 Selection into Over-education

To obtain the propensity scores, we need to conduct a probit regression on the selection into over-education. In our literature, many studies focus on the factors that significantly affect the probability of being over-educated. The PSM procedure provides us with an opportunity to cover both topics of the wage effect of over-education and selection to over-education together. The logistic regression results are shown in Table J.1 in Appendix J. It can be seen that becoming a university student would significantly decrease the risk of being over-educated. Also, though we conclude that skills would not significantly affect wage payoffs in the previous subsections, we find individuals with higher skill levels are less likely to be over-educated in selection regressions.

4.6.6.3 Wage Effect of Over-education under PSM

In the following Table 4.17, we illustrate the estimated parameters on the over-education wage effect by using the PSM method, compared with those obtained from OLS regressions. It needs to be mentioned that in the PSM method, we are not able to consider the selection bias on waged job participation. In fact, this would not generate too much trouble because no significant bias is found according to self-selection in the previous results. However, to maintain consistency with PSM, we also report OLS results without correcting selection bias in this part.

The algorithm of matching we use is the kernel matching with the bandwidth of 0.06. We also check other algorithms (kernel with bandwidth 0.02 and nearest neighbour with 1 and 4 neighbours) and the matching qualities on different over-education definitions and different covariates are shown in Table K.1 in Appendix K. In most cases, kernel matching with the bandwidth of 0.06 has the lowest MSB and r2 value, showing the highest matching quality. Besides the balance test, the test results on common support are also illustrated in Figure K.1 in the Appendix K. Distributions of propensity scores show that most of the observations are on support in both groups, which means the remaining sample is still representative.

Turning to the empirical results in Table 4.17, we can find that under different measurements, the returns to over-education are significantly negative under PSM, even if different kinds of skill-related covariates are introduced. This result is consistent with that under the OLS method that controlling skills variables would help little to explain the over-education wage penalty. It can also be found that the estimated coefficients are pretty similar under PSM and OLS results, showing high robustness for our analysis in terms of the methodologies. The result on the relationship between PSM and OLS is consistent with the finding in Palczyńska (2021), who focuses on the case of Poland.

Table 4.17: Estimates of over-education wage differences: PSM and OLS results

	Subjective		Objective		Statistical	
	PSM	OLS	PSM	OLS	PSM	OLS
Spec. (2)	-0.269***	-0.267***	-0.191***	-0.179***	-0.224***	-0.228***
(Without skills)	(0.055)	(0.046)	(0.048)	(0.044)	(0.058)	(0.047)
N	949	995	983	995	967	995
Treated	305	308	404	413	310	316
Untreated	644	687	579	582	657	679
Spec. (3)	-0.268***	-0.262***	-0.165***	-0.163***	-0.238***	-0.218***
(Skills utilisation)	(0.048)	(0.046)	(0.056)	(0.046)	(0.064)	(0.051)
N	950	995	978	995	974	995
Treated	305	308	399	413	311	316
Untreated	645	687	579	582	663	679
Spec. (4)	-0.275***	-0.270***	-0.189***	-0.181***	-0.222***	-0.231***
(Skills levels)	(0.048)	(0.046)	(0.047)	(0.044)	(0.052)	(0.048)
N	951	995	984	995	966	995
Treated	643	308	405	413	309	316
Untreated	308	687	579	582	657	679

PSM is under kernel algorithm (bandwidth 0.06). Standard errors in parentheses:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in PSM are based on bootstrapping with 50 replications.

Other covariates include: university type, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

4.6.7 Robustness Check IV: Further Regression Results Using Larger Samples

The analysis on the return to over-education in this chapter suffers from a limitation on the small sample size on graduates. The main reason is that CFPS is a household survey for all residents in China rather than a survey that focuses only on graduates. Further, after we implement the resampling method to conduct the national representative analysis, the number of observations decreases to less than 1000. The small sample size may affect the disaggregated analysis, for example, the return to over-education for different age cohorts and the robustness of the results obtained in the previous empirical models. Therefore, in this subsection, we further provide empirical results on the return to over-education and skills without using the resampling method to aim for higher robustness. Results are illustrated in Table M.1, M.2 and M.3 in Appendix M.

Comparing the results on return to over-education using resampled and not resampled data (Table 4.12 and Table M.1), we find the returns are quite similar, no matter what kind of over-education measurement we use. Returns under the larger sample size are still estimated to be positive and highly significant, ranging from 18.8% to 19.4%. In Table M.1 and M.2, we further provide results on return to education under the larger sample size by taking the skills heterogeneity into consideration. It can be seen that the return to over-skill and some of the non-cognitive skills are significant. However, the return to cognitive skills is still insignificantly different from zero, and the inclusion of skills heterogeneity can only explain the over-education wage penalty to a small extent. These results are consistent with those obtained under the resampled data. Therefore, with the updated empirical results, the robustness of the previous findings in this chapter should not be a concern.

4.7 Conclusion

The main purpose of our paper is to estimate the wage effect of over-education for Chinese graduates by measuring individuals' over-education status in three different ways. We also extend the research on the consequences of over-education by considering the individuals' skills heterogeneity in the same level of education. According to the theories in the literature, if the variables of skills utilisation or the skills levels are controlled, the wage penalty driven by over-education would be largely reduced or even become zero. These variables are often unobserved and ignored in many other studies and can be considered the resources of omitted variable bias. Results in our paper show that in the Chinese labour market, up to 40% of individuals suffer from the over-education problem that they are employed in jobs that do not require their current education achievements, supporting our first hypothesis illustrated in section 4.2.4. In addition, over-educated graduates also suffer from a significant wage penalty of 26.7%, 17.9% and 22.8% under subjective, objective and statistical measures on over-education, respectively. This result strongly supports our second hypothesis on significant lower wages for over-education. However, the skills heterogeneity would not largely help explain the over-education wage penalty. After controlling for the variables related to skills heterogeneity in the wage equation, the estimated effect of over-education remains large and significant. This result is robust to different categories of skills used, including cognitive and non-cognitive ones, supporting the third hypothesis in section 4.2.4. The most significant reduction in return to over-education is found to be 12 per cent after adding all the controls of cognitive and non-cognitive skills levels into regression, under the case of objective measured over-education. To achieve higher robustness of methodologies, we further compare the results from PSM and average treatment effect with those obtained from linear regression. However, no large differences are found in estimators between the methodologies used.

This analysis is not out of limitations. Firstly, the sample size of graduates is relatively small in CFPS, which makes us unable to examine the detailed heterogeneity in subgroups with respect to, for example, age cohorts or provinces. Secondly, it may be argued that neither numeracy nor literacy would perfectly capture individuals' cognitive skills. Some other studies also use problem solving (e.g. Hanushek, 2015) to measure cognitive skills, but the information on problem solving is not available in CFPS. In addition, even if different skill dimensions, such as cognitive and non-cognitive skills, are included in the analysis, other categories of human capital may also help explain the wages and over-education penalty, such as technical skills (Wu and Wang, 2018). Future analysis may overcome these drawbacks with the help of better data. Thirdly, Palczyńska (2021) argues that a reverse causality problem may exist in the selection model of over-education, where the mismatch would also be a reason for the decline of cognitive skills. However, in our analysis, the consequences of the possible reverse causality problem cannot be ruled out.

There are also some implications related to our obtained results. For example, though we find out variations in skills levels for individuals in the same education level, agents and policymakers need to be aware that the large and significant differences in economic outcomes are mainly driven by the job-education mismatch itself rather than the heterogeneity in individuals' skills levels, and related measures need to be taken into account. Firstly, educational agents need to provide comprehensive information to students on the possible employability outcomes at graduation before they decide to get into higher education. Secondly, policymakers need to re-consider carefully whether the current expansion policy still needs to be continued to increase the supply of higher education. However, arguments can be raised that measures should not be only restricted to the supply side of higher education. Otherwise, graduates from high schools would, in consequence, face significantly larger competition. Therefore, the most important job for the Chinese government is to propose labour demand policies to promote the 'right' kind of jobs that can use the higher education and skills. In fact, if the short-term over-education problem in the waged sector is not avoidable, graduates can be encouraged to take self-employed jobs (Nieto and Ramos, 2017). In recent years the Chinese government has been trying to provide specific support for those self-employed starters. However, there is still a tiny proportion of graduates who choose to have their own businesses after graduation.

Besides the recommendations to agents and policymakers, our analysis is also closely correlated to the interests of individuals. Firstly, students need to be very cautious about making investments in higher education when facing the risk of being over-educated. Though in China, most of the higher-education institutions are publicly funded and require low tuition fees, individuals may still suffer from the opportunity costs of not being employed earlier if they could only find jobs suitable for high school students, after several years of study. Secondly, though individuals' cognitive skills are often focused, in the Chinese labour market, non-cognitive skills, especially those correlated with personality traits, show more determinant effects on individuals' economic outcomes. Graduates may consider developing appropriate skills for jobs, such as always keeping an open mind but not being too agreeable.

Chapter 5 Return to Education Qualities and Subjects for Chinese Graduates

5.1 Introduction

The expansion of higher education is recognised by an increasing number of researchers to play an important role in economic development in China. For example, evidence shows that the expansion of the education system, especially the expansion of higher education, accounts for at least 10- 15% of the economic growth of China (Wang and Yao, 2003; Zhu, 2012; Whalley and Zhao, 2013).

Many researchers in China estimate the wage return for individuals attending colleges or the so-called college wage premium. However, the differences between education qualities and subjects are not well examined, and a homogeneous return among graduates is often assumed. In recent studies, a disequilibrium in the labour market is found in countries with the fast expansion of tertiary education where the supply of graduates exceeds the demand (see arguments on Chevalier, 2003), such as the US and the UK. Some individuals suffer from lower wages than others within the same tertiary education level, and evidence shows that the lower economic outcomes are often correlated with specific education qualities and subjects (Chevalier and Lindley, 2009; Walker and Zhu, 2008; Sloane et al., 2010). In China, after the "higher education expansion policy" proposed in 1999, the number of graduates has increased dramatically by 800% till 2018, which can be seen as a boom in the supply side of higher education. Therefore, it is timely to consider whether the assumption of homogeneous return is still satisfying and whether there are significant differences in returns to subjects and college types.

In our analysis, we are trying to test the implicit assumption in the returns to schooling studies that returns do not vary by college types and subjects or, on the other hand, one would expect higher returns to attending more selective universities, which admit more able students and are better resourced. Though in China most colleges are publicly funded, most individuals and families in China would still view tertiary education as an important private investment. Further, some individuals are still attracted by the general higher return to college qualifications and try to accept a trade-off between quantity and quality of education. Therefore, providing accurate estimates of returns to higher education with differences in education qualities and subjects can inform decisions regarding individual human capital investment and efficient allocation of resources. In addition, the expansion of higher education is also costly to the country. A comparison of the returns to higher education on varying qualities and subjects may comprehensively show the labour market's responses to different kinds of graduates and provide useful information for policymakers about the appropriate allocation of education resources.

The studies focusing on education qualities and subjects are quite limited in China mainly because of the unavailability of the data. However, thanks to the CFPS dataset, we can examine the effect of both the qualities and subjects in one paper. CFPS provides detailed information on college types, including the difference between academic/vocational and key/ordinary. In addition, subject information for each individual is also provided, and the classification of subjects is totally consistent with the national standard. We provide detailed explanations in the following subsection 3, and it is clear that CFPS data provides enough feasibility for our analysis.

In summary, we have the following research aims:

(1) Estimate the return to higher education in China with the heterogeneity of education qualities and subjects.

(2) Examine the interaction effect of quality and subjects, that is, the effect of subjects in different college types or the effect of different college types according to variations in subjects.

(3) Find out the heterogeneity in subgroups, such as gender and urban/rural.

The most important contribution of our analysis is that we fill in the gap in Chinese literature on individuals' wage disparities within the higher education level and directly question the homogeneous return to colleges often accepted by the previous research. We include the examination of both education qualities and subjects in one analysis, which is rarely seen in previous Chinese literature. In addition, the CFPS dataset provides comprehensive information to include different sets of controls into empirical models, including individuals' skills proficiency, from which we can examine whether the return to different education qualities and subjects can be explained by individuals' human capital achievements. The chapter is structured as follows. In the first part, we introduce the backgrounds and specific research aims. In the second part, we provide a review of the literature, including returns to education qualities and also subjects. From part three to part six, we explain the data, sample selection, variables and methodologies. In the seventh part, we provide estimation results from empirical models. In the last part we conclude.

5.2 Literature Review and Hypotheses

Since the idea of the heterogeneous return to graduates' qualifications is accepted, a number of researchers in the literature provide evidence on the payoff to different education qualities and subjects at the tertiary education level. However, most studies are from advanced countries such as the UK and the US, presumably due to the availability of data. In traditional studies, researchers focus on the return to education quality while treating subjects as given, and others examine the return to various subjects but hold the education qualities to be constant. However, in recent years, many analyses have tried to determine the effect of the interaction between qualities and subjects. In this brief review, we cover both topics on return to subjects and qualities according to our research questions.

5.2.1 Return to Education Qualities

5.2.1.1 College Qualities

In the literature, higher education qualities are often closely connected to college (institution) types, and many researchers try to find heterogeneous wage returns according to college qualities. For example, Long (2010) focuses on the case of America and compares three different datasets, which are National Longitudinal

Study of the High School Class of 1972 which followed high school seniors from 1972 to 1986; the sophomore cohort of High School and Beyond which were followed from 1980 to 1992; and the National Education Longitudinal Study of 1988 which followed eighth graders from 1988 to 2000. When analysing the effect of education quality, only individuals who have a 4-year experience are included. The index of college quality is constructed by using the first principal components analysis based on the following factors:

(1) College's median freshman SAT/ACT score

(2) The Proportion of the college's applicants who are rejected

(3) Tuition fees

(4) Full-time faculty-to-student ratio

(5) The per cent of the faculty with a doctorate degree

(6) The college's Barron's Index of Selectivity

Principal component analysis (PCA) is a popular technique for analysing datasets containing a high number of dimensions/features per observation, enabling the visualisation of multidimensional data. This is accomplished by linearly transforming the data into a new coordinate system where the variation in the data can be described with fewer dimensions than the initial data. One important difficulty in comparing three different datasets is that graduates would have different ages when taking the final year of interviews, which makes the results less comparative. Long (2010) uses linear extrapolation between the two estimated coefficients to estimate the effect after ten years graduated from high school for all the samples in different datasets. It is concluded that workers would have higher earnings from 2.6 to 4.8% with the increasing college qualities, according to different data used. Similar to Long, Borgan (2014) conducts an analysis based on the case of Norway, using the data from Norwegian administrative data with information on all Norwegian citizens born between 1955 and 1986. They argue that no study has a perfect measure of college quality. However, using a single quality indicator would result in attenuation bias. Therefore, in their analysis, the college quality comes from a latent index variable, which is composed of the following factors:

(1) Average GPA (the average of students' GPA from upper secondary education at the colleges)
(2) Faculty research points
(3) Faculty-student ratio
(4) The size of the student body

The estimated premium for college quality under linear regression is 5.76% with the growth of the quality index but decreases to 1.3% after considering the individual and family controls, self-revelation and sibling fixed effects. Self-revelation attempts to eliminate the possible confounding arose from unobserved endowments and ambitions, where the quality of students' college applications is used as an additional control. The sibling fixed effects are used to solve the problem of unobserved family or neighbourhood heterogeneity but assume that the variations are not for the siblings in the same family.

Besides using the quality index composed of several factors, a more simplified method to classify institution qualities is also accepted in literature, where only the difference between short-term vocational colleges and long-term academic universities is considered. For example, institutional quality is considered an important factor to affect graduates' wages by Chevalier (2003), alongside other explanatory variables such as degree qualities and postgraduate qualifications. The data comes from a postal survey organised by the University of Birmingham in the winter of 1996 among graduates from 30 higher education institutions covering a range of UK institutions. OLS results show that there would be no significant premium on individuals who graduated from universities compared with colleges. Following Chevalier (2003), Chevalier and Lindley (2009) also include the comparisons between colleges and universities in the analysis of over-education. Data comes from the 2006 UK Skills Survey, along with three earlier surveys: Employment in Britain in 1992, the 1997 Skills Survey, and the 2001 Skills Survey. However, the classification is more narrowed in their paper, which includes the following categories: (1) Old university (reference); (2) 1960s established universities; (3) New (post-1992) Universities; (4) Higher education colleges. Results from linear regression show that individuals who graduated from colleges suffer from 15% lower wages than those from old universities.

In China, the research on the return to college qualities is mainly based on the clear benchmarks for elite and non-elite institutions introduced officially by the government and widely accepted in the labour market. Li et al. (2011) find workers who graduated from 4-year universities would have 14.2% higher wages than those from 3-year colleges. Data used is the Chinese Twins Survey, carried out by the Urban Survey Unit (USU) of the National Bureau of Statistics (NBS) in June and July 2002 in five cities in China. This data is specifically designed for the analysis of twins. In the paper of Li et al., the within-twin fixed effect method is implemented to solve the possible bias generated by unobserved heterogeneity. Rather than roughly dividing higher education into colleges and universities, Li et al. (2012) also consider the elite universities defined by the unique "211" project in China. In the 1990s, the Chinese government put forward a proposal to ''enhance the quality of 100 colleges in the 21st century,'' which was later called the 211 Program. Although the proposal indicates only 100 colleges, in practice, 112 are covered by this program. The colleges covered by the Program have longer histories and offer high-quality education; more important, they also receive more financial support from the government. Taking the year 2008 as an example, 85% of the highest-ranked majors in China and 96% of national laboratories were reported to fall under these colleges, and the research funding received by these institutions accounted for 70% of total research funding received by all Chinese colleges. Therefore, three types of colleges are included in the analysis of Li: elite universities from the "211" project, non-elite ordinary universities and non-elite colleges. Data used are derived from the first round of the China College Social Survey (CCSS), carried out by the China Data Center of Tsinghua University in May and June 2010 and covers 19 institutions. Wage premium by attending elite colleges is found to be significant of 26.4% and decreases to 10.7% after adding controls such as location and household characteristics. Similar to Li, Zhong (2011) conduct an analysis based on the 2002 China Household Income Project (CHIP). It is concluded that individuals who graduated from 4-year universities have 25.9% higher wages than those who graduated from 3-year colleges, according to the OLS regression. The detailed college qualities are also considered but different from Li, the information comes from the respondents' self-evaluation, and the qualities consist of 5 categories: very poor, below average, average, good, and very good. Interaction terms are formed between college/university dummy and quality variables. Empirical results show that at the university level, wage returns would increase according to the growth of school qualities. The return condition for the college level is more complicated. The highest premium is found on very good colleges compared with poor colleges, but no significant premium on average colleges is found.

Though most of the studies focus on the differences between short-term colleges and long-term universities or elite and non-elite institutions, we still find an important example provided by Liu et al. (2021), who use different indicators to measure college qualities, similar to Long (2010) and Borgen (2014). Education qualities of different institutions are composed of 5 different factors, which are:

(1) Proportion of practical courses

(2) Student input

(3) Curriculum settings

(4) Teaching behaviours

(5) Graduate internship

The scores of each factor come from students' self-reported answers to related questions. For each question, there are four answers from totally disagree to totally agree, which indicates scores from 1 to 4. Instead of forming an overall index, these quality factors are separately added to the regression. It is concluded by Li et al. that no quality indicator would have a significant effect on graduates' starting salaries. However, for those individuals who cannot find jobs matching their graduate education levels, better curriculum settings and larger student input would help them decrease the wage penalty generated by job-education mismatch.

Though many studies conclude that elite colleges or institutions would result in higher returns in the labour market for graduates, few of them provide convincing explanations to the higher returns. In fact, theories covered in the return to education can also be used to explain the return to education qualities. Firstly, according to human capital theory (Becker, 1964), individuals who graduated from better resourced and higher ranked institutions would achieve higher levels of human capital and therefore have higher productivity and higher wages in jobs. However, the signalling theory (Spence, 1973) can also be referred to as that better education quality would serve as a signal of individuals having higher innate abilities, which would also contribute to the economic outcomes. Kang et al. (2021) emphasise that totally ignoring the unobserved heterogeneity that correlated with both the selection into different education qualities and wages would result in bias on the estimated returns. In addition, Li et al. (2012) further consider the effect of human capital factors that developed in the colleges alongside returns to education qualities, such as being a party member, having a technical certificate, being a leader for student unions and having part-time work experience. After controlling for these factors, it is found that the elite college premium is no longer significant, which provides evidence to the human capital explanation for the higher payoff to better education qualities. Aslam et al. (2012) divide the return to better educated individuals into three parts, which are returns to human capital accumulated, innate ability and credentials. Cognitive skills are used as proxies of skills or human capital, and individuals' innate abilities come from Raven Progressive Matrices Test scores. It is assumed that the return could also be a payoff to the specific diploma or qualification rather than individuals' actual productivity, also called the sheepskin effect (Belman and Heywood, 1990). The effect of innate ability is not found by Aslam et al., but a significant credential effect is concluded. However, the credential effect is not largely extended to the analysis of education qualities in the current literature.

5.2.1.2 Further Qualifications and Degree Classes

In our analysis, we would mostly focus on the education qualities that refer to the qualities (types) of institutions. We assume that graduates from better ranked or resourced colleges would have larger advantages in the labour market. However, some other criteria can be used to measure the educational achievements and excellence of graduates in the higher education level, such as holding postgraduate qualifications and having better classes of degrees. These classifications are based more on the individuals' input or investment into education rather than the original backgrounds. In fact, holding higher levels of qualifications and having better degrees are also treated as important determinants of wages in the literature, alongside institution qualities. Therefore, in the following, we list some important research findings.

Firstly, some researchers focus on the difference between various levels of qualifications in higher education. O'Leary and Sloane (2005) compare the wage return between postgraduates and undergraduates, using the Labour Force Survey in the UK from Spring 1994 to Winter 2000. It is found that postgraduates enjoy a higher wage return than individuals having first degrees, with 17 and 30% for males and females, respectively. O'Leary and Sloane also provide returns to a narrowed classification of postgraduates. Results show that individuals with PhD qualifications enjoy the highest return, but the wage difference between the PhD and master's degree is quite small for both males and females. Following O'Leary and Sloane, Walker and Zhu (2011) also use the Labour Force Survey, which includes pooled samples from 1994 to 2009. The postgraduate category contains degrees of PhD, Master, PGCE (a one-year professional training for those entering teaching) and others. It is estimated that male postgraduates have a higher return from 7.2-12.1% compared with undergraduates, according to different subject groups. Similar results are obtained from female graduates, that postgraduates also enjoy a higher return, from 15.8% - 20.1%. It is clear that females would enjoy a larger advantage by achieving postgraduate degrees. Also, similar to Walker and Zhu, Chevalier (2003) divides the postgraduate level into PhD, Master and PGCE. The returns are estimated separately for each category, but no wage premium is found for the postgraduate levels.

The analysis of the comparison between qualification levels is not easily conducted, mainly because of the data availability. Many social surveys do not provide detailed information on education levels higher than first degree, or even if provided, the number of observations would be an important restriction to the analysis because postgraduates only account for quite a small proportion among all the waged workers. Therefore, most of the researchers focus on another research idea, which is the heterogeneous return to various degree qualities (degree classes) within the undergraduate level. For example, Naylor et al. (2015) examine the degree class premium in the UK. They focus on the birth cohort of 1970 and compare three different datasets, which are British Cohort Study (BCS), Labour Force Survey (LFS) and University Statistical Record/First Destination Surveys (USR/FDS). Samples are divided into three parts according to the class of degrees: (1) graduates with "good" degree which contains first or upper-second degree classes; (2) graduates with "lower" degree which contains lower-second or below degree classes; (3) individuals with no tertiary education degrees but with two or more A level qualifications. Estimates show that for the 1970 cohort, the premium for a "good" degree relative to a "lower" degree is around 8% in both BCS and LFS data, whereas lower in USR/FDS data, with only 4.6%. These results clearly show the higher returns to earning a "good" quality of degree. Besides the UK, researchers also find a degree premium exists in German. Freier et al. (2015) use data from the University Graduates Panel provided by the DZHW organisation (German Centre for Research on Higher Education and Science Studies) in Hanover. Initial survey waves are from 1994 to 2006, conducted one year after students pass the first state bar exam. Only students from the subject of law are focused, and students with a degree of "honour" are defined as those who obtained more than a score of 9 (highest 15) in the bar exam, which accounts for around 30% of all the graduates. Empirical results show that graduates with honoured degrees would earn 21.8% higher monthly gross earnings, but the estimated parameter decreases to 12.5% if considering further controls such as parental backgrounds. The propensity score matching method is also used to compare with the results from linear regression. In the first step, each individual obtains a propensity score from the logit regression on selection into honoured degrees. In the second step, matching techniques are implemented to match those individuals in the treated and untreated groups according to their propensity scores and specific algorithms. Degree premium comes from the average treatment effect and is estimated to be 14.4%, which is quite similar to that under the linear regression model.

5.2.2 Return to Subjects

Similar to the education qualities, the heterogeneous returns to subjects of graduates are often considered in the literature. However, when subject return is considered, education quality variables often serve as important controls or interactions, especially in recent studies. O'Leary and Sloane (2011) consider the wage premium on graduates with different subjects to those who only achieve two or more A-level qualifications (or equivalent) but not college degrees. Data is derived from the UK Labour Force Survey and samples pooled from spring 1997 to winter 2006. In the regression model, O'Leary and Sloane introduce an inverse Mills ratio to correct the endogenous bias generated by the self-selection to colleges or universities. Subjects are divided into nine categories, and empirical results show that individuals who graduated from Medicine and related subjects enjoy the highest return for both males and females in the 1997-9 and 2004-6 year periods. Other high-payoff subjects include Math & Computing and Engineering & Technology. However, male graduates from the subject of Arts suffer from a negative premium, especially in low wage quartiles. Female graduates from Arts have a positive wage return but also rank at the bottom among all the subject groups. Chevalier (2011) also focuses on the case of the UK and includes a random sample of graduates from the academic year 2002/2003. Data comes from the Longitudinal Destinations of Leavers of Higher Education. Besides subjects, A-level scores, family backgrounds, institution types and degree classes are included as pre- and post-university characteristics. It is concluded that Medicine and related subjects enjoy the highest wage return, from 41.3 to 61.1% across different quartiles, compared with the subject of "others". Chevalier also proposes the estimated log wages for different subjects based on the mean value of individuals' characteristics and finds out that graduates from Medicine, Engineering & Computing and Accounting & Finance enjoy the highest three predicted log wages in different wage quartiles.

O'Leary and Sloane (2005) estimate the subject wage returns by using Arts as the baseline subject. In fact, graduates from 10 other subjects are shown to have higher wage returns than Art for both males and females. If considering student qualities, those ranked in the top three are Math & Computing, Engineering & Technology, and Business & Financial Studies for males. Regarding females, those ranked in the top three are Education, Medicine & related and Architecture & related. O'Leary and Sloane also provide results on a more narrowed classification of subjects, and in total, there are more than 25 subjects included. The subject return ranks at the top is Accountancy, for both males and females. However, the return to Arts still ranks at the bottom. More importantly, it is found that graduates learning Arts suffer from a negative premium to individuals with two or more A-level qualifications in the group of males. Though the narrowed and detailed classification of subjects is a prior choice when studying subject return, sometimes re-categorizing subjects into more broad groups is also acceptable, especially when the number of total observations imposes restrictions. Walker and Zhu (2011) re-categorize the subjects into the following four groups:

(1) STEM: Science, Technology, Engineering, Mathematics and Medicine

(2) LEM: Law, Economics and Management

(3) SSAH: Other Social Science, Arts and Humanities, which includes Languages

(4) COMB: Combined degrees with more than one subject

Using the Labour Force Survey in the UK, Walker and Zhu (2011) provide empirical results on the financial rate of returns to subjects. They calculate the net present values on the payoff of attending colleges (accounting for tuition fees and opportunity costs relative to workers with 2+A-levels) and obtain the internal rate of return (IRR) for different subjects with different degree classes. It is concluded that returns to different subjects are quite similar for females, but male workers who graduated from the LEM group enjoy considerably a larger return than those from other subjects, with 12.5%. In addition, graduates with a higher degree class (upper second and above compared with lower second and beneath) would earn higher payoffs in each subject group.

The research on subject return in China is limited, mainly because of the availability of data. Li et al. (2011) use subject dummies as controls in the analysis of elite college premiums, but they use data from CCSS, which is a non-public dataset and the results on return to different subjects are not clearly illustrated. However, we find one important paper written by Kang et al. (2021), which comprehensively analyses the return to subjects and institution qualities using the data from China Family Panel Studies (CFPS). Colleges are divided into three types, which are: key universities from "211" and "985" projects, other ordinary universities and vocational colleges. For each college type, there are three groups of subjects:

STEM: Sciences, Engineering, Agriculture and Medicine

LEM: Law, Economics and Management

Other Subjects: Philosophy, Education, Literature and History

Kang et al. take advantage of the longitudinal feature of the dataset and include observations from 2010, 2012 and 2014. Empirical results are obtained from pooled samples and random effects. It is concluded that college premiums (compared with high school qualifications) increase with the growth of school qualities. For example, from the STEM group, the premiums for college, ordinary university and key university are 25.4%, 34.6% and 62.1% for males, and 21.7%, 51.7% and 60.6% for females, respectively. This trend also exists in other subjects such as LEM and Others. Regarding the wage disparities in different subjects, the return to LEM and Others are quite similar under most education qualities. However, considerably larger returns to different institution types are found for females in STEM. For example, in the key university group, the returns are 60.6%, 55.9% and 48.4% for STEM, LEM and Others, respectively. In addition, in the ordinary university group, the returns are 51.7%, 39.8%, and 42.9% for STEM, LEM and Others, respectively.

5.2.3 Hypotheses for Return to Education Qualities and Subjects in China

In the previous studies in China, most researchers devote effects to examining the return to tertiary education or the higher education wage premium to emphasise the labour market payoff for entering colleges in China. However, for recent China, the higher education expansion policy has been proposed for decades, and gross enrollment has increased dramatically over the years. Concerns are driven by whether graduates could find appropriate graduate jobs in the labour market. The educational backgrounds, such as the skills and knowledge acquired in different education qualities and subjects, may show a more determinant role in labour market payoffs and lead to heterogeneous returns within the graduates' group. For example, Yang and Maresova (2020) point out that during the expansion period, the development of low-quality institutions is much faster than other conventional well-famous colleges. The supply shock on low-quality institutions may lead to a drop in equilibrium wages for workers who graduated from these institutions. Also, in colleges of low quality, students may find it harder to have networks with more creative and innovative students and will accumulate social capital considerably slower than those students in high-quality colleges. In addition, because of the limited vacancies in the labour market, some graduates are forced to choose jobs not closely related to their previously studied subjects. They will be tested to be less productive than counter-partners in jobs and suffer from a worse performance and lower payoff.

The previous empirical contributions in the literature support the idea of heterogeneous returns in different education qualities and subjects. Firstly, graduates from better colleges often enjoy a significantly higher return, for example, in the UK (Chevalier and Lindley, 2009) and the US (Long, 2010). Results are consistent according to various methods to define education quality, including using indexes or a more general way through the differences between vocational colleges and academic universities. In addition, studies in the literature often find a higher return for subjects of Engineering and Medicine (O'Leary and Sloane, 2011; Chevalier, 2011). The wage return to the subjects such as Arts and History often rank at the bottom. However, these results are not supported in some Chinese literature. For example, Fan and Zhang (2015) find out that graduates studying Economics and Law would have significantly higher returns than other subjects.

The study of the heterogeneous returns to education qualities and subjects has not been focused extensively in the Chinese literature, especially those studying subject returns. To our current knowledge, only Fan and Zhang (2015) and Kang et al. (2021) provide empirical evidence on the wage return to different subjects among Chinese graduates. Based on the existing research contributions in advanced countries and the inconsistent empirical results concluded from China and international studies, we propose the following hypotheses for this analysis:

(1) Workers graduated from colleges of higher quality enjoy significantly higher wage returns

(2) Returns to subjects are heterogeneous among graduates in the Chinese labour market

5.3 Institutional Background

China introduces 9-year compulsory education starting at age 6, with six years of primary education and three years of lower high school education. After nine years of studying, those capable students are able to attend upper high school education. At the high school level, individuals have the chance to choose their education types, including vocational and academic schools. The duration of both types of high schools is three years.

After 12 years of schooling, high school graduates can apply to colleges and universities through a centralised admissions system that directly leads to tiers based on the scores in the standardised National College Entrance Examinations, known as gaokao (Zhu 2014). Colleges and universities in China can be classified into three tiers in descending order of prestige (quality) and entry requirements: Key Universities, Ordinary Universities, and vocational training colleges (Kang et al., 2021). The duration of study for the Key Universities and Ordinary Universities is typically four years, leading to a bachelor’s degree and qualification. The duration of study for vocational training colleges is three years, leading to a vocational college qualification but no degrees. Specifically, the key university group include institutions in the "985" and "211" projects, which are considered top higher education institutions in China. In the following subsection, we will introduce the two projects in detail.

5.3.1 Introduction to "211" and "985" Projects

(1) "211" project: In the 1990s, the Chinese government put forward a proposal to ''enhance the quality of 100 colleges in the 21st century,'' which was later called the 211 Program. Although the proposal indicates only 100 colleges, in practice, 116 are covered by this program. The colleges covered by the Program have longer histories and offer high-quality education; more important, they also receive more financial support from the government. Taking the year 2008 as an example, 85% of the highest ranked majors in China and 96% of national laboratories were reported to fall under these colleges, and the research funding received by these institutions accounted for 70% of total research funding received by all Chinese colleges (Li et al., 2012).

(2) "985" project: This project is based on a major decision made by the Chinese government at the turn of the 21st century to build first-class universities with worldwide reputations in China. The name of the project comes from the idea put forward by President Jiang Zemin at the centennial celebration of Peking University in May 1998 (985). Initially, this project consisted of 9 universities, including two highest ranked schools, Peking University and Tsing Hua University. Till now, there are in total 39 universities covered by the project, which are normally considered as best universities in China. All the schools from the "985" project are also members of the "211" project.

5.4 Data, Sample and Variables

5.4.1 Data Description and Sample Restrictions

In this analysis, we still implement the data provided by China Family Panel Studies (CFPS) because it has important information that can help answer our research questions. Firstly, the information on the classification of college qualities is provided in the initial CFPS dataset, including the differences between short-term college/long-term universities and key/ordinary universities. Secondly, CFPS provides information on graduates' subjects, and the classification scheme is totally consistent with the national standard provided by the Chinese Ministry of Education. In the following part 3, we introduce how we define variables on education qualities and subjects used in our analysis based on initial information in CFPS.

For the observations, similar as before, we directly take advantage of the adult survey and focus on the self-reported answers from individuals. We only include individuals with college/university qualifications, consistent with the fourth chapter. Individuals with high school education levels are excluded because we do not want to estimate a college wage premium between education levels but only would like to examine the wage differences in different education qualities and subjects within the tertiary education level. In addition, individuals who have overseas education background are also excluded because their information is not available in the CFPS. Similar to previous chapters, we only include individuals within the working age (16-60 for males and 16-55 for females) who are doing waged work as main jobs and are not currently enrolled in education. We do not have information on labour market outcomes for self-employed workers. Therefore, these individuals are excluded from the wage equation. However, these observations, alongside those outside the labour market, can help solve the self-selection bias and are included in the first step of the Heckman (1979) method.

Besides the sample groups, we still need to consider the time periods to be included in our analysis. We decide to use the survey wave of 2010 and conduct a cross-section analysis. Some researchers consider using the longitudinal feature of the data to form a penal with larger observations, for example, Kang et al. (2021). In fact, the most important advantage of using the wave 2010 is that we can have full information on education qualities and skills with limited missing values. The main reason not to use waves after 2010 (for example, 2014 and 2018) is that the information to clarify key and ordinary universities is only provided in the baseline year 2010. Though CFPS has a longitudinal feature, the follow-up rate between years is only around 70%.

Therefore, we would suffer from large numbers of missing values on education qualities in the following years. Also, the information on individuals' skills suffers from large missing values in years after 2014. Since skills would vary for workers across years, unlike the education qualities and subjects, this problem cannot easily be solved using links in time. In addition, the educational variables, including education qualities and subjects, are not time-variant, which means we are not able to conduct the fixed effect method in the longitudinal analysis to solve the most important problem of unobserved heterogeneity. The pooled panel and random effects can be considered, but none of these methods can solve the possible bias generated by unobserved heterogeneity. Since the follow-up rate in CFPS is only 70%, individuals may show up with different times in different years in survey waves. If we obtain an unbalanced panel, different individuals will have various weights, possibly generating bias in estimation results. More importantly, another reason not to take advantage of the longitudinal feature is that the wage income in 2010 does not specify whether it is after-tax or not. However, in the waves after 2014, it is clearly emphasised by CFPS that all wages recorded are after tax and deduction of necessary payments, such as insurance and pensions. It does not mean that the wage information in 2010 cannot be used, but we need to be very cautious if we want to conduct empirical studies across the years. In summary, we still decide to conduct a cross-section analysis in this chapter.

For the variables, in each specification, we include three sets. The first is the individual characteristics, including ethnicity, gender, age, marriage status, and urban/rural registration status. The second is the job characteristics containing sector, industry, occupation, and previous job experience. We do not have any information on contract type and firm size in the first wave of CFPS, which is different from the waves used in the previous chapters. The third is the skills controls, including cognitive and non-cognitive skills. We would like to see to what extent the gaps between different education qualities and subjects are driven by individuals' human capital achievements. For non-cognitive skills, we only have information on the locus of control but not on personality traits. Therefore, the locus of control is the only representative of individuals' non-cognitive skills in this analysis. There are some variables that are specifically considered as controls in the analysis of subject return, such as scores of entrance examination, classes of degree and fee status (Chevalier, 2011). However, information on these factors is not available in CFPS. After dropping observations with missing values on important variables, the final sample is 870 graduates of wage earners. In the following Table 5.1, we show the steps of sample restrictions in detail. In Table 5.2, we illustrate the employment status composition, covering other sample graduates, such as those doing self-employed jobs.

Table 5.1: Sample restrictions

Actions	**Observations left**	**Percentage**
Total adult self-reported observations	33598	100%
Drop over-sampling observations	21810	64.91%
Drop age > 60	17766	52.88%
Drop age > 55 female	16720	49.76%
Labour market employment	12395	36.78%
Keep wage earners	5015	14.93%
Keep tertiary education level	956	2.85%
Drop missing values on core variables	870	2.59%

The Original CFPS dataset we use is from the adult survey that only with individuals older than 16

Table 5.2: Distribution of employment status for sample graduates

	Wage earners	**Non-wage earners**			**Total**
	Employed by others	Unemployed	Self-employed	Not in the labour market	
All	870 74.94%	55 4.74%	131 11.28%	105 9.04%	1161 100%
Male	454 76.17%	22 3.69%	85 14.26%	35 5.87%	596 100%
Female	416 73.63%	33 3.09%	46 9.12%	70 11.40%	565 100%
Urban	714 78.46%	36 3.96%	85 9.34%	75 8.24%	910 100%
Rural	156 62.15%	19 7.57%	46 18.32%	30 11.95%	251 100%

5.4.2 Definitions and Classifications on Education Qualities and Subjects

5.4.2.1 Education Qualities

It is mentioned in the previous subsection that CFPS provides some direct information to classify tertiary education qualities (institution types). Our measurements would base mostly on this information. Firstly, the classification between vocational college and academic university is commonly found in the analysis of tertiary education in the literature. Generally speaking, universities often aim to teach fundamental and advanced knowledge, whereas colleges normally focus on specific skills that would be directly used in the labour markets. The entry requirement on entrance examination scores is often higher for academic universities than vocational colleges, and universities are considered to be in a tier with higher prestige in China (Kang et al., 2021). Therefore, following the classification methods that are often used in the literature (e.g. Zhong, 2011; Li, Liu and Zhang, 2012), we can define two dummies indicating the university type, which are:

University: this dummy equals 1 if an individual has a university qualification and 0 otherwise

College: this dummy equals 1 if an individual has college qualification and 0 otherwise

In Chinese literature, the biggest difference between colleges and universities is considered to be the education qualities (Kang et al. 2021). However, there may be a potential overlap or conflation with the data between education quantity and quality. For example, when moving from three-year college to four-year university courses, there is a 33% increase in quantity (years) when moving from college to university, as well as a potential increase in quality, such as better qualified faculty and teaching resources. The effect of entering universities may be confounded by these two factors. However, because of the data limitation, we are not able to distinguish them. Therefore, we follow the normal measurements in Chinese literature and hold the idea that the gap between institutions is mainly driven by education qualities.

Secondly, besides roughly dividing tertiary education into two parts according to various systems, academic universities can still be classified further according to institution qualities. CFPS provides such information that divides universities into key and ordinary. Key universities are those defined officially by the country from the "985" and "211" projects, which are widely accepted as the top universities in China. Currently, there are 39 universities in the "985 project" and 116 universities in the "211" project, and the list has not been changed for decades. The rest of the universities are considered ordinary universities. Therefore, based on this criterion, we can form the following dummy variables for the quality of university institutions, similar to Li et al. (2012) and Kang et al. (2021):

KeyUni: this dummy equals 1 if an individual graduated from key universities and 0 otherwise.

OrdinaryUni: this dummy equals 1 if an individual graduated from ordinary universities and 0 otherwise.

5.4.2.2 Subjects

In China, according to the “Catalogue of Subjects for Degree Awarding and Talent Training” officially published by the Academic Degrees Committee of the State Council (2011), 12 subjects are defined which are Science, Engineering, Agriculture, Medical Science, Law, Economics, Management, Philosophy, Education, Literature, History and Military. The classification in CFPS totally follows the national standard. In fact, it is quite easy that we can form different dummies for each subject group and examine the wage differences between them. However, this measurement would be restricted by the low observations because there could be a very limited number of graduates in some of the subjects, even if we consider including different waves, such as philosophy and history. Therefore, we try to recategorise these subject units with the help of analyses in the literature.

Firstly, we categorise some of the subjects into two groups, STEM and LEM, following the suggestion of Kang et al. (2021), who also use the CFPS dataset. STEM is the abbreviation of “Science, Technology, Engineering and Mathematics”, and in our analysis, it includes Science (including Maths), Engineering, Agriculture and Medical Science. LEM includes the subjects of Law, Economics and Management. In our analysis, the rest of the subjects are included in the group of SSAH (abbreviation of Social Science, Art and Humanities) as introduced in Walker and Zhu (2018), which covers Philosophy, Education, Literature and History. We do not have observations in the subject of Military in the dataset. Therefore, we do not need to categorise it. In summary, the subject dummies after re-categorisation are shown as follows:

STEP: this dummy equals 1 if an individual graduated from subjects of Science, Engineering, Agriculture and Medical Science, and 0 otherwise.

LEM: this dummy equals 1 if an individual graduated from subjects of Law, Economics and Management, and 0 otherwise.

SSAH: this dummy equals 1 if an individual graduated from subjects of Philosophy, Education, Literature and History, and 0 otherwise.

After the dummies of education qualities and subjects are defined, we can form interaction terms of education qualities and subjects using these dummies. We will show this in detail in the following methodology part.

5.4.3 Variables

Despite the measurements on education qualities and subjects, in this part, we further introduce other variables used in the specifications in detail that are mentioned before. In fact, most of the variables have the same definitions as those 3.4 in Chapter 3, including individuals' wages, basic characteristic controls and most of the employment controls. In this part, we only cover the definitions of those new variables or those with different definitions. However, we provide a summation of notations and descriptive statistics on all the variables used in this chapter, illustrated in tables 5.4, 5.5 and 5.6 at the end of this part.

5.4.2.1 Individuals' Wages

Using hourly wages is considered the most precise measurement when estimating the return to education because sometimes individuals would have higher monthly or yearly wages due to their longer working hours rather than higher productivity. In Chapter 5, we have some slight variations in the measurements of hourly wages compared with previous chapters. For the first step, we acquire the information on the "average monthly wage income of last 12 months" in the dataset. Then we can generate the hourly wage by dividing the monthly wage by a worker's total hours worked in a month, which is the same measurement as the previous chapters.

However, in the 2010 wave, we do not need to assume that all individuals work every week in a month because we have direct information on how many days to work in a month and how many hours to work per day. From this information, in fact, we can generate a more accurate hourly wage for individuals. The formula is shown as follow:

hourly wage = monthly wage/days worked in a month/hours worked per day

The monthly wage is also the gross one, including net wage and different kinds of cash rewards, subsidies and bonuses. The net wage in China is the basic wage obtained regularly each month without considering other extras. The rewards are categorised into two parts. The first is the normal monthly reward, and the second is the annual one provided at the end of the year, which can also be transferred monthly. The components of hourly wage are consistent between chapters. However, the biggest difference is that the 2010 wave does not specify whether these income components are after-tax or not. However, in the waves after 2014, it is clearly emphasised by CFPS that all the wages recorded are after tax and deduction of necessary payments, such as insurance and pensions. It does not mean that the wage information in 2010 cannot be used, but we need to be very cautious if we want to conduct a longitudinal analysis across years.

5.4.2.2 Non-cognitive Skills

It is mentioned in the previous part that there is an increasing number of evidence in the literature that better non-cognitive skills would also help increase individuals' wages. Normally, a widely accepted comprehensive measurement of non-cognitive skills may include the "Big Five" personality traits and locus control. However, in the survey wave 2010, only scores of locus of control are available. Therefore, we only add the locus of control to represent non-cognitive skills in regressions.

The theory of locus of control is first raised by Rotter (1966), which mainly reflects an individual's attitudes to life and enthusiasm. Individuals with the characteristics of external control consider that their behaviour results are controlled by external forces such as opportunity, luck, fate and authority, and they are powerless and lack of self-belief. In contrast, individuals with the characteristics of internal control believe that their activities and results are determined by their own internal factors and that their own abilities and efforts can control the development of the situation. In our analysis, the locus of control is based on the following six questions in the table. Individuals will be scored from 1 to 5 according to their self-reported answers to the question. We make sure all the question answers are in the same direction that higher scores reflect more external control and take the average of all the scores to be the final score of locus of control[1].

Table 5.3: Skills and questions related

Skills	Related questions
Locus of control	Wealth reflects personal achievement
	Hard work pays off
	Intelligence pays off
	Social relationship is more important than hard work
	There are great opportunities to improve living standards
	I am Confidence in the future

Source: CFPS survey

5.4.2.3 First Job

In the survey wave of CFPS 2010, we can have access to information on the previous job experience for each individual. For the analysis using later survey waves, we only use age or potential job experience (age - education years - 6) but do not control the actual working experience. In this analysis, the information on job experience comes from the question: "Is the current job your first job?". This question only shows up in the survey wave of 2010. We can simply form a dummy equal to 1 if the answer is yes, and equal to 0 if no. Individuals may be more familiar with the job they are doing if they have previous experience and are more easily allocated to important positions, which would help them be more productive than their counter partners and achieve higher economic outcomes.

1. The score ranges from 1 to 5, indicating the answer of totally disagree, disagree, neutral, agree and strongly agree.

5.4.2.4 Descriptive Statistics

In this subsection, the notations and brief introductions of all the variables used are included in the following tables. We also provide statistics on all the variables included, according to different education qualities and subject groups. Important findings are summarised as follows:

(1) University graduates have higher hourly wages than college graduates. In addition, workers who experienced better education qualities in the university group would have better economic achievements. However, the gaps in wages between different subject groups are quite small.

(2) Gender difference between males and females is not found in China on tertiary education admissions, and female admissions are slightly higher than males, according to the information from wage earners.

(3) Most of the graduates choose to work in cities, regardless of their education qualities and subjects. Only 15% of graduates are employed in the rural labour market, which is smaller with better education qualities. Regarding the subjects, we find STEM group accounts for the highest proportion of workers in rural areas.

(4) For skills, university graduates generally have higher cognitive skills than college students. However, it is interesting to see that individuals with lower education qualities are not disadvantaged in cognitive skills, for both literacy and numeracy, within the university group. Individuals with key university experience even have slightly lower skill levels than ordinary ones. Regarding non-cognitive skills, we do not find large gaps between different education qualities. In addition, considering the subjects, limited variations are found regardless of the cognitive or non-cognitive skills.

Table 5.4: Summary statistics on variables for different education qualities (College/University)

Variable	All graduates		4-year university		3-year college	
	Mean	Sd.	Mean	Sd.	Mean	Sd.
Lnwage log hourly gross wage	2.482	0.682	2.632	0.616	2.391	0.705
Male male = 1, female = 0	0.522		0.520		0.523	
Age Individual's age	35.284	8.716	34.685	7.712	35.645	9.256
Age square Age square	1320.83	656.82	1262.34	584.13	1356.05	695.07
Minority Minorities = 1, "Han" = 0	0.074		0.073		0.074	
Marriage Currently married with living spouse = 1, others = 0	0.777		0.789		0.770	
Urban "Hukou" Registration status of urban = 1, others = 0	0.891		0.954		0.853	
Urban residence living in urban areas = 1, living in rural areas = 0	0.852		0.906		0.829	
Northeast Living in Northeast China = 1, others = 0	0.179	0.384	0.196	0.397	0.169	0.375
East Living in East China= 1, others = 0	0.324	0.468	0.330	0.471	0.320	0.467
Middle Living in Middle China = 1, others = 0	0.315	0.465	0.321	0.468	0.311	0.463
West Living in West China = 1, others = 0	0.182	0.428	0.153	0.425	0.200	0.469
Public sector Public sector = 1, others = 0	0.690		0.737		0.661	
Raw materials Raw materials = 1, others = 0	0.023	0.048	0.015	0.048	0.028	0.061
Manufacturing Manufacturing = 1, others = 0	0.230	0.421	0.141	0.348	0.284	0.451
Retailing and wholesaling Retailing and wholesaling = 1, others = 0	0.074	0.261	0.052	0.222	0.087	0.281
Other services Other services = 1, others = 0	0.673	0.361	0.792	0.363	0.601	0.365
First job First job ever = 1, having other jobs before = 0	0.636		0.679		0.610	
Numeracy Test scores on numeracy	19.055	2.185	19.434	2.209	18.827	2.140
Literacy Test scores on literacy	29.280	3.756	30.355	3.093	28.634	3.969
Locus of control Self-assessment scores on locus of control	3.259	0.538	3.249	0.561	3.264	0.525
Young children Number of children younger than 14 years old in the family	0.497	0.567	0.554	0.551	0.462	0.575
Old people Number of elderly greater than 65 years old in the family	0.199	0.485	0.177	0.494	0.212	0.480

Samples for the descriptive statistics are for wage earners, except the number of young children and old people in the family are based on samples from different employment status

Table 5.5: Summary statistics on variables for different education qualities (Key/Ordinary)

Variable	Key university		Normal university		College	
	Mean	Sd.	Mean	Sd.	Mean	Sd.
Lnwage log hourly gross wage	2.843	0.651	2.572	0.593	2.391	0.705
Male male = 1, female = 0	0.500		0.525		0.523	
Age Individual's age	33.556	7.087	35.004	7.863	35.645	9.256
Age square Age square	1175.500	525.400	1286.863	598.418	1356.057	695.074
Minority Minorities = 1, "Han" = 0	0.056		0.078		0.074	
Marriage Currently married with living spouse = 1, others = 0	0.778		0.792		0.770	
Urban "Hukou" Registration status of urban = 1, others = 0	0.944		0.957		0.853	
Urban residence living in urban areas = 1, living in rural areas = 0	0.914		0.891		0.829	
Northeast Living in Northeast China = 1, others = 0	0.153	0.362	0.208	0.407	0.169	0.375
East Living in East China= 1, others = 0	0.417	0.496	0.306	0.462	0.320	0.467
Middle Living in Middle China = 1, others = 0	0.361	0.484	0.310	0.463	0.311	0.463
West Living in West China = 1, others = 0	0.069	0.497	0.176	0.482	0.200	0.469
Public sector Public sector = 1, others = 0	0.653		0.761		0.661	0
Raw materials Raw materials = 1, others = 0	0.006	0.018	0.020	0.012	0.028	0.061
Manufacturing Manufacturing = 1, others = 0	0.139	0.348	0.141	0.349	0.284	0.451
Retailing and wholesaling Retailing and wholesaling = 1, others = 0	0.097	0.298	0.039	0.194	0.087	0.281
Other services Other services = 1, others = 0	0.758	0.251	0.800	0.283	0.601	0.365
First job First job ever = 1, having other jobs before = 0	0.653		0.686		0.610	
Numeracy Test scores on numeracy	19.403	2.193	19.443	2.217	18.827	2.140
Literacy Test scores on literacy	30.375	3.124	30.349	3.090	28.634	3.969
Locus of control Self-assessment scores on locus of control	3.157	0.498	3.275	0.576	3.264	0.525
Young children Number of children younger than 14 years old in the family	0.597	0.573	0.541	0.545	0.462	0.575
Old people Number of elderly greater than 65 years old in the family	0.139	0.387	0.188	0.521	0.212	0.480

Samples for the descriptive statistics are for wage earners, except the number of young children and old people in the family are based on samples from different employment status

Table 5.6: Summary statistics on variables for different subjects (re-categorization)

Variable	STEM		LEM		SSAH	
	Mean	Sd.	Mean	Sd.	Mean	Sd.
Lnwage log hourly gross wage	2.468	0.698	2.493	0.702	2.477	0.626
Male male = 1, female = 0	0.605		0.535		0.390	
Age Individual's age	33.535	8.747	35.884	8.169	36.429	9.337
Age square Age square	1200.834	644.158	1354.239	620.517	1413.810	716.585
Minority Minorities = 1, "Han" = 0	0.059		0.082		0.076	
Marriage Currently married with living spouse = 1, others = 0	0.712		0.802		0.814	
Urban "Hukou" Registration status of urban = 1, others = 0	0.867		0.910		0.886	
Urban residence living in urban areas = 1, living in rural areas = 0	0.821		0.901		0.887	
Northeast Living in Northeast China = 1, others = 0	0.177	0.382	0.172	0.378	0.195	0.397
East Living in East China= 1, others = 0	0.325	0.469	0.326	0.470	0.319	0.467
Middle Living in Middle China = 1, others = 0	0.299	0.459	0.334	0.472	0.300	0.459
West Living in West China = 1, others = 0	0.199	0.523	0.168	0.498	0.186	0.519
Public sector Public sector = 1, others = 0	0.646		0.650		0.819	
Raw materials Raw materials = 1, others = 0	0.048	0.120	0.018	0.072	0.008	0.010
Manufacturing Manufacturing = 1, others = 0	0.343	0.476	0.231	0.422	0.081	0.273
Retailing and wholesaling Retailing and wholesaling = 1, others = 0	0.055	0.229	0.111	0.314	0.029	0.167
Other services Other services = 1, others = 0	0.604	0.369	0.640	0.328	0.882	0.343
First job First job ever = 1, having other jobs before = 0	0.649		0.568		0.743	
Numeracy Test scores on numeracy	19.624	2.368	18.661	2.091	19.052	1.942
Literacy Test scores on literacy	29.192	3.604	29.031	3.909	29.857	3.613
Locus of control Self-assessment scores on locus of control	3.290	0.548	3.213	0.542	3.304	0.514
Young children Number of children younger than 14 years old in the family	0.454	0.575	0.519	0.545	0.510	0.597
Old people Number of elderly greater than 65 years old in the family	0.125	0.374	0.221	0.515	0.252	0.543

Samples for the descriptive statistics are for wage earners, except the number of young children and old people in the family are based on samples from different employment status

5.5 Methodologies

5.5.1 Return to Education Qualities

We start with a specification on the effect of education qualities on wages:

$$\mathrm{lnwage_i} = \beta_0 + \beta_1 \mathrm{University_i} + \boldsymbol{\beta_2 X_1} + \boldsymbol{\beta_3 X_2} + \boldsymbol{\beta_4 X_3} + \mathrm{u_i} \qquad (1)$$

In this specification, as defined in the previous part, University is a dummy variable which equals 1 if individuals have a long-term university qualification and 0 otherwise. The reference group is the short-term college graduates, and the coefficient β_1 indicates the wage premiums on average of university graduates to those only with short-term college qualifications. $\mathbf{X_1}$ is a set of variables including individual characteristics, such as gender, ethnicity, age, marriage status, provinces, urban areas and registration status. $\mathbf{X_2}$ is a set of variables including employment characteristics such as sector, occupation, industry and previous job experience. $\mathbf{X_3}$ is a set of skill variables, including cognitive skills (numeracy/literacy) and non-cognitive skills (locus of control).

Second, we can consider a more detailed classification of long-term universities, including key and ordinary universities:

$$\mathrm{lnwage_i} = \gamma_0 + \gamma_1 \mathrm{KeyUni_i} + \gamma_2 \mathrm{OrdinaryUni_i} + \boldsymbol{\gamma_3 X_1} + \boldsymbol{\gamma_4 X_2} + \boldsymbol{\gamma_5 X_3} + \varepsilon_\mathrm{i} \qquad (2)$$

In this specification, as defined before, KeyUni is a dummy variable which equals 1 if an individual graduated from key universities and 0 otherwise. OrdinaryUni is a dummy variable which equals 1 if an individual graduated from ordinary universities and 0 otherwise. The reference group is also the short-term college graduates. Other variables are totally the same as in specification (1).

5.5.2 Return to Subject Groups

Now we can consider the wage return to different subjects:

$$\text{lnwage}_i = \delta_0 + \delta_1\text{STEM}_i + \delta_2\text{LEM}_i + \boldsymbol{\delta_3 X_1} + \boldsymbol{\delta_4 X_2} + \boldsymbol{\delta_5 X_3} + \epsilon_i \qquad (3)$$

In this specification, it is clear that we have two dummies of STEM, LEM indicating two different groups of subjects, and the reference subject group is SSAH. Detailed definitions are proposed in section 3. Other variables are totally the same as in specification (1).

5.5.3 Return to Education Qualities and Subjects

In this part, we would like to add both dummies of education qualities and subjects together in one specification to see the effect of education qualities and subjects simultaneously. Firstly, we add only add one dummy of education quality:

$$\begin{aligned}\text{lnwage}_i = {} & \mu_0 + \mu_1\text{University}_i + \mu_2\text{STEM}_i + \mu_3\text{LEM}_i + \boldsymbol{\mu_4 X_1} + \boldsymbol{\mu_5 X_2} + \boldsymbol{\mu_6 X_3} \\ & + \sigma_i \qquad (4)\end{aligned}$$

Secondly, we consider two dummies of education quality, including key and ordinary universities:

$$\begin{aligned}\text{lnwage}_i = {} & \rho_0 + \rho_1\text{KeyUni}_i + \rho_2\text{OrdinaryUni}_i + \rho_3\text{STEM}_i + \rho_4\text{LEM}_i + \boldsymbol{\rho_5 X_1} \\ & + \boldsymbol{\rho_6 X_2} + \boldsymbol{\rho_7 X_3} + \tau_i \qquad (5)\end{aligned}$$

Based on specifications 4 and 5, we can further form interaction terms between education qualities and subject groups. In specification 4, we have one dummy on education quality and two dummies on subject groups, leading to two interactions. In specification 5, we have two dummies on education quality and two dummies on subject groups, leading to four interactions. Based on the interactions, we can examine the wage effect of education qualities in different subject groups and also the return to different subjects in different college types. Detailed empirical results on interaction terms are shown in the following section.

The OLS estimation of the previous specifications may suffer from the problem of selection bias because wages observed are only for employees. This may result in the expected value of the error term not being equal to zero, which violates the basic assumption of OLS. Therefore, we follow the Heckman (1979) two-step method to solve the selection bias, which is also a widely accepted method in the literature. In the first step, we run a probit model on paid job participation and obtain an inverse Mills ratio. In this model, the dependent variable of paid job participation is a dummy where wage earners = 1 and non-wage earners (including those self-employed, unemployed and not in the labour market) = 0. In the second step, we add the inverse Mills ratio as an extra explanatory variable into the wage equation to eliminate the possible selection bias. To satisfy the exclusion restriction and achieve higher identification, in the first step, we need to add (at least) one instrument variable that affects individuals' choices to be waged workers but has no partial effect on individuals' labour market outcomes (Wooldridge, 2016). We follow the literature to use the number of elderly and young persons in the family as instruments. Though in our analysis, we only include those individuals with higher education, the rationale of the choosing instrument variables is still acceptable where we can assume workers may need more time to take care of family members and choose a job with more flexible time arrangements or even decide not to participate into the labour market. The Heckman method is used in all of the specifications previously mentioned.

5.6 Summary Statistics on Sample Size by Education Qualities and Subject Groups

In this part, we show descriptive tables on the composition of graduate samples for different types of education qualities and subjects.

5.6.1 Education Qualities

From Table 5.7, we can find that more than 60% of graduates have taken short-term courses in higher education in China. Individuals who graduated from universities only account for 37.59% of all the 870 observations. However, though more people are holding short-term qualifications in the existing labour market, Kang et al. (2021) point out that after the expansion period after 1999, total enrollments of students are quite similar in universities and colleges, showing the universities benefit more in the scale development under the “expansion policy”.

From Table 5.8, we further disaggregate the university group into two parts by key and ordinary. It can be seen that only 8.28% of individuals graduated from key universities. This number is quite smaller than that of normal universities, and the proportion of graduates from colleges is 8 times higher than key universities. As mentioned before, these individuals come from the “985” and “211” projects and are considered the best students in China. The low supply of this group of students helps them to be more preferable in the labour market.

Table 5.7: Distribution of graduate samples by education qualities (College/University)

College types	Frequency	
4-year university	327	37.59%
3-year college	543	62.41%
total	870	100%

Table 5.8: Distribution of graduate samples by education qualities (Key/Ordinary)

College types	Frequency	
Key university	72	8.28%
Ordinary university	255	22.27%
3-year college	543	62.41%
Total	870	100%

5.6.2 Subjects

Table 5.9 illustrates the frequencies of graduates in different subject groups. It can be seen that the number of graduates learning LEM is the largest among all the observations. Around 31.1% of graduates hold the qualification with STEM subjects, but the proportion is still 13.4% lower than that of LEM. For the subject unit, most individuals studied Engineering at school in the group of STEM. Also, in the LEM group, the number of graduates studying Economics and Law is quite similar, with a proportion of about 18%. The number of graduates holding SSHA qualification only

Table 5.9: Distribution of graduate samples by subjects (before and after re-categorization)

Subjects	Subject groups	Frequencies
Science	STEM	37 4.25%
Engineering		150 17.24%
Agriculture		19 2.18%
Medical Science		65 7.47%
Total		**271 31.15%**
Law	LEM	73 8.39%
Economics		159 18.28%
Management		157 18.05%
Total		**389 44.71%**
Philosophy	SSHA	6 0.69%
Education		90 10.34%
Literature		107 12.30%
History		7 0.80%
Total		**210 24.14%**
Total		**870 100%**

accounts for 24.1% of all the workers, which is the lowest among all the subject groups. In this group, we find most individuals studied Education and Literature, but a very limited proportion of graduates tried to have qualifications in Philosophy and History. This is mainly driven by the low demand in the labour market. Some subjects do not provide specific knowledge or training which can be applied directly to industrial or occupational contexts.

In Table 5.10, we further show the frequencies in different subjects according to various education qualities. It is interesting to find that the number of different subject groups is closer in key universities. However, in ordinary universities and short-term colleges, most graduates still choose to study subjects in LEM. In fact, in recent years, the non-public economy has developed fast in the activity sectors such as Finance, Banking, International Trade, and Business Management. Modern enterprises create a number of vacancies in the subjects of Law, Economics and Management, which also drives the growth of supply in the graduates. In addition, in the aspect of school, developing subjects of LEM would make them suffer from lower costs than other subjects, such as those in STEM, because fewer facilities are required, such as laboratories and experiential equipment. Developing LEM subjects has advantages in increasing employment and generating lower costs. Therefore, it is the prior choice in education expansion when considering the return, especially for those colleges with limited educational resources.

Table 5.10: Distribution of graduate samples by education qualities (Key/Ordinary) and subject groups

Subject groups	Key	Ordinary	College
STEM	22 30.56%	78 30.59%	171 31.49%
LEM	25 34.72%	102 40.00%	262 48.25%
SSHA	25 34.72%	75 29.41%	110 20.25%
Total	**72 100%**	**255 100%**	**543 100%**

5.7 Empirical Results

Firstly, as mentioned in the methodologies part, we try to control for the self-selection bias into waged jobs in wage equations. In the following, we show results by adding inverse Mills ratios as extra control factors into all the specifications. We find the coefficients on Mills ratios are mostly insignificant, showing that the estimates are not biased because of self-selection. Results for the first step probit regression are included in Appendix O.

5.7.1 Return to Education Qualities and Subject Groups

In Table 5.11, we show the return to different education qualities. It can be seen that, in general, long-term university graduates enjoy higher wages than short-term college graduates in the labour market. From column 1, workers who graduated from universities earn 19.8% higher wages than workers from colleges and the coefficient is estimated to be significantly different from zero. When we further consider the different qualities in the University group, we find a significantly larger return to key universities, nearly three times higher than ordinary universities, with a wage premium of 39.3%. The return gap between key and ordinary universities is tested to be highly significant at 1% level. However, though the return to Ordinary universities is smaller, the estimated coefficient is still significant at the 5% significance level.

Table 5.11: Return to different education qualities

	(1)	(2)	(3)	(4)
University	0.198***	0.182***		
	(0.054)	(0.055)		
Key University			0.393***	0.382***
			(0.081)	(0.081)
Ordinary University			0.140**	0.122**
			(0.060)	(0.060)
Minority	0.054	0.050	0.053	0.048
	(0.086)	(0.085)	(0.086)	(0.086)
Male	0.056	0.052	0.056	0.052
	(0.045)	(0.045)	(0.045)	(0.045)
Age	-0.034	-0.036	-0.037	-0.038
	(0.039)	(0.039)	(0.039)	(0.039)
Age square/100	0.065	0.063	0.062	0.059
	(0.058)	(0.058)	(0.059)	(0.059)
Marriage	0.118*	0.124*	0.115*	0.121*
	(0.065)	(0.066)	(0.065)	(0.066)
Urban residence	0.018	0.012	0.013	0.007
	(0.105)	(0.104)	(0.104)	(0.104)
Urban "Hukou"	0.252***	0.268***	0.248***	0.266***
	(0.076)	(0.076)	(0.076)	(0.076)
Northeast	0.113	0.106	0.108	0.101
	(0.074)	(0.074)	(0.074)	(0.074)
East	0.437***	0.425***	0.421***	0.409***
	(0.068)	(0.069)	(0.069)	(0.069)
Middle	0.041	0.033	0.028	0.020
	(0.065)	(0.065)	(0.065)	(0.065)
Public sector	-0.018	-0.019	-0.015	-0.015
	(0.052)	(0.052)	(0.052)	(0.052)
Raw materials	-0.054	-0.037	-0.070	-0.053
	(0.430)	(0.429)	(0.428)	(0.426)
Manufacturing	0.099*	0.095	0.102*	0.098*
	(0.058)	(0.058)	(0.058)	(0.058)
Retailing and wholesaling	0.179**	0.181**	0.176**	0.179**
	(0.087)	(0.087)	(0.087)	(0.087)
First job	-0.094**	-0.090**	-0.096**	-0.093**
	(0.046)	(0.046)	(0.045)	(0.045)
Literacy skill		0.012*		0.012**
		(0.006)		(0.006)
Locus of control		0.043		0.052
		(0.041)		(0.041)
Lambda	-0.327	-0.328	-0.349	-0.352
	(0.263)	(0.263)	(0.262)	(0.262)
Constant	2.580***	2.130**	2.667***	2.184**
	(0.885)	(0.888)	(0.880)	(0.879)
Occupations	Yes	Yes	Yes	Yes
Observations	870	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected Standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

These results are quite similar to those findings in the literature, such as Li et al. (2012) on elite colleges and Zhong (2011) on the comparison between short-term and long-term higher education.

To explain the higher returns to better education qualities, it can be assumed that the different returns correspond to the variations in human capital achievements in different categories of education institutions. Therefore, in columns 3 and 4, we further add controls of individuals' skills into the specifications. It is shown that after controlling for skills, including both cognitive and non-cognitive ones, the estimated returns are slightly lower but remain significant, showing that individuals' skills heterogeneity is not the main driver of the higher payoff to better education qualities.

Besides the explanations of accumulated human capital, the signalling theory (Spence, 1973) can also be referred to as that better education quality would signal individuals having higher innate abilities, which are not observed in our analysis. In addition, the credential effect, or the so-called sheepskin effect, would also help explain the higher returns. Employers would provide higher payoffs to the productivity that the qualifications signal or credential rather than the individuals' actual productivity (Belman and Heywood, 1990; Aslam et al., 2012).

Besides signalling theories, another factor that could be used to explain the higher return in key universities is social capital achievements (Chua, 2011). For example, in key or top universities, students could have networks with other talented students to share ideas and innovations. These achievements are not closely correlated with those academic skills or knowledge taught in classes, thus resulting in a different explanation for the higher return in key universities besides the human capital theory. In addition, in the labour market, workers from key universities will be easier to obtain ideas, knowledge, information, and even financial support, from networks with other workers who also graduated from key universities. Also, these individuals could fast enhance their productivity by formally cooperating with other talented individuals through the so-called "learning by doing" process (Lave and Wenger, 1991). Social capital would help individuals be more innovative and productive in the labour market, leading to better performance and higher wages.

However, the previous explanation on human capital is based on one premise that individuals' skills are correctly measured. In the literature, there are arguments that it is not perfect to capture cognitive skills using a single dimension of literacy (Sohn, 2010). Therefore, in the following subsection, we further include numeracy skills as a robustness check. Nevertheless, one should be aware of the difficulties in quantifying individuals' skills. Even if the cognitive skills are measured correctly, there are other domains of skills that can be considered, such as non-cognitive skills (especially personality traits) and technical skills (STEP survey, Wu and Wang, 2018). If all these skills are controlled, we may expect a larger effect on the return to education qualities. However, cognitive skills and locus of control are the only information available to us in the 2010 wave, and this can be considered a limitation of our research.

For other variables, we find equal treatment in the labour market across genders that there are no significant wage differences between males and females in all the specifications. Also, it is clear that living in urban or rural areas does not help explain the wages for graduates. People working in eastern areas are paid more than other areas in China, which would reflect a gap in regional development in China. In fact, under the classification in our analysis, eastern areas include all the Chinese first-tier cities. In addition to these, the effect of previous working experience is also confirmed to help with current job outcomes. Individuals taking their first jobs would have about 10% lower wages than those with previous experience. Individuals' literacy skills levels are found to significantly affect wages, though the effect cannot largely explain the premiums of education qualities.

In Table 5.12, we illustrate the estimated results on return to different subject groups. The reference group is SSAH, and we show results on specifications with and without skills controls, similar to the analyses before. It can be seen that the coefficients on STEM and LEM are positive but insignificantly different from zero, showing that the gaps between subjects are quite small and are not significant. This result remains after adding skills controls in the specifications, showing that the small and insignificant differences between subject returns are not driven by variations in skills. Similar returns between subjects are also found in Walker and Zhu (2011), who also focus on

Table 5.12: Return to different subject groups

	(1)	(2)
STEM	0.068	0.080
	(0.068)	(0.069)
LEM	0.060	0.072
	(0.068)	(0.069)
Minority	0.061	0.054
	(0.088)	(0.088)
Male	0.060	0.052
	(0.047)	(0.047)
Age	-0.033	-0.039
	(0.041)	(0.041)
Age square/100	0.059	0.058
	(0.062)	(0.062)
Marriage	0.115*	0.125*
	(0.067)	(0.068)
Urban residence	0.041	0.022
	(0.111)	(0.110)
Urban "Hukou"	0.268***	0.288***
	(0.077)	(0.078)
Northeast	0.140*	0.129*
	(0.075)	(0.075)
East	0.454***	0.433***
	(0.072)	(0.072)
Middle	0.054	0.040
	(0.067)	(0.068)
Public sector	-0.013	-0.013
	(0.053)	(0.053)
Raw materials	-0.119	-0.088
	(0.436)	(0.433)
Manufacturing	0.055	0.053
	(0.059)	(0.059)
Retailing and wholesaling	0.149*	0.154*
	(0.088)	(0.088)
First job	-0.086*	-0.080*
	(0.046)	(0.046)
Literacy skill		0.016***
		(0.006)
Locus of control		0.054
		(0.043)
Lambda	-0.394	-0.413
	(0.271)	(0.272)
Constant	2.602***	2.060**
	(0.896)	(0.897)
Occupations	Yes	Yes
Observations	870	870

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

graduates and divide the subjects into three groups.

However, it can also be argued that the estimates may be biased because of not controlling for education qualities. Therefore, in the following specifications in Table 5.13, we further add variables of education qualities with both measurements alongside subject groups. It is clear that returns for different subjects are still quite similar, and the coefficients are nearly unchanged for subjects after adding education qualities. In addition, we still find that higher education qualities can result in significantly higher wages for workers, consistent with those results obtained in Table 5.11.

5.7.2 Interaction Effects between Education Qualities and Subjects

In this subsection, we further examine the interaction effect between education qualities and subject groups. By adding the interaction terms into the specifications, we are able to find out the effect of education qualities in different subject groups. At the same time, we can also check whether subjects still show insignificant effects on individuals' wages in different education qualities.

It can be seen from columns 1 and 2 in Table 5.14 that coefficients on the college quality variables are both positive and significant. However, these coefficients only reflect a wage premium for university graduates in the SSAH group. For the return to education qualities in other subject groups, we need to sum up the coefficients on the interaction terms. It is found that all the coefficients on interaction terms are negative and insignificant, showing a lower university premium in STEM and LEM subject groups, compared with SSAH, but to a small and insignificant extent. The higher returns in better education qualities for different subjects are also concluded by Kang et al. (2012), who also focus on a Chinese case. Regarding the coefficients on subjects, it is interesting we find a weak significant premium on the LEM subject group. It needs to be mentioned that this premium is only for graduates in colleges. If we consider about different education qualities, we do not find significant gaps in the premium of LEM subjects, according to the insignificant coefficients on interaction

Table 5.13: Return to different education qualities and subject groups

	(1)	(2)	(3)	(4)
University	0.201***	0.185***		
	(0.053)	(0.054)		
Key University			0.400***	0.390***
			(0.082)	(0.082)
Ordinary University			0.142**	0.124**
			(0.059)	(0.059)
STEM	0.074	0.080	0.083	0.090
	(0.066)	(0.066)	(0.066)	(0.066)
LEM	0.060	0.066	0.073	0.080
	(0.065)	(0.065)	(0.065)	(0.065)
Minority	0.057	0.052	0.055	0.049
	(0.086)	(0.086)	(0.086)	(0.086)
Male	0.046	0.041	0.046	0.040
	(0.046)	(0.046)	(0.046)	(0.046)
Age	-0.037	-0.038	-0.040	-0.041
	(0.039)	(0.039)	(0.039)	(0.039)
Age square/100	0.061	0.059	0.060	0.058
	(0.058)	(0.057)	(0.058)	(0.057)
Marriage	0.117*	0.124*	0.114*	0.120*
	(0.066)	(0.066)	(0.066)	(0.066)
Urban residence	0.012	0.007	0.004	-0.000
	(0.105)	(0.104)	(0.104)	(0.104)
Urban “Hukou”	0.248***	0.264***	0.243***	0.261***
	(0.076)	(0.076)	(0.076)	(0.076)
Northeast	0.114	0.107	0.109	0.102
	(0.074)	(0.074)	(0.074)	(0.074)
East	0.434***	0.423***	0.417***	0.405***
	(0.069)	(0.069)	(0.070)	(0.070)
Middle	0.038	0.029	0.024	0.016
	(0.066)	(0.066)	(0.066)	(0.066)
Public sector	-0.015	-0.015	-0.011	-0.010
	(0.052)	(0.052)	(0.052)	(0.052)
Raw materials	-0.052	-0.036	-0.070	-0.055
	(0.429)	(0.428)	(0.426)	(0.425)
Manufacturing	0.095	0.091	0.098*	0.094
	(0.058)	(0.058)	(0.058)	(0.058)
Retailing and wholesaling	0.177**	0.179**	0.173**	0.176**
	(0.087)	(0.087)	(0.087)	(0.086)
First job	-0.094**	-0.090**	-0.096**	-0.092**
	(0.046)	(0.046)	(0.045)	(0.045)
Literacy skill		0.012**		0.012**
		(0.006)		(0.006)
Locus of control		0.046		0.055
		(0.041)		(0.041)
Lambda	-0.350	-0.345	-0.377	-0.376
	(0.262)	(0.262)	(0.261)	(0.261)
Constant	2.587***	2.090**	2.689***	2.158**
	(0.864)	(0.856)	(0.861)	(0.850)
Occupations	Yes	Yes	Yes	Yes
Observations	870	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.14: Return to education qualities and subject groups with interactions

	(1)	(2)	(3)	(4)
University	0.291***	0.273***		
	(0.095)	(0.095)		
Key University			0.409***	0.394***
			(0.152)	(0.151)
Ordinary University			0.252**	0.231**
			(0.099)	(0.099)
University*STEM	-0.098	-0.092		
	(0.112)	(0.111)		
University*LEM	-0.108	-0.104		
	(0.120)	(0.119)		
Key University*STEM			-0.106	-0.118
			(0.204)	(0.203)
Ordinary University*STEM			-0.082	-0.090
			(0.128)	(0.127)
Key University*LEM			0.044	0.049
			(0.205)	(0.204)
Ordinary University*LEM			-0.131	-0.148
			(0.122)	(0.122)
STEM	0.109	0.113	0.114	0.119
	(0.080)	(0.080)	(0.079)	(0.079)
LEM	0.156*	0.158*	0.159*	0.162**
	(0.082)	(0.082)	(0.081)	(0.081)
Minority	0.055	0.051	0.058	0.053
	(0.087)	(0.086)	(0.086)	(0.086)
Male	0.050	0.045	0.050	0.044
	(0.046)	(0.046)	(0.046)	(0.046)
Age	-0.043	-0.044	-0.042	-0.043
	(0.039)	(0.039)	(0.038)	(0.038)
Age square/100	0.085	0.087	0.092	0.096*
	(0.059)	(0.058)	(0.057)	(0.057)
Marriage	0.114*	0.122*	0.113*	0.119*
	(0.066)	(0.066)	(0.066)	(0.066)
Urban residence	-0.004	-0.007	0.000	-0.004
	(0.105)	(0.105)	(0.103)	(0.103)
Urban "Hukou"	0.246***	0.262***	0.238***	0.256***
	(0.076)	(0.077)	(0.076)	(0.076)
Northeast	0.114	0.107	0.108	0.100
	(0.074)	(0.074)	(0.074)	(0.074)
East	0.435***	0.424***	0.423***	0.411***
	(0.070)	(0.070)	(0.070)	(0.070)
Middle	0.037	0.029	0.024	0.016
	(0.066)	(0.066)	(0.066)	(0.066)
Public sector	-0.016	-0.017	-0.012	-0.011
	(0.052)	(0.052)	(0.052)	(0.052)
Raw materials	-0.062	-0.046	-0.080	-0.064
	(0.427)	(0.426)	(0.424)	(0.423)
Manufacturing	0.091	0.086	0.096*	0.091
	(0.058)	(0.058)	(0.058)	(0.058)
Retailing and wholesaling	0.179**	0.182**	0.175**	0.178**
	(0.087)	(0.087)	(0.087)	(0.086)
First job	-0.095**	-0.090**	-0.097**	-0.094**
	(0.045)	(0.046)	(0.045)	(0.045)

Table 5.14: Continued

	(1)	(2)	(3)	(4)
Literacy skill		0.012**		0.012**
		(0.006)		(0.006)
Locus of control		0.046		0.053
		(0.041)		(0.041)
Lambda	-0.389	-0.380	-0.385	-0.381
	(0.262)	(0.262)	(0.253)	(0.254)
Constant	2.693***	2.192**	2.694***	2.171***
	(0.870)	(0.862)	(0.843)	(0.837)
Occupations	Yes	Yes	Yes	Yes
Observations	870	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

terms[2]. The advantage of LEM is also found in Walker and Zhu (2011), but only for male graduates. In the last two columns, we implement the second classification of education qualities, which divides universities into key and ordinary.

Wage premiums are confirmed in the SSAH group for both key and ordinary universities, compared with colleges, and a better university would further generate a higher premium. Similar to the previous specifications, all the coefficients on the interaction terms, including interactions with key and ordinary universities, are estimated to be insignificant, showing that the premiums of education qualities are not largely affected by subject groups. In addition, the premium of LEM subjects is also found in the college group.

It needs to be mentioned that in our analysis, the sample size for the interactions is relatively small, especially for those in the key university group, because our graduate samples come from a national household survey rather than from surveys specifically designed for graduates. Therefore, though we conclude that coefficients on the interactions are insignificant, this result may remain debate mostly because of the restriction of sample size. This can be seen as an important limitation of our analysis but could be overcome by other researchers in the future if better data is available.

2. Though the coefficients on interaction terms are insignificant, it only shows the gap in premium, but the actual returns to subjects for different education qualities equal the summation of coefficients for subject variables and interaction terms. For example, the return to LEM at the university level is (0.156 - 0.108) in Column 1, which is tested to be insignificantly different from zero.

5.7.3 Heterogeneity in Subgroups

In this subsection, we examine the heterogeneity of return to education qualities and subjects in different subgroups. More specifically, we want to find out the possible various returns according to subgroups of gender and urban/rural areas.

Firstly, gender inequality is long considered an important topic in social and Micro-economic studies. Many previous studies examine the gender gap in the overall college premium, but few of them extend the analysis to the level of return to education qualities and subjects. China implements a policy of wage equality between gender if they are employed in similar occupations and have similar education and training backgrounds (Budig, 2002). However, when individuals from good universities compete for highly paid jobs, gender segmentation also exists where employers may still offer higher wages to male graduates based on assumptions or stereotypes about gender roles and productivity. Also, women may face barriers to entering certain fields or advancing to higher positions, leading to lower wages than their male counterparts. In addition, graduates also experience gender-based occupational segregation in the Chinese labour market. Females are often steered towards "feminine" occupations such as teaching, nursing, or social work, whereas males are often employed in "masculine" occupations such as engineering, finance, or law. This will lead to a different demand condition for job-related subjects, resulting in various returns to subjects between males and females (Goldin, 2014). Therefore, in the empirical process, only using one variable of gender difference in specifications may hide the gap in returns between gender on education qualities and subjects.

Regarding the urban/rural differences, geographic segmentation is an important characteristic of the Chinese labour market, mainly driven by the man-made barriers between urban and rural areas based on a strict household registration system. Urban areas tend to have a greater concentration of high-skilled jobs in industries such as finance, technology, and professional services. These industries may require a number of talented graduates with good educational backgrounds (Ihlanfeldt, 1994). However, rural areas may have fewer high-skilled job opportunities that can fully match the education, skills and experience in good quality universities, which can result in lower wages for individuals with advanced degrees. In addition, the demand for labour in rural areas also has a significant industrial and occupational orientation. Since the dominant sector in rural areas is still raw materials, such as agriculture, the demand for graduates with related subjects such as STEM will be higher than other subjects. However, in urban areas, the demand for subjects would be more balanced, and those subjects correlated with high-tech services, such as law and finance, will be more demanded than in rural areas to serve the requirement of innovation and development.

In the following specifications, we add interactions of gender and urban residence to the variables of education qualities and subject groups. It needs to be mentioned that only the general measurement of education quality is used because the number of graduates from key universities is quite limited after dis-aggregation, especially in rural areas (only seven graduates from key universities are rural residents), which restricts us from obtaining precise estimation results.

Table 5.15 shows that for female workers, the wage premium of attending universities rather than colleges is about 22.6%. The wage gap between males and females in education qualities is tested to be not significantly different from zero, according to the coefficients on interactions. This result shows that females with better education backgrounds are not disadvantaged in the Chinese labour markets, compared with males. Regarding return to subjects, we still find an insignificant wage gap between different kinds of subjects for females and the gender gap is also estimated to be insignificant. Our result on the insignificant gap between genders is generally similar to those obtained by Kang et al. (2021), who also focus on a Chinese case.

Table 5.16 shows estimated results with urban/rural differences. Significant wage premiums are found in both rural and urban areas for better education qualities. Urban workers with university qualifications have no significantly different premiums compared with rural workers. It would normally be assumed that graduates with better educational backgrounds would be treated differently in rural markets because of the limited supply of individuals with good quality education. However, the interpretation should not be restricted to the supply side. It is also possible that in rural areas, limited job opportunities are suitable for better-educated graduates, and employers are not

Table 5.15: Return to education qualities and subject groups with the gender difference

	(1)	(2)	(3)
University	0.226^{***}		0.229^{***}
	(0.071)		(0.070)
University*Male	-0.078		-0.081
	(0.087)		(0.087)
STEM		-0.035	-0.004
		(0.085)	(0.083)
LEM		0.002	0.026
		(0.085)	(0.081)
STEM*Male		0.137	0.107
		(0.225)	(0.122)
LEM*Male		0.128	0.099
		(0.113)	(0.109)
Minority	0.047	0.051	0.047
	(0.085)	(0.088)	(0.085)
Male	0.081	-0.080	-0.029
	(0.055)	(0.095)	(0.100)
Age	-0.033	-0.039	-0.032
	(0.039)	(0.041)	(0.039)
Age square/100	0.069	0.065	0.063
	(0.059)	(0.061)	(0.061)
Marriage	0.123^{*}	0.121^{*}	0.119^{*}
	(0.065)	(0.067)	(0.065)
Urban residence	0.017	0.025	0.018
	(0.104)	(0.111)	(0.104)
Urban "Hukou"	0.268^{***}	0.290^{***}	0.265^{***}
	(0.076)	(0.077)	(0.076)
Northeast	0.100	0.123^{*}	0.096
	(0.074)	(0.075)	(0.073)
East	0.423^{***}	0.428^{***}	0.418^{***}
	(0.068)	(0.072)	(0.069)
Middle	0.030	0.035	0.023
	(0.065)	(0.067)	(0.065)
Public sector	-0.020	-0.015	-0.018
	(0.052)	(0.053)	(0.052)
Raw materials	-0.053	-0.100	-0.061
	(0.429)	(0.434)	(0.429)
Manufacturing	0.096^{*}	0.047	0.086
	(0.058)	(0.059)	(0.059)
Retailing and wholesaling	0.186^{**}	0.149^{*}	0.180^{**}
	(0.087)	(0.088)	(0.087)
First job	-0.091^{**}	-0.081^{*}	-0.091^{**}
	(0.046)	(0.046)	(0.046)
Literacy skill	0.011^{*}	0.016^{***}	0.012^{**}
	(0.006)	(0.006)	(0.006)
Locus of control	0.043	0.053	0.044
	(0.040)	(0.042)	(0.041)
Lambda	-0.305	-0.393	-0.292
	(0.263)	(0.273)	(0.263)
Constant	2.056^{**}	2.096^{**}	1.995^{**}
	(0.885)	(0.906)	(0.861)
Occupations	Yes	Yes	Yes
Observations	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.
Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.16: Return to education qualities and subject groups with urban/rural difference

	(1)	(2)	(3)
University	0.211**		0.153**
	(0.105)		(0.082)
University*Urban residence	-0.034		-0.043
	(0.166)		(0.173)
STEM		0.112	0.073
		(0.177)	(0.172)
LEM		-0.262	-0.268
		(0.184)	(0.183)
STEM*Urban residence		-0.031	0.017
		(0.179)	(0.175)
LEM*Urban residence		0.329*	0.331*
		(0.185)	(0.184)
Minority	0.049	0.061	0.058
	(0.086)	(0.089)	(0.087)
Male	0.052	0.050	0.041
	(0.045)	(0.047)	(0.046)
Age	-0.038	-0.045	-0.046
	(0.039)	(0.040)	(0.039)
Age square/100	0.058	0.059	0.062
	(0.061)	(0.061)	(0.062)
Marriage	0.125*	0.125*	0.123*
	(0.066)	(0.068)	(0.067)
Urban residence	0.006	0.017	0.001
	(0.107)	(0.110)	(0.108)
Urban "Hukou"	0.278***	0.200	0.149
	(0.089)	(0.138)	(0.149)
Northeast	0.107	0.132*	0.112
	(0.074)	(0.076)	(0.075)
East	0.424***	0.438***	0.426***
	(0.069)	(0.073)	(0.070)
Middle	0.033	0.043	0.032
	(0.065)	(0.068)	(0.066)
Public sector	-0.018	-0.018	-0.019
	(0.052)	(0.052)	(0.052)
Raw materials	-0.037	-0.114	-0.057
	(0.428)	(0.431)	(0.424)
Manufacturing	0.095	0.062	0.098*
	(0.058)	(0.059)	(0.058)
Retailing and wholesaling	0.181**	0.151*	0.174**
	(0.087)	(0.088)	(0.087)
First job	-0.091**	-0.077*	-0.090**
	(0.046)	(0.046)	(0.046)
Literacy skill	0.011*	0.017***	0.013**
	(0.006)	(0.006)	(0.006)
Locus of control	0.043	0.056	0.049
	(0.041)	(0.043)	(0.042)
Lambda	-0.345	-0.455*	-0.406
	(0.266)	(0.271)	(0.265)
Constant	2.173**	2.258**	2.362***
	(0.890)	(0.879)	(0.842)
Occupations	Yes	Yes	Yes
Observations	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.
Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

willing to provide high payoffs to individuals even if they have better qualifications, which would decrease the demand of better educated graduates and lead to a no difference on the return between urban and rural areas.

Regarding the subjects, in rural areas, no significant premium is found for any subject compared with the reference group, SSAH. However, in urban areas, we find a considerably higher return to the LEM group compared with rural areas, with a gap of 33%, which is tested to be significant at 10% level. Possible explanations would be that some subjects, such as Law, Economics and Management, do not provide specific knowledge or training which can be applied directly to industrial or occupational contexts of rural areas. However, the services these subjects provide are more demanded in urban areas, especially in large-scale modernised enterprises, and employers are willing to pay higher returns to better use the skills related to LEM.

5.7.4 Robustness Checks

In this subsection, we conduct four robustness checks on the previous estimation results. Firstly, we test the robustness of coefficients under different measurements of wages. We exclude all the rewards and bonuses to cover only net wages in the specifications. Estimation results are shown in Tables N.1 and N.2 in Appendix N. Results are consistent with previous parts that significant premiums on better education qualities exist. The only difference is that when we use the original wage measurement, we find a weak significant wage premium on LEM subjects within the college graduates group. However, this premium disappears under the net wage.

Secondly, following the arguments that literacy proficiency may not be a perfect proxy of cognitive skills, we use individuals' numeracy proficiency as a robustness check. Estimation results on all the main specifications are included in Tables N.3 and N.4 in Appendix N. We cannot find large changes in the coefficients of interest with the varying cognitive controls. The only difference is that numeracy proficiency has no significant effect on wages, which is inconsistent with literacy proficiency. This can be explained by the fact that the correlation coefficient between these two skills is only 0.45. Therefore, one should be cautious when using literacy or numeracy to measure cognitive skills in Chinese studies because it may be the case that none of them could perfectly capture the actual individuals' cognitive skills, although they are normally used in the literature. Some other studies also compare results by using problem-solving skills, but in our survey, we have no information on this.

Thirdly, in the previous empirical analysis, we implement a method to re-categorise the 11 subject units (no observations in the subject of Military) into three groups to avoid the low observations, mostly in the analysis of interaction effects. However, this measurement may suffer from the limitation that aggregation may hide the heterogeneity in return to different subject units. In fact, if the interaction effect is not focused, most of the subjects have enough observations to examine the heterogeneity between units, except History and Philosophy, with observations smaller than 10. Therefore, in this subsection, we re-categorise History and Philosophy as "others", which is treated as the reference group, and try to estimate the returns to different subject units. Results are shown in Table N.5 in Appendix N. We find significant premiums for subjects of Engineering, Economics, Management, Law, Literature and Science compared to the reference group of History and Philosophy. Graduates from Engineering enjoy the highest return, with about 60% higher wages than those in the "other" group. Interestingly, no significant return is found for Medicine in China. This is inconsistent with most of the findings in the literature that graduates from Medicine often enjoy the highest return, and the wage gap is quite large compared with the second-highest subject (Chevalier, 2011; O'Leary and Sloane, 2011). Regarding returns to education qualities, we have a consistent result with previous analyses that better education qualities would generate significant wage premiums after controlling for detailed subject units. However, the return to ordinary universities is relatively larger affected that the wage gap between ordinary universities and colleges is only about 10% and is estimated to be weak significant. This number is nearly four times lower than the return to key universities, showing a larger gap between education qualities within the university level, compared with previous findings.

Fourthly, similar to Chapter 4, the analysis in Chapter 5 also suffers from the limitation of small sample size, especially when the resampled data is used to conduct the empirical analysis. Higher education in China has developed over the years, which results in the fact that in 2010, we even have a smaller sample size of graduates than in 2014 and 2018. In the previously obtained empirical results, we find the returns to different subject groups are insignificant. However, arguments may arise that the larger sample might suggest that some of the insignificant findings can be explained by the small sample size problem. Therefore, in this subsection, we provide updated empirical results on the return to education qualities and subjects to be compared with the previous findings. Results are shown in Appendix N.

According to the empirical results obtained from the smaller and the larger sample size (Table 5.11 and Table N.6), we find the returns to higher education qualities are both positive and highly significant. The only variation is that under the not resampled data, the return to ordinary universities is slightly higher, which also leads to a slightly smaller return gap between key and ordinary universities. Besides the return to education qualities, we still find insignificant returns to different subjects from empirical models by using the larger sample size in Table N.7. This result on insignificant return to subjects remains unchanged after the education qualities are also added into the model, based on the insignificant coefficients on subject groups in Table N.8. Therefore, with the updated empirical results, we do not find large variations in the results on return to education qualities and subjects that would affect the robustness of our findings.

5.8 Conclusion

The main research objective of this paper is to analyse the wage returns to different education qualities and subjects. Empirical results show that graduates with better education qualities would have significant premiums on wages. Specifically, graduates from key universities enjoy the highest premium, with 25% and 40% higher earnings than ordinary university and college graduates, respectively. These wage premiums of better education qualities cannot be largely explained by variations in individuals' skills, supporting our hypothesis one in section 5.2.6 that workers who graduated from institutions of higher quality enjoy higher wage returns. The wage gaps between different subject groups are estimated to be insignificant, which does not support the second hypothesis on heterogeneous return to subjects. However, in the analysis of the subject unit, we find significant premiums in Engineering, Economics, Management, Law, Literature and Science compared with the base group of History and Philosophy. In addition, according to the heterogeneity in subgroups, we find there are no large and significant differences in return to education qualities between gender and urban/rural, but the LEM subject is tested to be more advantaged in urban areas. In terms of the interaction effect, all the coefficients for interaction terms are insignificant. We find out that graduates with better education qualities would have higher wages in the base subject group SSAH, and there are no large variations in the premiums for other subject groups. Also, we find LEM enjoys a weak significant premium than other subjects in the college graduates group. Other subjects, such as SSAH and LEM, do not enjoy premiums in different institution categories.

However, it is important to take into consideration that our analysis also has some limitations. First, because of the restriction on the sample size, most of the interactions are based on small samples. Also, because of the small sample size of key university graduates, we are not able to find the urban/rural differences on the return to key universities and also cannot form interactions between different subject units and the key university dummy. These drawbacks are expected to be improved in future studies by pooling data from different waves or using better datasets. Second, because of the restriction on the information on skills, we can only control for numeracy/literacy skills, which can be argued to be insufficient to capture different domains of individuals' cognition. Some other skills often used in the literature may be considered, such as problem-solving skills, technical skills and personality traits. However, in the wave 2010, we do not have information on such skills. Third, though we find methods to eliminate the self-selection bias due to the composition of employment statuses in this chapter, other kinds of selection issues may also drive concerns. For example, some factors would simultaneously affect individuals' selection into specific education qualities or subjects and the labour market earnings, such innate abilities, enthusiasm and family inputs. However, these factors are unobserved in the CFPS data, which may cause the possible omitted variable bias. This problem can also be solved by using a more comprehensive dataset.

There are also some implications associated with the obtained results. Firstly, we find large gaps in wages between key universities and other educational backgrounds at the higher education level and the wage premium between universities and colleges is mainly driven by key universities. However, these graduates enjoying high returns are from very selective institutions in China and only account for smaller than 10% of all the graduates in the labour market, which seems quite unbalanced. There are still some other good universities in China that are not included in the conventional "985" and "211" systems. Graduates in these universities are generally categorised into "ordinary" graduates and are most disadvantaged. In fact, they may have no significant differences in skills compared with graduates from key universities. Employers may consider whether the institution qualities defined by the current system truly reflect individuals' productivity since we find slightly higher cognitive skills on average for graduates from ordinary universities and a large and significant wage gap between key and ordinary universities, even if cognitive and non-cognitive skills are controlled. Though it could be argued that skills covered in this analysis may not capture all aspects of individuals' skills, employers may consider carefully what the remaining premiums on education qualities reflect. It is possible that individuals with better education qualities may have higher abilities that are not observed (e.g. innate ability), following the arguments of the signalling theory. However, there is another explanation that individuals in better institutions just enjoy the advantage of the credential effect that is not correlated with actual productivity. In fact, Employers could be aware that there would be other methods to value the excellence of graduates alongside college qualities, for example, using the degree qualities that reflect more on individuals' education outcomes and skills at graduation.

Finally, besides the policymakers, empirical results from our analysis can also provide suggestions to individuals. It is clear that the investment in better education quality still pays off in the Chinese labour market, especially for the key and top-ranked universities. Besides the improvements in knowledge and skills, graduates from better institutions may also provide an important signal to employers about having higher innate abilities. However, individuals also need to take into account the fees that are required to enter institutions with better qualities. Though most of the higher education institutions are publicly funded in China and require similar tuition fees, other expenses also need to be paid if individuals want to enter better colleges, such as the fees for training and after-school classes at the high school level. The training could help them have better performance in the college entrance examination, which is the decisive factor for individuals entering better institutions. It needs to be mentioned that only very selective individuals (around 10% in the current labour market) would hold qualifications of key universities in China and enjoy high returns. The payoff decreases largely if they can only achieve normal universities, though there would still be a small and significant wage gap compared with short-term colleges. Therefore, individuals may face large risks in the competition of getting into better education institutions and need to be very cautious before making decisions on investment.

Chapter 6 Conclusion

6.1 Concluding Remarks and Contributions

The thesis explores the connection between individuals' education achievements and wages in the Chinese labour market. There are three empirical chapters in this thesis. Chapter 3 estimates the wage return to years of education. We also extend the analysis into urban/rural differences, corresponding to the gap in the literature that the comparison in return to education between areas is rarely studied in China. The return is estimated by using the Mincer (1974) wage equation. Chapter 4 analyses the return to over-education for graduates, corresponding to a dramatic change in the supply side of tertiary educated workers in recent China. We study the over-education incidence and the wage penalty of over-education under three different measurements, which are subjective, objective and statistical methods. We implement the revised Verdugo and Verdugo (1989) methodology to empirically estimate the return to over-education. We also incorporate individuals' skills into the analysis to see whether skills heterogeneity can explain the wage effect of over-education. Chapter 5 studies the return to different education qualities and subjects also for graduate workers, corresponding to the concerns and dissatisfaction on the homogeneous return to college that often obtained in the previous literature. Education qualities and subjects are both divided into three groups according to specific classification criteria. The methodology used is also the Mincer wage equation with a revised version and the OLS regression method.

Samples for the analyses in this thesis are from the data provided by China Family panel studies (CFPS). Survey waves of 2010, 2014 and 2018 are covered to solve specific research questions in chapters. The CFPS data holds several advantages because it provides important information that is closely correlated with research topics, such as information on hourly earnings, over-education, individuals' skills achievements and graduates' institution types and subjects.

In detail, Chapter 3 highlights several key points. We find urban workers enjoy a return to education of 6.3%. However, for rural workers, the return is only 4.6%. After controlling employment characteristics, the returns decrease to 3.7% and 2.5% in urban and rural areas, respectively, but remain significant in both areas. Also, the difference between coefficients is estimated to be highly significant at 1% level. Explanations of the gap between returns in different areas could be the lower education quality in rural areas that would generate lower productivity growth with the variations in education (Yang et al., 2010). It also could rely on the demand side differences that the rural labour market suffers from lower functionality that wages would reward more to other factors such as backgrounds, social relationships and employers' preferences, rather than productivity (Li et al., 2005).

For the subgroups, estimation results show that the return to education for females is higher than that of males in both urban and rural areas, showing consistently higher rewards to female workers between areas. Possible explanations would be the lower supply of skilled female workers and the different skills requirements in female- and male-oriented jobs (Ren and Miller, 2012). In addition, in terms of sectors, the private sector is often considered more marketised and can provide returns closer to workers' marginal products. However, our analysis finds a significantly higher return for the public sector in urban areas. This may be explained by the fact that the public sector is responsible for a number of skill- and technology-oriented industries that are essential to the country, such as energy, education, and scientific research and development. These jobs have a higher demand for skills, and better-educated workers or professions would be rewarded with higher payoffs. In addition, wage rigidities are often shown in public-owned institutions that the earnings would be stable for a specific education level. However, in private institutions, wages would also be determined by the performances and achievements in jobs, reducing the explanatory ability of education to wages since our measurement of wages includes different kinds of benefits, rewards and bonuses.

The robustness of the results obtained by the OLS method is also tested, following the arguments in the literature on possible endogenous and self-selection biases. Firstly, the IV method is conducted to help solve the problem of omitted innate ability variables by using two sets of instruments which are parental education and policy changes. However, estimation results show that returns of education are higher under the IV method for both instruments, which is contrary to the original assumption that the effect of education on wages would be smaller after controlling for omitted variables. The estimated returns to education increase to 9.0% and 4.4% when parental education levels are used as instruments for urban and rural workers, respectively. Also, the estimated returns to education increase to 13.9% and 6.6% when policy changes are used as instruments. Explanations may rely on possible measurement errors in education or the Local Average Treatment Effect (Imbens and Angrist, 1994). Secondly, by using the Heckman two-step method, we conclude that rural areas suffer from significant self-selection bias. The main reason for this circumstance is that about 56% of working age individuals are not wage earners in rural areas, resulting in many missing observations in the wage equation. Estimation results show that the return for rural workers increases from 2.5% to 4.2%, resulting in a largely narrowed gap between urban and rural areas after the correction of self-selection bias.

Chapter 4 examines one of the consequences of higher education expansion in China: over-education. The definition of individuals' over-education status is based on three different measurements, which are subjective, objective and statistical. It is found that up to 40% of Chinese graduates are over-educated. In addition, over-educated workers suffer from significantly lower wages compared to matched ones, estimated to be 26.7%, 17.9% and 22.8% according to subjective, objective and statistical methods, respectively.

In this analysis, we also try to use skills heterogeneity to explain the wage penalty of over-education. However, the coefficients on over-education remain large and significant no matter of measurements used after adding the variables of skills heterogeneity into the specifications. More specifically, when controlling the effect of over-skill, the returns to over-education only decrease by 0.5, 1.6 and 1.1% under three different measurements, respectively. Also, when adding skills proficiency as extra explanatory variables in specifications, the coefficients on over-education are nearly unchanged. In addition, the result does not change after further considering non-cognitive skills. These findings confirm that the wage penalties for over-education rely mostly upon the difference in job characteristics rather than the variations in individuals' human capital, including the utilisation of skills or skills proficiency.

The robustness of estimation results on the linear regression model is also tested by using Propensity Score Matching (PSM) method. This method would help with the possible bias from Functional Form Miss-specification (FFM), and the estimation results come from the average treatment effect. In PSM, we still follow the three measurements on over-education. Significant and negative returns to over-education are also found, with 26.9%, 19.1% and 22.4% under subjective, objective and statistical methods, respectively, similar to that obtained under the OLS method. In addition, these returns are still significant after controlling variables of skills heterogeneity, also consistent with the results concluded by OLS.

The last empirical chapter finds significant wage premiums for individuals who graduated from institutions with better qualities. Following the rough classification by dividing institutions into colleges and universities, we find graduates from universities enjoy 19.8% higher wages than those from colleges. If we further divide the university group based on key and ordinary, we find premiums for key and ordinary universities to colleges are 39.3% and 14.0%, respectively, showing that the premium for universities is driven more by the key universities. These premiums cannot be largely explained by variations in individuals' skills proficiency, and no significant differences are found between region and gender subgroups. Regarding the return to subjects, no significant wage gaps are found between STEM, LEM and SSAH subject groups. The results remain consistent if further controlling for the variations in education qualities in specifications. Possible explanations may be that the reclassification of subjects hides the heterogeneity between the 12 original subject units. Also, some graduate individuals may find jobs in industries or occupations unrelated to the original subjects learned at school, and their wages cannot be explained largely by subjects. Considering the subgroups, we find returns to subjects would not vary significantly across gender groups. However, in urban areas, we find a significantly higher premium on LEM than in rural areas, compared to the base group SSAH.

The interaction effect between education qualities and subjects is also examined in the chapter. The interaction effect would help us find out how subjects with different education qualities can affect individuals' wages or, in another aspect, how education qualities in specific subject groups can affect individuals' wages. From the results, all the coefficients for interaction terms are insignificant. Firstly, we find that return to higher education qualities, including key and ordinary universities, enjoy higher returns in the base subject group of SSAH. According to the insignificant coefficients on interactions, there are no variations in the premiums for other subject groups. Secondly, in the analysis of subjects, we find LEM enjoys a weak significant premium than other subjects in the college graduates group. Also, regarding the insignificant coefficients on interactions, there are no differences in this premium for other education qualities compared with colleges.

The analyses of three different research topics make some specific contributions to the current literature. Firstly, it confirms an explanatory ability of individuals' education achievements to wages and finds a positive and significant effect. Though different theories, including human capital theory and assignment theory, indicate a positive relationship between education and wages, they are supported by limited evidence in the Chinese labour market. Secondly, though CFPS enjoys many advantages for analysing the connection between individuals' wages and education achievements, very few studies focus on this dataset. To the author's current knowledge, this study is the first to use CFPS for the topic of return to years of education, return to over-education and the second for return to education qualities and subjects. In fact, our analyses fill the gap in the literature on the shortage of using the CFPS dataset. Thirdly, regarding over-education, the key challenge for the analysis is how to correctly measure an individual's over-education status. Three methods in the literature are often used, including subjective, objective and statistical, but no agreements are achieved for the most preferred method. Therefore, the comparison between different measurements is the way to achieve the highest robustness. CFPS provides information that makes it feasible to make the comparison, an important feature rarely seen in other datasets. We conclude that over-education would generate a wage loss for graduates, no matter which measurement we use. Fourthly, in the previous studies on education qualities, only a rough classification between college and university is often made to divide the institution types or education qualities. However, in our analysis, we further make a more detailed classification of key and ordinary universities with the help of information provided in CFPS, which is also consistent with the classification method formally provided by the Chinese government. Lastly, in our analysis, we examine the effect of education on wages by disentangling education from skills. CFPS provide information on individuals' cognitive and non-cognitive skills, which are considered closely correlated with individuals' productivity. In the topics of return to over-education and return to education qualities, we both use skills heterogeneity to explain the estimated returns and conclude that the returns cannot be largely explained by skills heterogeneity. Very limited studies in Chinese literature provide similar evidence.

6.2 Implications and Limitations

Several key findings are concluded in the empirical analyses in this thesis, such as: positive and significant returns to years of education for both urban and rural workers; significant difference between returns in urban and rural areas; considerable and significant wage penalties for over-educated graduates; significant wage premiums for individuals graduated from better education qualities. Besides illustrating the results, we also propose some implications in this subsection, and the findings would help us provide recommendations to both individuals and policymakers.

The positive return to education in both urban and rural areas in China would encourage individuals and families to continue investing in education, which would also explain why, in current China, education is always focused on and treated seriously in Chinese families. Also, the significant return proves to policymakers that education still pays off in the labour market under the current expansion policy. However, it needs to be mentioned that the estimated return (6.3% for urban and 3.7% for rural) is considerably lower than those obtained in the last decade (Ding et al., 2012). Therefore, the policies on education should be adjusted not only based on the current labour market condition but also considering the time variations. In addition, the returns to different levels of education need to be paid enough attention for policies in specific education levels rather than just focusing on the effect of years of education.

Our analysis further finds a considerable gap between returns in urban and rural areas. This finding may imply that individuals in different areas would have various motivations to invest in education. Also, based on the different labour market conditions, there may be restrictions on the proposal of consistent education policies at the national level. For example, in recent years Chinese government wants to propose a 12-year compulsory education policy to decrease the dropout rate in high schools. However, based on the lower return, residents in rural areas would less support this policy, and the policymakers need to consider whether it is worthwhile to promote this policy to rural areas in terms of the payoff, considering the limited education expenditure each year.

The higher return in urban areas may also drive the outflow of labourers from rural to urban areas. In recent years, the education expansion in China significantly decreases the illiteracy rate and increases the average education achievements of the population, especially in rural areas. Therefore, workers, especially those with higher education achievements, would migrate to a labour market that provides higher returns to their human capital, which can be an explanation for the increasing urbanisation rate in recent China.

However, till 2020, there are still 40% of the labour force resides in rural areas, and these individuals should also be focused. The gap in return to human capital would drive the concerns of policymakers who want to achieve a balanced development across different areas. Since the return gap can be driven by the difference in education qualities, the government can devote more efforts to making rural schools better resourced, providing good quality teachers, facilities and equipment to ensure rural students would achieve similar productivity as urban ones within the same duration of education. Also, on the demand side, the government can attract companies with larger skills demand to rural areas, for example, through subsidies and tax exemption, to encourage them to make better use of educated workers in rural areas. The employment service agents or institutions can also try to provide enough employment information to workers in rural areas to help individuals more easily find jobs where the payoff is close to the actual supply and demand of skilled workers, increasing the functionality of rural markets.

However, the previous implications are based on the OLS estimation results. The self-selection results imply that ignoring the sample selection issue may lead to significant bias in estimating return to education, especially in rural areas. There are about 56% of individuals in rural areas are not waged workers. After correcting for the self-selection bias among rural workers, the return gap between regions is largely moderated. Therefore, we need to be very cautious about the results consistently shown in the previous literature that urban areas enjoy the advantage of higher payoff to education, especially for those studies not considering the self-selection issue.

The expansion of education and the fast economic development in recent China makes it possible for more families and individuals to invest in higher levels of education, especially tertiary education. However, individuals need to be aware that even if at the same tertiary level, there would be a heterogeneous return in the labour market after graduation. Our analysis shows a significant disequilibrium in graduates in the current Chinese labour market. Up to 40% of individuals are over-educated and suffer from significantly lower wages than those matched. Therefore, individuals need to be quite cautious before investing in tertiary education because the investment in low return tertiary education may be a waste of actual cost (tuition fees and costs for preparing for entrance examinations) and opportunity cost (time wasted for not doing paid jobs earlier).

The over-education circumstance reflects the existing disequilibrium in the labour market's supply and demand of highly skilled workers. Originally, the labour market experienced a segmentation between tertiary and non-tertiary educated workers. These individuals are treated as non-competing groups. However, under the disequilibrium, the segmentation is not strict anymore, and tertiary educated workers will also compete for jobs that are normally suitable for non-tertiary educated workers. Policymakers should also take action to solve this problem. On the supply side, policymakers may need to consider whether the expansion of tertiary education still needs to be continued. However, arguments can be raised that measures should not be only restricted to the supply side. If the universities or colleges suddenly decrease enrollments, a number of high school graduates would lose the opportunities to take tertiary education and be forced to find jobs after graduation from high school, which could also affect the equilibrium of the labour market for high school students. Therefore, actions should be focused more on the demand side, where the core target of policymakers should be promoting the usage of skilled workers in the labour market. For example, subsidies or tax exceptions can be provided to those technology-oriented companies that make better use of high-educated professionals. In addition, actions should not be restricted to the private sector but also to public sectors that can be directly affected by the government, such as education, health care and public services.

In fact, it often takes time for the policies from the government to take effect and the labour market to be adjusted. Therefore, individuals could also take action to avoid the over-education penalty in the short run. Self-employment could be a solution to the disequilibrium in the waged market, which is also suggested by Nieto and Ramos (2017). According to CFPS, till 2018, only 4% of self-employed workers held tertiary education qualifications in the Chinese labour market, and it seems not likely that an excess supply of skilled workers would exist in the self-employed market. In recent years, a number of researchers have provided evidence of positive returns to higher education in the self-employed workers group (e.g. Hu, 2015; Tokila and Tervo, 2011). However, it is reported that only 3% of new graduates would choose to become self-employed workers in China (Employment Report on Chinese Graduates, 2020).

Heterogeneous returns at the tertiary education level are also found to be correlated with different education qualities, or in other words, the institution types. Graduates from key universities would have 25% and 39% higher wages than those from ordinary universities and colleges, respectively. However, ordinary universities only enjoy a 14% premium compared with colleges. In China, most tertiary education institutions are publicly funded, and students do not need to pay higher tuition fees or suffer from other extra costs for studying in key universities. High returns in key universities may drive the motivations of individuals and families to invest in higher education. However, they should be aware that only very selective students can have the chance to be admitted to key universities, which only account for smaller than 10% of all the graduates in China. At the same time, the key universities are defined according to a "good university" list determined decades ago. Therefore, some new schools with short histories but high education qualities are largely disadvantaged because employers often use the "key university" list as an important signal. However, in our analysis, we find very similar cognitive skills between graduates from key and ordinary universities, and the returns are estimated to be slightly affected after controlling for skills variables. Therefore, it may largely drive the concern that the returns to higher education qualities, especially to key universities, are only the payoff to credentials rather than actual productivity. Therefore, two recommendations can be provided to policymakers and employers. Firstly, attentions need to be paid to the payoff to graduates in ordinary universities, who devote at least four years and invest in similar tuition fees to achieve higher education qualifications. Policymakers may consider updating the list of good universities according to the new development condition of tertiary education. The previous empirical results show that the traditional ranking system is essential for employers in employee screening and wage allocation. However, it is clear that this system provides incomprehensive information and is not up to date. Policymakers may consider refining it through access to information for QS and other international rankings. For example, the list can provide scores to each higher education institution to show clearer education quality gaps rather than just dividing schools into "key" and "ordinary". Also, the rankings for subjects can be provided. The old system only shows the overall competitive power of colleges, but some institutions are specialised in performing well in specific subjects. In addition, policymakers need to make sure the system is updated in time, for example, by refining it on a yearly basis. Secondly, employers need to provide higher payoffs to those individuals with actual higher productivity rather than just using the credentials as a signal. Some other criteria can be used to justify the excellence of a graduate, such as grades of qualifications and awarded scholarships or certificates, which are more correlated with the individuals' education outcomes and skills at graduation.

Our analyses are clearly not out of limitations. In the following, I summarise some most important limitations that may be improved in future studies. Firstly, when measuring individuals' urban/rural status, we refer to the residence locations and social backgrounds (registration status) and compare them. However, another method in the literature uses the working location as the benchmark to divide urban/rural workers. The difference between working and residence locations is mainly driven by commuting between different areas. However, in CFPS, individuals' working locations are unavailable. Therefore, we are not able to compare different returns using working and residence locations to achieve more robust results. Secondly, CFPS only provides information on wage income for employees. Therefore, we cannot compare the return to education between self-employed workers and those employed by others. In recent years the comparison between these two groups of workers is more focused, and evidence shows that there would be significant differences in the return to education between them (Tokila and Tervo, 2011). In addition, it also argued that the estimation of return to education for self-employed workers does not suffer from the omitted variable bias because in the self-employment market, education does not need to play the role of signal (Harmon et al., 2003). However, we are not able to check this assumption in our analysis. This limitation can be solved by using better data that provide income information for self-employed workers in future studies. Thirdly, we use the IV method to solve the possible omitted variable bias in the third chapter. However, the returns under the IV method are considerably larger using different instruments, which is inconsistent with the original assumption that returns would decrease if considering the unobserved heterogeneity. Though we propose some rationale explanations, such as measurement error or Local Average Treatment Effect, the results look less convincing, and we cannot further conduct tests to confirm these explanations. Therefore, it is better to use some direct measures to find proxies for the omitted ability, such as the IQ test score (Aslam et al., 2012). However, in CFPS, we do not have such information related to individuals' innate abilities. Fourthly, the measurements of individuals' skills in the thesis may suffer from two limitations, even if we cover different domains of skills, including cognitive and non-cognitive ones. First, it can be argued that cognitive skills would not be comprehensively measured by numeracy, literacy achievements, or even both. Some other researchers (e.g. Hanushek et al., 2015) also include problem-solving skills in the analysis, but such information is not available in CFPS. Second, even if cognitive skills can be successfully measured, other domains of individuals' skills may also significantly affect individuals' labour market outcomes, such as technical skills mentioned by Wu and Wang (2018). However, the information on technical skills is also not available in CFPS. In fact, skills have the feature of multi-dimensions and are not easy to be comprehensively measured. This is also why researchers often prefer to use education achievements as proxies of individuals' human capital rather than skills. Fifthly, in the analyses, we face restrictions on the sample size, especially when we adopt the "resampling" method to obtain nationally representative samples. For example, we only have a sample size smaller than 1000 when analysing the return for graduates. Also, in chapter five, subjects can be divided into 12 categories in the standard classification. However, in CFPS, with the limited sample size, we need to re-categorize the subject into groups, especially when we want to examine the interaction effect between subjects and education qualities. In addition, since the number of graduates working in rural areas is quite smaller than that in urban areas, we are not able to make a detailed classification of education qualities between key and ordinary universities when we study the different returns between urban/rural subgroups. Though we provide further robustness checks that empirical results in different chapters will not be affected largely if using larger samples without resampling, future empirical work may investigate the use of weighted regression analysis or pooling of samples across different years.

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Appendices

Appendix A: Test Results on Equal Coefficients on Return to Education between Urban and Rural Areas

Table A.1: Equal coefficient tests on return to education

		Urban	Rural	Difference in coefficients	P-value
T-test	Coefficients	0.046	0.025	0.021	0.0003
SUR test	Coefficients	0.046	0.025	0.021	0.0002

T-test follows the method provided by O'Leary and Sloane (2011) where the standard error of the difference of the two point estimates are $\Delta\mathrm{se} \ = (\mathrm{se}_1^2 + \mathrm{se}_2^2)^{1/2}$
SUR test comes from the Seemingly Uncorrelated Method. It is based on the simultaneous distribution of estimators and uses suest command in Stata. Test statistics follow the chi-square distribution.

Table A.2: Equal coefficient tests on return to education with correction on self-selection

		Urban	Rural	Difference in coefficients	P-value
T-test	Coefficients	0.049	0.042	0.007	0.520
SUR test	Coefficients	0.049	0.042	0.007	0.526

T-test follows the method provided by O'Leary and Sloane (2011) where the standard error of the difference of the two point estimates are $\Delta\mathrm{se} \ = (\mathrm{se}_1^2 + \mathrm{se}_2^2)^{1/2}$
SUR test comes from the Seemingly Uncorrelated Method. It is based on the simultaneous distribution of estimators and uses suest command in Stata. Test statistics follow the chi-square distribution.

Appendix B: Return to Education Using Education Categories

Table B.1: Return to education in urban and rural areas using education categories

	Urban		Rural	
	(1)	(2)	(1)	(2)
Primary school	0.135^{**}	0.126^{**}	0.059	0.027
	(0.061)	(0.061)	(0.060)	(0.061)
Lower middle school	0.217^{***}	0.178^{***}	0.139^{**}	0.121^{**}
	(0.054)	(0.055)	(0.057)	(0.058)
Upper middle school	0.351^{***}	0.266^{***}	0.256^{***}	0.170^{***}
	(0.057)	(0.058)	(0.065)	(0.065)
Tertiary undergraduate	0.732^{***}	0.668^{***}	0.612^{***}	0.459^{***}
	(0.057)	(0.061)	(0.071)	(0.074)
Male	0.320^{***}	0.319^{***}	0.356^{***}	0.340^{***}
	(0.021)	(0.022)	(0.029)	(0.031)
Age	0.033^{***}	0.030^{***}	0.035^{***}	0.028^{***}
	(0.009)	(0.009)	(0.010)	(0.010)
Age square/100	-0.036^{***}	-0.032^{***}	-0.023^{***}	-0.021^{***}
	(0.008)	(0.007)	(0.007)	(0.007)
Minority	0.108^{**}	0.101^{**}	0.005	0.005
	(0.048)	(0.049)	(0.042)	(0.042)
Marriage status	0.030	0.038	0.026	0.030
	(0.031)	(0.030)	(0.036)	(0.036)
Urban "Hukou"	0.049^{**}	0.032	0.190^{***}	0.170^{***}
	(0.025)	(0.025)	(0.051)	(0.050)
Northeast	-0.142^{***}	-0.130^{***}	-0.039	-0.046
	(0.037)	(0.036)	(0.067)	(0.065)
East	0.170^{***}	0.163^{***}	0.103^{***}	0.090^{***}
	(0.027)	(0.027)	(0.033)	(0.032)
Middle	0.020	0.028	0.004	0.000
	(0.030)	(0.030)	(0.039)	(0.038)
Contract		0.102^{***}		0.196^{***}
		(0.024)		(0.030)
Public sector		-0.010		0.005
		(0.027)		(0.043)
Raw materials		0.100		-0.034
		(0.093)		(0.121)
Manufacturing		-0.011		0.167^{***}
		(0.035)		(0.053)
Retailing and wholesaling		0.009		0.148^{***}
		(0.031)		(0.051)
Small firm		-0.109^{***}		-0.060
		(0.026)		(0.038)
Medium firm		0.014		0.008
		(0.029)		(0.044)
Constant	1.582^{***}	1.604^{***}	1.673^{***}	1.950^{***}
	(0.164)	(0.196)	(0.191)	(0.327)
Occupations	No	Yes	No	Yes
N	3642	3642	1949	1949
Adj. R^2	0.217	0.243	0.168	0.203

Robust Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix C: Return to Education with Residential and "Hukou" Status

Table C.1: Return to education with urban/rural and hukou status

	Urban		Migrants		Rural	
	(1)	(2)	(3)	(4)	(5)	(6)
Education years	0.085***	0.063***	0.044***	0.032***	0.037***	0.025***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)
Male	0.225***	0.240***	0.376***	0.375***	0.327***	0.321***
	(0.030)	(0.033)	(0.029)	(0.030)	(0.028)	(0.030)
Age	0.027**	0.028**	0.040***	0.032***	0.038***	0.031***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)
Age square/100	-0.042***	-0.048***	-0.082***	-0.084***	-0.092***	-0.096***
	(0.013)	(0.013)	(0.032)	(0.032)	(0.036)	(0.036)
Minority	0.123*	0.115	0.087	0.080	0.006	0.005
	(0.072)	(0.070)	(0.066)	(0.067)	(0.043)	(0.044)
Marriage status	-0.005	-0.005	0.053	0.078*	0.002	0.012
	(0.044)	(0.043)	(0.044)	(0.043)	(0.037)	(0.038)
Urban "Hukou"	0.000	0.000	0.000	0.000	0.231***	0.198***
					(0.050)	(0.046)
Northeast	-0.159***	-0.138***	-0.085	-0.041	-0.056	-0.062
	(0.046)	(0.046)	(0.079)	(0.080)	(0.068)	(0.070)
East	0.231***	0.243***	0.142***	0.120***	0.092***	0.083**
	(0.044)	(0.044)	(0.034)	(0.034)	(0.033)	(0.034)
Middle	-0.034	-0.016	0.085**	0.082**	-0.007	-0.009
	(0.045)	(0.045)	(0.041)	(0.040)	(0.039)	(0.038)
Contract		0.063*		0.161***		0.199***
		(0.034)		(0.034)		(0.031)
Public sector		0.030		-0.081**		0.022
		(0.037)		(0.040)		(0.040)
Raw materials		-0.136		0.418***		-0.020
		(0.124)		(0.123)		(0.113)
Manufacturing		-0.073		0.086*		0.165***
		(0.050)		(0.049)		(0.049)
Retailing and wholesaling		-0.014		0.066		0.151***
		(0.042)		(0.047)		(0.047)
Small firm		-0.167***		-0.072**		-0.071**
		(0.037)		(0.037)		(0.035)
Medium firm		0.003		0.005		-0.000
		(0.039)		(0.041)		(0.042)
Constant	1.108***	1.496***	1.387***	1.323***	1.498***	1.816***
	(0.249)	(0.287)	(0.217)	(0.257)	(0.191)	(0.257)
Occupations	Yes	Yes	Yes	Yes	Yes	Yes
N	1789	1789	1853	1853	1949	1949
Adj. R^2	0.235	0.271	0.181	0.213	0.157	0.197

Robust Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix D: Full Results on the IV and Heckman Second Stage

Table D.1: Full results of IV regression second stage

	Parental education		Institutional change	
	Urban	Rural	Urban	Rural
Education years	0.090***	0.044*	0.139***	0.066***
	(0.017)	(0.019)	(0.035)	(0.025)
Male	0.285***	0.325***	0.275***	0.287***
	(0.025)	(0.038)	(0.027)	(0.038)
Age	0.041***	0.031***	0.035***	0.038***
	(0.009)	(0.011)	(0.009)	(0.011)
Age square/100	-0.048***	-0.029***	-0.046***	-0.027***
	(0.015)	(0.015)	(0.012)	(0.012)
Minority	0.182***	-0.037	0.167***	0.050
	(0.055)	(0.049)	(0.058)	(0.053)
Marriage status	0.015	-0.006	0.028	-0.001
	(0.034)	(0.040)	(0.033)	(0.037)
Urban “Hukou”	-0.057	0.166***	-0.152**	0.133**
	(0.041)	(0.063)	(0.074)	(0.062)
Northeast	-0.134***	-0.041	-0.155***	-0.091
	(0.041)	(0.072)	(0.041)	(0.068)
East	0.149***	0.113***	0.120***	0.055
	(0.031)	(0.040)	(0.035)	(0.037)
Middle	0.029	-0.010	0.000	-0.027
	(0.034)	(0.043)	(0.035)	(0.040)
Contract	0.075**	0.222***	-0.004	0.135***
	(0.032)	(0.051)	(0.046)	(0.049)
Public sector	-0.054	0.032	-0.106**	-0.002
	(0.035)	(0.048)	(0.047)	(0.047)
Raw materials	0.145	0.000	0.129	0.024
	(0.103)	(0.121)	(0.105)	(0.135)
Manufacturing	0.005	0.138**	0.014	0.197***
	(0.038)	(0.063)	(0.039)	(0.057)
Retailing and wholesaling	0.011	0.107*	0.013	0.161***
	(0.034)	(0.058)	(0.034)	(0.052)
Small firm	-0.086***	-0.076*	-0.073**	-0.075*
	(0.030)	(0.039)	(0.032)	(0.038)
Medium firm	0.019	-0.007	0.005	-0.025
	(0.031)	(0.050)	(0.031)	(0.047)
Constant	0.725**	2.023***	0.322	1.280***
	(0.315)	(0.449)	(0.463)	(0.451)
Occupations	Yes	Yes	Yes	Yes
N	3118	1659	3642	1949
R^2	0.203	0.180	0.092	0.157

Robust Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D1: Full results of Heckman two-step regression second stage

	Urban	Rural
Education years	0.049***	0.042***
	(0.007)	(0.008)
Male	0.315***	0.395***
	(0.024)	(0.044)
Age	0.032***	0.030***
	(0.008)	(0.010)
Age square/100	-0.048***	-0.082***
	(0.016)	(0.028)
Minority	0.100**	-0.050
	(0.050)	(0.051)
Marriage status	0.025	-0.078
	(0.035)	(0.055)
Urban "Hukou"	0.042	0.312***
	(0.035)	(0.068)
Northeast	-0.127***	-0.108
	(0.039)	(0.075)
East	0.172***	0.152***
	(0.032)	(0.046)
Middle	0.037	0.032
	(0.031)	(0.043)
Contract	0.098***	0.200***
	(0.024)	(0.030)
Public sector	-0.001	0.022
	(0.026)	(0.040)
Raw materials	0.105	-0.017
	(0.110)	(0.111)
Manufacturing	-0.013	0.161***
	(0.033)	(0.049)
Retailing and wholesaling	0.002	0.147***
	(0.030)	(0.047)
Small firm	-0.117***	-0.071**
	(0.026)	(0.035)
Medium firm	0.012	0.000
	(0.029)	(0.042)
Lambda	0.053	0.387**
	(0.133)	(0.161)
Constant	1.328***	1.472***
	(0.266)	(0.301)
Occupations	Yes	Yes
N	3642	1949

Lambda is the inverse Mills Ratio for the correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E: Empirical Results on Return to Education without the Resampling Method

Table E.1: Return to education in urban and rural areas under the larger sample size

	Urban		Rural	
	(1)	(2)	(3)	(4)
Education years	0.068***	0.049***	0.037***	0.026***
	(0.003)	(0.003)	(0.004)	(0.004)
Male	0.290***	0.282***	0.359***	0.358***
	(0.019)	(0.020)	(0.025)	(0.027)
Age	0.040***	0.038***	0.026***	0.017*
	(0.008)	(0.008)	(0.009)	(0.009)
Age square/100	-0.048***	-0.046***	-0.083***	-0.085***
	(0.015)	(0.016)	(0.028)	(0.024)
Minority	0.070	0.053	0.037	0.032
	(0.046)	(0.046)	(0.038)	(0.038)
Marriage status	0.034	0.033	0.051	0.067**
	(0.029)	(0.028)	(0.034)	(0.034)
Urban "Hukou"	0.103***	0.077***	0.224***	0.188***
	(0.022)	(0.022)	(0.042)	(0.042)
Northeast	-0.149***	-0.127***	0.010	-0.009
	(0.031)	(0.031)	(0.045)	(0.045)
East	0.269***	0.256***	0.143***	0.128***
	(0.025)	(0.025)	(0.029)	(0.029)
Middle	-0.014	-0.005	0.060*	0.051
	(0.029)	(0.029)	(0.035)	(0.035)
Contract		0.110***		0.151***
		(0.023)		(0.027)
Public sector		0.013		0.035
		(0.024)		(0.039)
Raw materials		-0.065		0.061
		(0.139)		(0.115)
Manufacturing		0.014		0.115***
		(0.032)		(0.043)
Retailing and wholesaling		0.038		0.100**
		(0.029)		(0.043)
Small firm		-0.110***		-0.137***
		(0.025)		(0.034)
Medium firm		-0.012		-0.069*
		(0.026)		(0.039)
Constant	1.099***	1.150***	1.619***	2.044***
	(0.147)	(0.202)	(0.168)	(0.293)
Occupations	No	Yes	No	Yes
N	5109	5109	2710	2710
adj. R^2	0.231	0.262	0.147	0.178

Robust Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Heckman two-step results on return to education under the larger sample size

	Urban		Rural	
	OLS	Heckman	OLS	Heckman
Second Stage				
Education years	0.049***	0.051***	0.026***	0.042***
	(0.003)	(0.007)	(0.004)	(0.008)
Lambda		0.054		0.439***
		(0.118)		(0.155)
Constant		1.059***		1.706***
		(0.286)		(0.324)
N	5109	5109	2710	2710
First Stage				
Education years		0.078***		0.064***
		(0.004)		(0.004)
Male		0.256***		0.362***
		(0.027)		(0.031)
Age		0.050***		0.014
		(0.011)		(0.011)
Age square/100		-0.072***		-0.063***
		(0.021)		(0.025)
Minority		-0.175***		-0.125**
		(0.059)		(0.049)
Marriage status		-0.099**		-0.179***
		(0.044)		(0.048)
Urban “Hukou”		0.195***		0.503***
		(0.031)		(0.061)
Northeast		0.123***		-0.089*
		(0.046)		(0.052)
East		0.236***		0.286***
		(0.036)		(0.038)
Middle		0.080**		0.133***
		(0.040)		(0.041)
Young children		-0.137***		-0.108***
		(0.016)		(0.015)
Old people		-0.023		-0.001
		(0.021)		(0.022)
Constant		-1.420***		-0.701***
		(0.208)		(0.212)
N		9618		8996
Pseudo R^2		0.324		0.428

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Other variables in the second stage include: gender, age, age square, marriage status, “Hukou” status and province controls, contract type, sector, firm size, industry and occupation controls

Appendix F: Correlation between Over-education and Skills Levels

Table F.1: Correlation coefficients and significance levels between over-education and skills levels

	Over-ed (Subjective)	Over-ed (Objective)	Over-ed (Statistical)
Skills level (literacy)	-0.11	-0.10	-0.12
	p = 0.00	p = 0.00	p = 0.00
Skills level (numeracy)	-0.11	-0.10	-0.10
	p = 0.00	p = 0.00	p = 0.00

Appendix G: Robustness Checks on Return to Over-education

Table G.1: Return to over-education with different statistical measurements

	Mode	Mean
Over	-0.228***	-0.224***
	(0.047)	(0.047)
Lambda	-0.156	-0.144
	(0.417)	(0.416)
Constant	1.063	1.024
	(0.817)	(0.815)
N	995	995
R^2	0.23	0.19

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses :* p < 0.1 , ** p < 0.05, *** p < 0.01

Other controls include: university type, subjects, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

Table G.2: Return to over-education and skills heterogeneity without under-skill (literacy)

	Subjective		Objective		Statistical		No-over	
	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)
Over	-0.263***	-0.269***	-0.151***	-0.172***	-0.206***	-0.222***		
	(0.047)	(0.048)	(0.047)	(0.045)	(0.053)	(0.048)		
Over-skill	-0.140**		-0.098		-0.055		-0.164***	
	(0.062)		(0.065)		(0.068)		(0.063)	
Skill level		0.004		0.005		0.003		0.008
		(0.009)		(0.009)		(0.009)		(0.009)
Lambda	-0.454	-0.147	-0.469	-0.184	-0.454	-0.141	-0.093	-0.043
	(0.297)	(0.405)	(0.301)	(0.410)	(0.297)	(0.427)	(0.379)	(0.430)
N	949	949	949	949	949	949	949	949
R^2	0.21	0.23	0.19	0.18	0.22	0.21	0.17	0.16

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses :* p < 0.1 , ** p < 0.05, *** p < 0.01

Other controls include: university type, subjects, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

Table G.3: Return to over-education controlling for utilisation of non-cognitive skills

	Subjective		Objective		Statistical	
	Spe (2)	Spe (4)	Spe (2)	Spe (4)	Spe (2)	Spe (4)
over	-0.304***	-0.303***	-0.180***	-0.167***	-0.224***	-0.214***
	(0.055)	(0.056)	(0.054)	(0.057)	(0.060)	(0.063)
Over-skill (literacy)		-0.106		-0.046		-0.031
		(0.075)		(0.080)		(0.081)
Over-conscientiousness		0.027		0.024		0.031
		(0.086)		(0.087)		(0.087)
Over-extroversion		0.045		0.055		0.051
		(0.067)		(0.069)		(0.067)
Over-agreeableness		0.041		0.059		0.053
		(0.070)		(0.071)		(0.071)
Over-openness		-0.029		-0.012		-0.016
		(0.069)		(0.070)		(0.070)
Over-neuroticism		0.028		0.023		0.032
		(0.063)		(0.064)		(0.064)
Over-locus of control		-0.078		-0.048		-0.039
		(0.080)		(0.081)		(0.081)
Lambda	0.219	0.231	0.255	0.269	0.250	0.315
	(0.436)	(0.496)	(0.443)	(0.346)	(0.442)	(0.346)
Constant	0.149	0.100	0.044	0.053	0.083	0.122
	(1.004)	(0.852)	(1.022)	(0.870)	(1.019)	(0.871)
N	661	661	661	661	661	661
R^2	0.22	0.23	0.21	0.22	0.20	0.21

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses :* p < 0.1 , ** p < 0.05, *** p < 0.01

Other controls include: university type, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

Appendix H: Full Results on Return to Over-education with Skills

Table H.1: Full regression results on return to over-education controlling for cognitive skills heterogeneity, literacy

	Subjective		Objective		Statistical		No-over	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Over	-0.262***	-0.270***	-0.163***	-0.181***	-0.218***	-0.231***		
	(0.046)	(0.046)	(0.046)	(0.044)	(0.051)	(0.048)		
Over-skill	-0.118**		-0.071		-0.034		-0.136**	
	(0.059)		(0.062)		(0.064)		(0.059)	
Skill level		-0.003		-0.003		-0.003		-0.002
		(0.004)		(0.004)		(0.004)		(0.004)
University	0.168***	0.172***	0.187***	0.187***	0.178***	0.179***	0.218***	0.222***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Male	0.041	0.042	0.044	0.043	0.041	0.046	0.038	0.039
	(0.045)	(0.046)	(0.046)	(0.047)	(0.046)	(0.047)	(0.046)	(0.047)
Age	0.039	0.041	0.030	0.030	0.030	0.029	0.026	0.030
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Age square/100	-0.023	-0.023	-0.034	-0.034	-0.056	-0.057	-0.062	-0.063
	(0.061)	(0.062)	(0.072)	(0.070)	(0.043)	(0.043)	(0.042)	(0.043)
Minority	-0.046	-0.040	-0.045	-0.039	-0.056	-0.051	-0.062	-0.058
	(0.087)	(0.087)	(0.088)	(0.089)	(0.088)	(0.089)	(0.089)	(0.089)
Marriage status	-0.022	-0.025	-0.013	-0.014	-0.014	-0.013	-0.012	-0.017
	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Urban residence	-0.020	-0.020	-0.013	-0.013	-0.014	-0.017	-0.024	-0.020
	(0.064)	(0.065)	(0.065)	(0.065)	(0.065)	(0.066)	(0.065)	(0.066)
Urban "Hukou"	0.182**	0.184**	0.186**	0.187**	0.185**	0.189**	0.188**	0.184**
	(0.085)	(0.085)	(0.086)	(0.086)	(0.086)	(0.086)	(0.087)	(0.087)
Northeast	-0.057	-0.060	-0.038	-0.040	-0.039	-0.041	-0.054	-0.055
	(0.084)	(0.084)	(0.085)	(0.085)	(0.085)	(0.086)	(0.086)	(0.086)
East	0.041	0.045	0.033	0.035	0.036	0.035	0.031	0.037
	(0.060)	(0.060)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
Middle	-0.089	-0.090	-0.079	-0.078	-0.083	-0.079	-0.086	-0.090
	(0.089)	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.091)
Contract	0.186***	0.189***	0.198***	0.199***	0.194***	0.193***	0.207***	0.212***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)
Public sector	-0.025	-0.030	0.010	0.008	-0.006	-0.006	-0.001	-0.008
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)	(0.050)
Raw materials	0.296	0.270	0.233	0.218	0.263	0.253	0.206	0.178
	(0.195)	(0.195)	(0.196)	(0.197)	(0.196)	(0.196)	(0.197)	(0.198)
Manufacturing	0.203***	0.190***	0.202***	0.198***	0.222***	0.221***	0.166***	0.150**
	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)	(0.059)	(0.059)
Retailing and wholesaling	0.242***	0.236***	0.263***	0.262***	0.270***	0.271***	0.232***	0.224***
	(0.056)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)	(0.056)	(0.057)
Small firm	-0.112**	-0.114**	-0.117**	-0.119**	-0.122***	-0.125***	-0.115**	-0.116**
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)
Medium firm	-0.072	-0.070	-0.049	-0.049	-0.048	-0.049	-0.038	-0.035
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.068)
Lambda	-0.129	-0.134	-0.149	-0.173	-0.159	-0.211	-0.149	-0.117
	(0.412)	(0.420)	(0.416)	(0.424)	(0.416)	(0.425)	(0.419)	(0.426)
Constant	1.000	1.031	1.025	1.104	1.069	1.208	0.889	0.826
	(0.807)	(0.831)	(0.817)	(0.842)	(0.815)	(0.844)	(0.821)	(0.843)
N	995	995	995	995	995	995	995	995

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table H.2: Full regression results on return to over-education controlling for cognitive skills heterogeneity, numeracy

	Subjective		Objective		Statistical		No-over	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Over	-0.265***	-0.270***	-0.175***	-0.182***	-0.233***	-0.232***		
	(0.046)	(0.046)	(0.045)	(0.044)	(0.050)	(0.048)		
Over-skill	-0.041		-0.020		0.018		-0.057	
	(0.047)		(0.048)		(0.050)		(0.048)	
Skill level		-0.003		-0.003		-0.004		-0.002
		(0.005)		(0.005)		(0.005)		(0.005)
University	0.176***	0.177***	0.193***	0.193***	0.185***	0.186***	0.224***	0.226***
	(0.047)	(0.047)	(0.048)	(0.048)	(0.048)	(0.048)	(0.047)	(0.047)
Male	0.041	0.042	0.043	0.042	0.041	0.044	0.038	0.039
	(0.045)	(0.046)	(0.046)	(0.047)	(0.046)	(0.047)	(0.046)	(0.047)
Age	0.046	0.044	0.039	0.032	0.045	0.031	0.029	0.033
	(0.029)	(0.031)	(0.029)	(0.031)	(0.029)	(0.031)	(0.029)	(0.031)
Age square/100	-0.022	-0.023	-0.032	-0.032	-0.056	-0.055	-0.065	-0.065
	(0.062)	(0.063)	(0.072)	(0.072)	(0.045)	(0.045)	(0.048)	(0.049)
Minority	-0.051	-0.049	-0.051	-0.047	-0.067	-0.061	-0.063	-0.065
	(0.086)	(0.086)	(0.087)	(0.087)	(0.087)	(0.087)	(0.088)	(0.088)
Marriage status	-0.032	-0.029	-0.024	-0.017	-0.030	-0.017	-0.017	-0.021
	(0.059)	(0.059)	(0.059)	(0.060)	(0.059)	(0.060)	(0.060)	(0.060)
Urban residence	-0.007	-0.014	0.002	-0.009	0.008	-0.012	-0.017	-0.014
	(0.062)	(0.064)	(0.063)	(0.065)	(0.063)	(0.065)	(0.063)	(0.066)
Urban “Hukou”	0.181**	0.184**	0.185**	0.187**	0.185**	0.188**	0.188**	0.185**
	(0.085)	(0.085)	(0.086)	(0.086)	(0.086)	(0.086)	(0.087)	(0.087)
Northeast	-0.067	-0.064	-0.052	-0.044	-0.061	-0.046	-0.056	-0.060
	(0.082)	(0.082)	(0.082)	(0.083)	(0.082)	(0.083)	(0.083)	(0.084)
East	0.050	0.049	0.040	0.038	0.043	0.038	0.038	0.040
	(0.060)	(0.060)	(0.060)	(0.061)	(0.060)	(0.060)	(0.061)	(0.061)
Middle	-0.109	-0.101	-0.103	-0.088	-0.120	-0.090	-0.094	-0.102
	(0.085)	(0.088)	(0.085)	(0.089)	(0.086)	(0.089)	(0.086)	(0.090)
Contract	0.188***	0.189***	0.198***	0.199***	0.193***	0.193***	0.210***	0.212***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)
Public sector	-0.028	-0.030	0.009	0.010	-0.008	-0.006	-0.004	-0.007
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)	(0.050)
Raw materials	0.290	0.278	0.230	0.225	0.256	0.261	0.202	0.183
	(0.195)	(0.195)	(0.197)	(0.196)	(0.196)	(0.196)	(0.198)	(0.198)
Manufacturing	0.196***	0.193***	0.200***	0.201***	0.220***	0.225***	0.159***	0.152**
	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.059)
Retailing and wholesaling	0.240***	0.237***	0.264***	0.263***	0.271***	0.272***	0.229***	0.225***
	(0.056)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
Small firm	-0.114**	-0.114**	-0.118**	-0.120**	-0.122***	-0.126***	-0.118**	-0.116**
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)
Medium firm	-0.073	-0.071	-0.049	-0.050	-0.046	-0.050	-0.040	-0.035
	(0.067)	(0.067)	(0.068)	(0.067)	(0.067)	(0.067)	(0.068)	(0.068)
Lambda	0.008	-0.062	0.016	-0.112	0.098	-0.141	-0.093	-0.043
	(0.373)	(0.423)	(0.377)	(0.428)	(0.377)	(0.427)	(0.379)	(0.430)
Constant	0.760	0.883	0.747	0.985	0.627	1.068	0.789	0.685
	(0.757)	(0.841)	(0.764)	(0.852)	(0.764)	(0.851)	(0.771)	(0.854)
N	995	995	995	995	995	995	995	995

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses :* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table H.3: Full regression results on return to over-education controlling for non-cognitive skills

	Subjective	Objective	Statistical
Over	-0.283***	-0.157***	-0.206***
	(0.056)	(0.054)	(0.060)
University	0.162***	0.194***	0.190***
	(0.063)	(0.063)	(0.063)
Male	0.055	0.056	0.158
	(0.052)	(0.053)	(0.053)
Age	0.069**	0.065*	0.066*
	(0.035)	(0.036)	(0.036)
Age square/100	-0.066	-0.052	-0.059
	(0.049)	(0.048)	(0.051)
Minority	-0.154	-0.164	-0.177
	(0.110)	(0.112)	(0.111)
Marriage status	-0.010	-0.009	-0.012
	(0.071)	(0.072)	(0.072)
Urban residence	-0.047	-0.037	-0.040
	(0.065)	(0.066)	(0.065)
Urban "Hukou"	0.192*	0.216**	0.183*
	(0.111)	(0.113)	(0.113)
Northeast	-0.134	-0.122	-0.135
	(0.097)	(0.098)	(0.098)
East	0.016	0.013	0.014
	(0.077)	(0.078)	(0.078)
Middle	-0.135	-0.138	-0.145*
	(0.084)	(0.085)	(0.084)
Contract	0.151***	0.158***	0.149**
	(0.057)	(0.058)	(0.058)
Public sector	-0.018	0.016	0.004
	(0.060)	(0.061)	(0.060)
Raw materials	0.467**	0.402*	0.421*
	(0.226)	(0.229)	(0.229)
Manufacturing	0.240***	0.246***	0.272***
	(0.072)	(0.074)	(0.075)
Retailing and wholesaling	0.217***	0.236***	0.248***
	(0.069)	(0.071)	(0.071)
Small firm	-0.103*	-0.096	-0.107*
	(0.059)	(0.059)	(0.059)
Medium firm	0.002	0.034	0.039
	(0.082)	(0.083)	(0.083)
Skill-level (literacy)	0.004	0.005	0.004
	(0.005)	(0.005)	(0.005)
Conscientiousness	0.007	0.008	0.006
	(0.050)	(0.051)	(0.050)
Extroversion	0.040	0.044	0.048
	(0.038)	(0.038)	(0.038)
Agreeableness	-0.138**	-0.129**	-0.126**
	(0.058)	(0.058)	(0.058)
Openness	0.082**	0.090**	0.091**
	(0.037)	(0.038)	(0.038)
Neuroticism	0.014	0.020	0.019
	(0.042)	(0.043)	(0.043)
Locus control	-0.018	-0.008	0.001
	(0.063)	(0.064)	(0.064)
Lambda	-0.007	0.063	0.066

	(0.434)	(0.440)	(0.439)
Constant	0.401	0.062	0.038
	(0.974)	(0.984)	(0.980)
N	661	661	661

Lambda is the inverse Mills ratio for correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses: * p < 0.1 , ** p < 0.05, *** p < 0.01

Appendix I: First Step Results on Heckman Method

Table I.1: Heckman first stage results: selection into waged jobs

	(1)	(2)	(3)
University	0.110	0.109	0.079
	(0.088)	(0.089)	(0.091)
Male	0.119	0.120	0.121
	(0.083)	(0.084)	(0.084)
Age	0.151***	0.151***	0.154***
	(0.038)	(0.038)	(0.038)
Age square/100	-0.212***	-0.232***	-0.246***
	(0.034)	(0.038)	(0.042)
Minority	-0.097	-0.097	-0.083
	(0.168)	(0.168)	(0.168)
Marriage status	-0.069	-0.069	-0.072
	(0.114)	(0.114)	(0.114)
Urban residence	0.196*	0.195*	0.193*
	(0.101)	(0.102)	(0.101)
Urban "Hukou"	0.281***	0.280**	0.272**
	(0.108)	(0.109)	(0.108)
Northeast	-0.292*	-0.291*	-0.269*
	(0.150)	(0.152)	(0.151)
East	0.044	0.044	0.043
	(0.124)	(0.124)	(0.124)
Middle	-0.375***	-0.374***	-0.359***
	(0.127)	(0.128)	(0.128)
Skill level (literacy)		0.001	
		(0.007)	
Skill level (Numeracy)			0.011
			(0.007)
Young children	-0.168***	-0.168***	-0.160***
	(0.061)	(0.061)	(0.061)
Old people	-0.026	-0.026	-0.025
	(0.078)	(0.078)	(0.078)
Constant	-2.660***	-2.668***	-2.729***
	(0.775)	(0.784)	(0.776)
N	1265	1265	1265
Pseudo R2	0.18	0.20	0.22

Over-education dummy is not included in the first step thus for different measurements the first step results are consistent

Standard errors in parentheses :* p < 0.1 , ** p < 0.05, *** p < 0.01

Appendix J: First Step Results on PSM Method

Table J.1: Selection into over-education

	Panel A: specification (2)		
	Subjective	Objective	Statistical
University	-1.058***	-0.856***	-1.001***
	(0.171)	(0.152)	(0.172)
Male	0.149	0.376***	0.623***
	(0.153)	(0.142)	(0.157)
Age	0.230***	0.086	0.080
	(0.075)	(0.071)	(0.077)
Age square/100	-0.212***	-0.092	-0.081
	(0.082)	(0.073)	(0.084)
Minority	0.332	0.412	0.047
	(0.303)	(0.284)	(0.314)
Marriage status	-0.169	-0.000	-0.006
	(0.199)	(0.186)	(0.202)
Urban residence	0.033	0.285	0.242
	(0.194)	(0.184)	(0.198)
Urban “Hukou”	-0.063	0.191	0.024
	(0.215)	(0.205)	(0.222)
Northeast	-0.056	0.327	0.202
	(0.273)	(0.250)	(0.276)
East	0.175	-0.009	0.017
	(0.215)	(0.203)	(0.220)
Middle	-0.031	0.143	-0.036
	(0.232)	(0.216)	(0.236)
Contract	-0.427**	-0.343**	-0.463***
	(0.170)	(0.161)	(0.177)
Public sector	-0.457**	0.411**	0.018
	(0.178)	(0.170)	(0.181)
Raw materials	1.722**	1.056	1.753***
	(0.698)	(0.643)	(0.665)
Manufacturing	0.766***	1.210***	1.642***
	(0.210)	(0.201)	(0.220)
Retailing and wholesaling	0.262	0.976***	1.188***
	(0.206)	(0.191)	(0.215)
Small firm	0.047	-0.064	-0.185
	(0.170)	(0.160)	(0.174)
Medium firm	-0.880***	-0.384	-0.391
	(0.285)	(0.236)	(0.262)
Constant	0.800	1.934	2.336
	(1.492)	(1.391)	(1.528)
N	995	995	995
Pseudo R^2	0.106	0.095	0.147
	Panel B: specification (3)		
	Subjective	Objective	Statistical
University	-1.064***	-0.969***	-1.252***

	(0.171)	(0.162)	(0.194)
Male	0.141	0.369**	0.682***
	(0.153)	(0.149)	(0.171)
Age	0.234***	0.118	0.129
	(0.075)	(0.075)	(0.083)
Age square/100	-0.212***	-0.092	-0.081
	(0.082)	(0.073)	(0.084)
Minority	0.350	0.508*	0.175
	(0.303)	(0.293)	(0.334)
Marriage status	-0.174	-0.046	-0.095
	(0.199)	(0.195)	(0.218)
Urban residence	0.035	0.322*	0.297
	(0.194)	(0.194)	(0.215)
Urban “Hukou”	-0.079	0.145	-0.066
	(0.215)	(0.215)	(0.241)
Northeast	-0.029	0.465*	0.426
	(0.275)	(0.264)	(0.302)
East	0.201	0.063	0.165
	(0.216)	(0.215)	(0.244)
Middle	-0.022	0.189	0.024
	(0.233)	(0.229)	(0.263)
Contract	-0.417**	-0.273	-0.400**
	(0.171)	(0.168)	(0.191)
Public sector	-0.484***	0.319*	-0.201
	(0.179)	(0.177)	(0.198)
Raw materials	1.681**	0.816	1.592**
	(0.697)	(0.685)	(0.729)
Manufacturing	0.731***	1.111***	1.638***
	(0.212)	(0.210)	(0.242)
Retailing and wholesaling	0.244	0.928***	1.211***
	(0.206)	(0.200)	(0.236)
Small firm	0.045	-0.067	-0.225
	(0.170)	(0.167)	(0.188)
Medium firm	-0.877***	-0.386	-0.418
	(0.285)	(0.247)	(0.284)
Over-skill	0.366*	1.985***	2.578***
	(0.205)	(0.234)	(0.247)
Constant	0.717	1.689	2.299
	(1.497)	(1.461)	(1.675)
N	995	995	995
Pseudo R^2	0.109	0.160	0.256
	Panel C: specification (4)		
	Subjective	Objective	Statistical
University	-1.010***	-0.815***	-0.949***
	(0.172)	(0.154)	(0.174)
Male	0.124	0.354**	0.594***
	(0.153)	(0.143)	(0.157)
Age	0.235***	0.090	0.083
	(0.075)	(0.071)	(0.077)
Age square/100	-0.212***	-0.092	-0.081

	(0.082)	(0.073)	(0.084)
Minority	0.346	0.421	0.057
	(0.303)	(0.285)	(0.315)
Marriage status	-0.174	-0.006	-0.010
	(0.199)	(0.187)	(0.203)
Urban residence	0.037	0.290	0.250
	(0.194)	(0.184)	(0.199)
Urban “Hukou”	-0.013	0.235	0.085
	(0.218)	(0.208)	(0.226)
Northeast	-0.155	0.255	0.101
	(0.279)	(0.254)	(0.281)
East	0.158	-0.023	-0.005
	(0.216)	(0.203)	(0.221)
Middle	-0.078	0.103	-0.091
	(0.233)	(0.217)	(0.238)
Contract	-0.445^{***}	-0.358^{**}	-0.482^{***}
	(0.170)	(0.161)	(0.178)
Public sector	-0.444^{**}	0.427^{**}	0.035
	(0.179)	(0.170)	(0.182)
Raw materials	1.659^{**}	0.994	1.680^{**}
	(0.707)	(0.649)	(0.676)
Manufacturing	0.755^{***}	1.202^{***}	1.635^{***}
	(0.211)	(0.201)	(0.221)
Retailing and wholesaling	0.269	0.982^{***}	1.197^{***}
	(0.206)	(0.191)	(0.215)
Small firm	0.030	-0.078	-0.203
	(0.170)	(0.160)	(0.174)
Medium firm	-0.903^{***}	-0.391^{*}	-0.411
	(0.286)	(0.238)	(0.265)
Skill level	-0.027^{**}	-0.022^{*}	-0.029^{**}
	(0.014)	(0.013)	(0.014)
Constant	1.235	2.293	2.833^{*}
	(1.508)	(1.407)	(1.547)
N	995	995	995
Pseudo R^2	0.110	0.097	0.151

Logit regression coefficients are illustrated

Standard errors in parentheses :* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix K: Tests on Matching Qualities of PSM Method

Table K.1: Matching qualities (covariate balance)

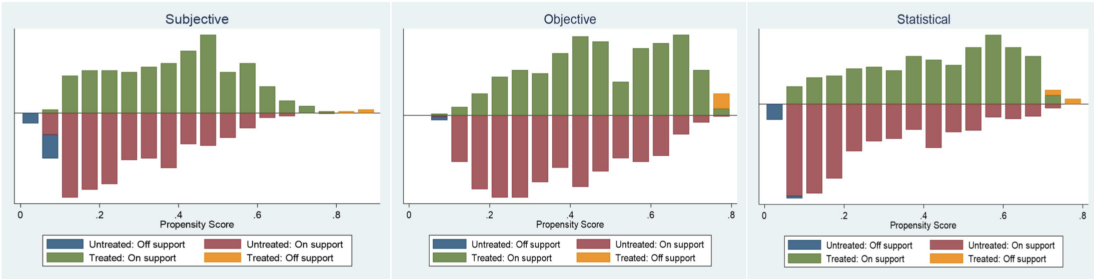
	Subjective				Objective				Statistical			
	Before		After		Before		After		Before		After	
Spec. (2)	MB	r2	MB	r2	MB	r2	MB	r2	MB	r2	MB	r2
NN_1	13.9	0.107	2.8	0.007	12.3	0.095	5.5	0.019	15.7	0.147	5.5	0.021
NN_4	13.9	0.107	2.6	0.003	12.3	0.095	3.6	0.008	15.7	0.147	2.8	0.004
Kernel _0.02	13.9	0.107	1.4	0.002	12.3	0.095	2.3	0.003	15.7	0.147	1.3	0.001
Kernel _0.06	13.9	0.107	1.6	0.002	12.3	0.095	2.3	0.002	15.7	0.147	1.6	0.002
Spec. (3)	MB	r2	MB	r2	MB	r2	MB	r2	MB	r2	MB	r2
NN_1	13.9	0.109	3.7	0.012	14.9	0.160	6.0	0.014	18.9	0.254	6.5	0.018
NN_4	13.9	0.109	2.4	0.004	14.9	0.160	4.1	0.007	18.9	0.254	3.6	0.009
Kernel _0.02	13.9	0.109	1.8	0.002	14.9	0.160	3.8	0.006	18.9	0.254	4.2	0.009
Kernel _0.06	13.9	0.109	1.5	0.002	14.9	0.160	2.8	0.004	18.9	0.254	3.6	0.008
Spec.(4)	MB	r2	MB	r2	MB	r2	MB	r2	MB	r2	MB	r2
NN_1	14.4	0.110	5.4	0.015	12.6	0.098	6.1	0.019	11.5	0.151	6.7	0.028
NN_4	14.4	0.110	2.4	0.005	12.6	0.098	3.1	0.005	11.5	0.151	3.1	0.009
Kernel _0.02	14.4	0.110	2.0	0.003	12.6	0.098	2.9	0.005	11.5	0.151	2.5	0.005
Kernel _0.06	14.4	0.110	1.9	0.002	12.6	0.098	2.4	0.003	11.5	0.151	2.4	0.004

Matching algorithms: NN_1: nearest neighbour (NN) with 1 neighbour; NN_4: NN with 4 neighbours; Kernel_0.02: Epanechnikov kernel with a bandwidth of 0.02; Kernel_0.06: Epanechnikov kernel with a bandwidth of 0.06;

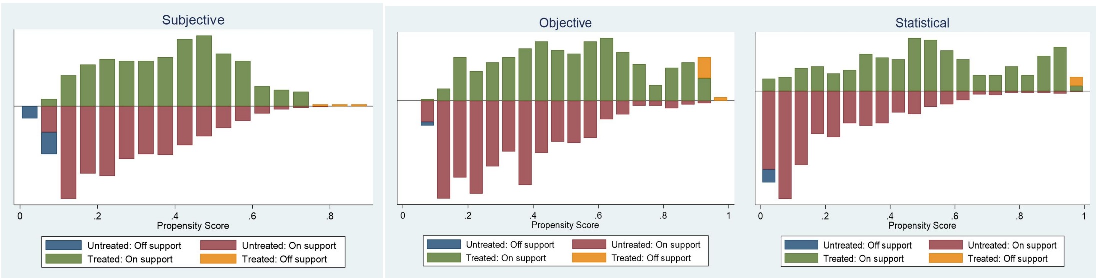
Quality measures: MB_bef: the mean absolute standardised bias before matching; MB_aft: the mean absolute standardised bias after matching; r2bef: Pseudo R2 from probit estimation of the propensity score on all the variables on raw samples; r2aft: Pseudo R2 from probit estimation of the propensity score on all the variables on matched samples

Figure K.1: Matching quality (common support)

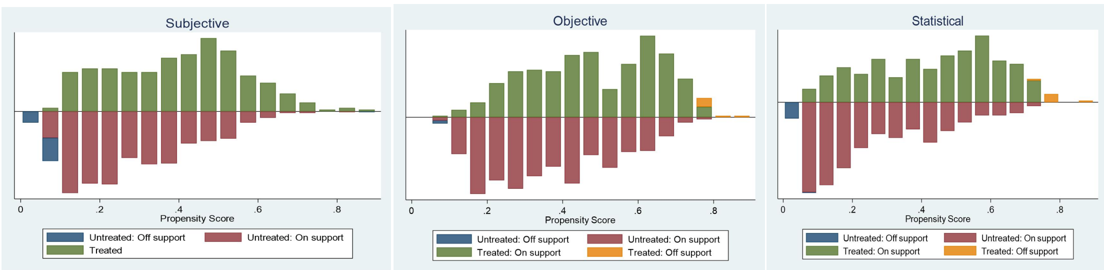
Panel A: Results from specification (2)



Panel B: Results from specification (3)



Panel C: Results from specification (4)



The graphs present distribution of propensity scores on common support with kernel matching for three different specifications

Matching algorithms: Epanechnikov kernel with a bandwidth of 0.06

Appendix L: Classifications of Occupations in CFPS

Table L.1: Classifications of occupations in CFPS and descriptive statistics on required education

Occupation Code and Title			**Summary statistics of education years**			
Original code	**Current code**	**Title**	**N**	**Mode level of Education**	**Mean years of education**	**Standard Deviation of education**
10000	**1-X**	**Leading cadres: state organizations, the Chinese Communist Party (CPC Party) and mass organizations, enterprises and public institutions**				
10100, 10200, 10400	11	Leading cadres: Central Committee and provincial organizations of the Chinese Communist Party, government agencies and relevant functional organizations, public institutions(1)	17	4	14.882	4.136
10300	12	Leading cadres: democratic parties, social groups and relevant functional organizations(2)	40	3	11.550	3.080
10500	13	Leading cadres of enterprises(3)	165	3	12.582	3.717
20000	**2-X**	**Professionals & technicians**				
20100	21	Science researchers(4)	12	4	17.333	1.862
20200, 20300, 20400	22	Agriculture, engineering and aircraft and ship technical staff(5)	104	4	13.548	3.321
20500	23	Medical Technical Personnel(6)	90	4	13.878	2.600
20600, 20800	24	Economic and Legal personnel(7)	122	4	13.795	2.781
20700	25	Financial personnel(8)	52	4	13.154	3.038
20900	26	Teaching professionals(9)	228	4	14.101	2.617
21000, 21300	27	Personnel for literature, arts and religion(10)	16	4	13.188	3.371
21100, 21200	28	Personnel for press, publishing, culture and sports(11)	14	4	13.286	4.953
30000	**3-X**	**Office workers and related staff**				
30100	31	Administrative office staff(12)	333	4	13.237	2.999
30200	32	Security guards and firefighters(13)	153	2	9.856	4.111
30300	33	Postal and telecommunications service personnel(14)	12	4	11.333	3.525

40000	**4X**	**Commercial staff and Service workers**				
40100	41	Wholesale buyers and sellers(15)	465	2	10.649	3.282
40200	42	Warehousemen(16)	106	2	10.330	3.173
40300	43	Catering service workers(17)	221	2	8.027	3.528
40400	44	Staff in hotels, tourist sites, sports & recreation services(18)	47	2	9.872	3.803
40500	45	Transportation services staff(19)	25	3	10.080	3.451
40600, 40700	46	Auxiliary medical personnel, Social services staff and Community Services staff(20)	233	2	8.077	4.030
40900	47	Other commercial staff and Service workers(21)	55	3	11.109	4.250
50000	**5-X**	**Agricultural, Forestry, Animal husbandry, Fishery and water conservancy workers**				
50100, 50200	51	Workers in Forestry and Plantation production and the protection of Wildlife (22)	36	1	6.944	4.635
50300, 50400, 50500	52	Livestock, Fish production workers and Maintenance staff of Water Infrastructure(23)	22	2	8.591	4.563
60000	**6-X**	**Production workers, transport equipment operators and other laborers**				
60100	61	Geology and mineral Industry workers(24)	77	2	8.104	3.303
60200	62	Workers in metal smelting and refining industry(25)	28	2	10.714	3.599
60300, 60900	63	Rubber and plastic product manufacturing workers and other Chemical product manufacturing personnel(26)	59	2	9.627	3.173
60400	64	Processing worker of Machinery manufacturing(27)	161	2	8.671	3.701
60500	65	Assembly Line Worker of Mechanical and Electrical Products(28)	93	2	8.731	4.139
60600	66	Repair technicians of mechanical equipment(29)	96	2	9.833	3.161
60700	67	Installation, commissioning and repair professionals of Electrical equipment and Power supply personnel(30)	83	2	9.880	3.753
60800	68	Production, installation, commissioning and repair professionals of electronic devices and components(31)	59	2	8.542	3.380
61000	69	Textile workers(32)	48	2	7.063	3.634

61100	610	Worker of sewing and tailoring and Processing worker of leather, furs and related products(33)	158	2	7.367	3.276
61200, 61300	611	Production and processing workers of Grain and oil, Food and Drink, animal feed and tobacco(34)	35	1	7.057	4.043
61500	612	Production workers of wood processing, artificial board,wood products, pulp and paper industry(35)	62	2	7.887	3.270
61600, 61700	613	Production and processing worker of Glass, ceramic, enamel and construction materials(36)	42	1	7.214	3.633
61800, 61900, 62000, 62100	614	Printing and related workers,handicraft article makers and Makers of materials for sport, education and culture(37)	38	2	7.974	3.901
62200	615	Construction personnel (Engineering)(38)	316	2	6.674	3.723
62300	616	Equipment/Machinery operators of transport facilities(39)	270	2	9.222	3.220
62400, 62500	617	Inspection and measuring staff, monitoring personnel and Waste management personnel (40)	100	12	11.130	3.472
62900, 61400	618	Pharmaceutical production personnel and others workers of Production a nd transport equipment (41)	257	2	7.109	3.977
90000	**9-X**	**Other workers**				
99700 99800 99900	91	General production workers(42)	47	1	8.809	4.426
99999	92	Other workers not elsewhere classified(43)	34	2	10.941	3.094

Mode levels of education: primary school = 1; lower middle = 2; upper middle = 3, tertiary = 4

Table L.2 Classifications of occupations in CFPS and descriptive statistics on required skills (literacy)

Occupation Code and Title			Summary statistics of skills		
Original code	**Current code**	**Title**	**N**	**Mean of skill levels**	**Standard deviation of skill levels**
10000	**1-X**	**Leading cadres: state organizations, the Chinese Communist Party (CPC Party) and mass organizations, enterprises and public institutions**			
10100, 10200, 10400	11	Leading cadres: Central Committee and provincial organizations of the Chinese Communist Party, government agencies and relevant functional organizations, public institutions(1)	17	28.353	8.381
10300	12	Leading cadres: democratic parties, social groups and relevant functional organizations(2)	40	22.850	7.533
10500	13	Leading cadres of enterprises(3)	165	25.703	7.908
20000	**2-X**	**Professionals & technical**			
20100	21	Science researchers(4)	12	30.667	1.966
20200, 20300, 20400	22	Agriculture, engineering and aircraft and ship technical staff(5)	104	26.692	7.574
20500	23	Medical Technical Personnel(6)	90	27.489	5.767
20600, 20800	24	Economic and Legal personnel(7)	122	28.156	6.224
20700	25	Financial personnel(8)	52	28.846	3.958
20900	26	Teaching professionals(9)	228	28.772	5.777
21000, 21300	27	Personnel for literature, arts and religion(10)	16	25.625	9.373
21100, 21200	28	Personnel for press, publishing, culture and sports(11)	14	28.429	6.892
30000	**3-X**	**Office workers and related staff**			
30100	31	Administrative office staff(12)	333	27.505	6.427
30200	32	Security guards and firefighters(13)	153	20.627	10.175
30300	33	Postal and telecommunications service personnel(14)	12	26.583	5.648

40000	**4X**	**Commercial staff and Service workers**			
40100	41	Wholesale buyers and sellers(15)	465	24.686	7.784
40200	42	Warehousemen(16)	106	25.236	6.888
40300	43	Catering service workers(17)	221	21.059	9.142
40400	44	Staff in hotels, tourist sites, sports & recreation services(18)	47	24.596	7.534
40500	45	Transportation services staff(19)	25	23.480	6.545
40600, 40700	46	Auxiliary medical personnel, Social services staff and Community Services staff(20)	233	20.588	9.251
40900	47	Other commercial staff and Service workers(21)	55	25.291	7.651
50000	**5-X**	**Agricultural, Forestry, Animal husbandry, Fishery and water conservancy workers**			
50100, 50200	51	Workers in Forestry and Plantation production and the protection of Wildlife (22)	36	16.889	11.328
50300, 50400, 50500	52	Livestock, Fish production workers and Maintenance staff of Water Infrastructure(23)	22	19.409	7.035
60000	**6-X**	**Production workers, transport equipment operators and other labourers**			
60100	61	Geology and mineral Industry workers(24)	77	19.714	7.764
60200	62	Workers in metal smelting and refining industry(25)	28	22.821	7.528
60300, 60900	63	Rubber and plastic product manufacturing workers and other Chemical product manufacturing personnel(26)	59	22.220	8.753
60400	64	Processing worker of Machinery manufacturing(27)	161	19.776	9.722
60500	65	Assembly Line Worker of Mechanical and Electrical Products(28)	93	21.935	9.028
60600	66	Repair technicians of mechanical equipment(29)	96	23.417	6.707
60700	67	Installation, commissioning and repair professionals of Electrical equipment and Power supply personnel(30)	83	22.964	8.794
60800	68	Production, installation, commissioning and repair professionals of electronic devices and components(31)	59	18.915	12.031
61000	69	Textile workers(32)	48	20.229	9.654

61100	610	Worker of sewing and tailoring and Processing worker of leather, furs and related products(33)	158	20.209	8.639
61200, 61300	611	Production and processing workers of Grain and oil, Food and Drink, animal feed and tobacco(34)	35	20.200	7.091
61500	612	Production workers of wood processing, artificial board,wood products, pulp and paper industry(35)	62	19.194	8.337
61600, 61700	613	Production and processing worker of Glass, ceramic, enamel and construction materials(36)	42	19.167	9.569
61800, 61900, 62000, 62100	614	Printing and related workers,handicraft article makers and Makers of materials for sport, education and culture(37)	38	22.079	8.553
62200	615	Construction personnel (Engineering)(38)	316	18.228	8.990
62300	616	Equipment/Machinery operators of transport facilities(39)	270	22.093	7.977
62400, 62500	617	Inspection and measuring staff, monitoring personnel and Waste management personnel (40)	100	25.430	7.367
62900, 61400	618	Pharmaceutical production personnel and others workers of Production a nd transport equipment (41)	257	18.560	9.592
90000	**9-X**	**Other workers**			
99700 99800 99900	91	General production workers(42)	47	21.511	10.238
99999	92	Other workers not elsewhere classified(43)	34	25.500	7.308

Table L.3: Classifications of occupations in CFPS and descriptive statistics on required skills ((numeracy)

Occupation Code and Title			Summary statistics of skills		
Original code	**Current code**	**Title**	**N**	**Mean of skill levels**	**Standard deviation of skill levels**
10000	**1-X**	**Leading cadres: state organizations, the Chinese Communist Party (CPC Party) and mass organizations, enterprises and public institutions**			
10100, 10200, 10400	11	Leading cadres: Central Committee and provincial organizations of the Chinese Communist Party, government agencies and relevant functional organizations, public institutions(1)	17	16.647	5.937
10300	12	Leading cadres: democratic parties, social groups and relevant functional organizations(2)	40	10.550	4.320
10500	13	Leading cadres of enterprises(3)	165	12.794	6.203
20000	**2-X**	**Professionals & technical**			
20100	21	Science researchers(4)	12	20.667	3.445
20200, 20300, 20400	22	Agriculture, engineering and aircraft and ship technical staff(5)	104	15.663	6.668
20500	23	Medical Technical Personnel(6)	90	13.622	5.684
20600, 20800	24	Economic and Legal personnel(7)	122	14.836	5.314
20700	25	Financial personnel(8)	52	14.923	5.718
20900	26	Teaching professionals(9)	228	14.873	6.103
21000, 21300	27	Personnel for literature, arts and religion(10)	16	14.063	6.708
21100, 21200	28	Personnel for press, publishing, culture and sports(11)	14	14.786	5.191
30000	**3-X**	**Office workers and related staff**			
30100	31	Administrative office staff(12)	333	13.685	5.929
30200	32	Security guards and firefighters(13)	153	9.595	5.567
30300	33	Postal and telecommunications service personnel(14)	12	12.500	4.622

40000	**4X**	**Commercial staff and Service workers**			
40100	41	Wholesale buyers and sellers(15)	465	10.832	5.438
40200	42	Warehousemen(16)	106	11.009	5.200
40300	43	Catering service workers(17)	221	8.751	4.975
40400	44	Staff in hotels, tourist sites, sports & recreation services(18)	47	11.043	5.373
40500	45	Transportation services staff(19)	25	9.680	5.210
40600, 40700	46	Auxiliary medical personnel, Social services staff and Community Services staff(20)	233	8.833	5.176
40900	47	Other commercial staff and Service workers(21)	55	10.709	5.490
50000	**5-X**	**Agricultural, Forestry, Animal husbandry, Fishery and water conservancy workers**			
50100, 50200	51	Workers in Forestry and Plantation production and the protection of Wildlife (22)	36	7.583	5.896
50300, 50400, 50500	52	Livestock, Fish production workers and Maintenance staff of Water Infrastructure(23)	22	7.955	3.735
60000	**6-X**	**Production workers, transport equipment operators and other labourers**			
60100	61	Geology and mineral Industry workers(24)	77	8.623	4.280
60200	62	Workers in metal smelting and refining industry(25)	28	10.643	5.314
60300, 60900	63	Rubber and plastic product manufacturing workers and other Chemical product manufacturing personnel(26)	59	10.695	5.309
60400	64	Processing worker of Machinery manufacturing(27)	161	9.106	5.245
60500	65	Assembly Line Worker of Mechanical and Electrical Products(28)	93	8.753	5.023
60600	66	Repair technicians of mechanical equipment(29)	96	10.865	5.192
60700	67	Installation, commissioning and repair professionals of Electrical equipment and Power supply personnel(30)	83	11.398	6.010
60800	68	Production, installation, commissioning and repair professionals of electronic devices and components(31)	59	8.678	6.434
61000	69	Textile workers(32)	48	8.125	5.022

61100	610	Worker of sewing and tailoring and Processing worker of leather, furs and related products(33)	158	9.019	4.798
61200, 61300	611	Production and processing workers of Grain and oil, Food and Drink, animal feed and tobacco(34)	35	7.943	3.472
61500	612	Production workers of wood processing, artificial board,wood products, pulp and paper industry(35)	62	8.532	4.175
61600, 61700	613	Production and processing worker of Glass, ceramic, enamel and construction materials(36)	42	7.810	4.250
61800, 61900, 62000, 62100	614	Printing and related workers,handicraft article makers and Makers of materials for sport, education and culture(37)	38	9.237	4.271
62200	615	Construction personnel (Engineering)(38)	316	7.924	4.149
62300	616	Equipment/Machinery operators of transport facilities(39)	270	9.130	5.063
62400, 62500	617	Inspection and measuring staff, monitoring personnel and Waste management personnel (40)	100	12.060	5.646
62900, 61400	618	Pharmaceutical production personnel and others workers of Production a nd transport equipment (41)	257	8.027	5.003
90000	**9-X**	**Other workers**			
99700 99800 99900	91	General production workers(42)	47	10.191	6.368
99999	92	Other workers not elsewhere classified(43)	34	11.765	6.334

Appendix M: Empirical Results on Return to Over-education without the Resampling Method

Table M.1: Return to over-education with three measurements under the larger sample size

	Subjective	Objective	Statistical
Over	-0.294***	-0.188***	-0.205***
	(0.040)	(0.038)	(0.041)
University	0.137***	0.160***	0.158***
	(0.037)	(0.038)	(0.038)
Male	0.018	0.018	0.020
	(0.036)	(0.036)	(0.036)
Age	0.052***	0.045***	0.046***
	(0.017)	(0.017)	(0.017)
Age square/100	-0.042***	-0.043***	-0.024*
	(0.012)	(0.012)	(0.013)
Minority	-0.055	-0.053	-0.065
	(0.078)	(0.079)	(0.079)
Marriage status	-0.043	-0.039	-0.042
	(0.048)	(0.049)	(0.049)
Urban residence	0.153	0.158	0.146
	(0.040)	(0.041)	(0.041)
Urban "Hukou"	0.012	0.041	0.026
	(0.046)	(0.047)	(0.047)
Northeast	-0.098*	-0.073	-0.080
	(0.059)	(0.060)	(0.060)
East	0.200***	0.196***	0.188***
	(0.051)	(0.051)	(0.051)
Middle	-0.111**	-0.099*	-0.115**
	(0.055)	(0.055)	(0.055)
Contract	0.196***	0.209***	0.207***
	(0.041)	(0.041)	(0.041)
Public sector	-0.009	0.025	0.015
	(0.042)	(0.042)	(0.042)
Raw materials	0.265*	0.218	0.243
	(0.161)	(0.162)	(0.163)
Manufacturing	0.180***	0.188***	0.204***
	(0.051)	(0.052)	(0.053)
Retailing and wholesaling	0.238***	0.265***	0.261***
	(0.047)	(0.049)	(0.049)
Small firm	-0.099**	-0.107***	-0.110***
	(0.040)	(0.040)	(0.040)
Medium firm	-0.047	-0.032	-0.033
	(0.057)	(0.057)	(0.057)
Lambda	-0.012	-0.018	-0.022
	(0.057)	(0.059)	(0.064)
Constant	0.800**	0.751**	0.735**
	(0.344)	(0.348)	(0.348)
N	1513	1513	1513

Lambda is the inverse Mills Ratio for the correction of self-selection

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table M.2: Return to over-education with skills heterogeneity (literacy) under the larger sample size

	Subjective		Objective		Statistical		No-over	
	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)	Spe (3)	Spe (4)
Over	-0.282***	-0.291***	-0.161***	-0.184***	-0.185***	-0.202***		
	(0.040)	(0.040)	(0.041)	(0.038)	(0.046)	(0.043)		
Over-skill	-0.124**		-0.082		-0.046		-0.168***	
	(0.062)		(0.068)		(0.073)		(0.063)	
Skill level		0.003		0.004		0.004		0.004
		(0.003)		(0.003)		(0.003)		(0.003)
Lambda	-0.135	-0.148	-0.153	-0.185	-0.152	-0.202	-0.158	-0.123
	(0.468)	(0.490)	(0.522)	(0.497)	(0.491)	(0.545)	(0.546)	(0.489)
Constant	0.798**	0.728**	0.858***	0.701**	0.868***	0.716**	0.725**	0.682*
	(0.365)	(0.351)	(0.335)	(0.355)	(0.346)	(0.354)	(0.346)	(0.354)
N	1513	1513	1513	1513	1513	1513	1513	1513

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Other controls include: university type, subjects, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

Table M.3: Return to over-education controlling for non-cognitive skills under the larger sample size

	Subjective		Objective		Statistical	
	Spe (2)	Spe (4)	Spe (2)	Spe (4)	Spe (2)	Spe (4)
over	-0.289***	-0.272***	-0.184***	-0.161***	-0.191***	-0.173***
	(0.049)	(0.049)	(0.046)	(0.047)	(0.051)	(0.052)
Skill-level (literacy)		0.007		0.007		0.008
		(0.005)		(0.005)		(0.006)
Conscientiousness		0.004		0.010		0.012
		(0.039)		(0.040)		(0.040)
Extroversion		0.020		0.022		0.026
		(0.032)		(0.032)		(0.032)
Agreeableness		-0.078*		-0.073		-0.074
		(0.047)		(0.048)		(0.048)
Openness		0.063**		0.068**		0.071**
		(0.030)		(0.031)		(0.031)
Neuroticism		0.021		0.020		0.017
		(0.030)		(0.030)		(0.030)
locus control		-0.041		-0.028		-0.027
		(0.044)		(0.044)		(0.044)
Lambda	0.325	0.198	0.344	0.203	0.297	0.225
	(0.448)	(0.432)	(0.427)	(0.465)	(0.435)	(0.468)
Constant	0.539	0.393	0.464	0.182	0.407	0.095
	(0.417)	(0.509)	(0.422)	(0.512)	(0.422)	(0.510)
N	1014	1014	1014	1014	1014	1014

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Other controls include: university type, sex, age, age square, ethnicity, marriage, province dummies, registration status, urban status, firm size, contract type, sector and industry.

Appendix N: Robustness Checks on Return to Education Qualities and Subjects

Table N.1: Return to education qualities and subject groups using net wages

	(1)	(2)	(3)	(4)	(5)
University	0.189***			0.188***	
	(0.051)			(0.050)	
Key University		0.354***			0.351***
		(0.076)			(0.076)
Ordinary University		0.140**			0.139**
		(0.057)			(0.055)
STEM			-0.032	-0.029	-0.021
			(0.064)	(0.062)	(0.062)
LEM			-0.037	-0.021	-0.010
			(0.064)	(0.061)	(0.061)
Minority	0.091	0.089	0.096	0.093	0.091
	(0.080)	(0.080)	(0.082)	(0.080)	(0.080)
Male	0.056	0.056	0.069	0.058	0.057
	(0.042)	(0.042)	(0.044)	(0.043)	(0.043)
Age	-0.024	-0.025	-0.023	-0.024	-0.026
	(0.037)	(0.037)	(0.038)	(0.037)	(0.036)
Age square/100	0.022	0.023	0.028	0.029	0.019
	(0.038)	(0.039)	(0.039)	(0.039)	(0.039)
Marriage	0.114*	0.112*	0.114*	0.113*	0.110*
	(0.061)	(0.061)	(0.063)	(0.061)	(0.061)
Urban residence	0.062	0.059	0.081	0.061	0.056
	(0.098)	(0.098)	(0.103)	(0.098)	(0.098)
Urban “Hukou”	0.244***	0.242***	0.269***	0.246***	0.244***
	(0.072)	(0.071)	(0.072)	(0.071)	(0.071)
Northeast	0.129*	0.125*	0.150**	0.129*	0.125*
	(0.069)	(0.069)	(0.070)	(0.069)	(0.069)
East	0.400***	0.387***	0.410***	0.399***	0.385***
	(0.064)	(0.065)	(0.067)	(0.065)	(0.065)
Middle	0.029	0.019	0.040	0.029	0.018
	(0.061)	(0.061)	(0.063)	(0.061)	(0.061)
Public sector	-0.024	-0.021	-0.026	-0.027	-0.023
	(0.050)	(0.049)	(0.050)	(0.050)	(0.050)
Raw materials	-0.070	-0.084	-0.112	-0.063	-0.079
	(0.412)	(0.410)	(0.417)	(0.412)	(0.410)
Manufacturing	0.081	0.083	0.049	0.085	0.088
	(0.055)	(0.055)	(0.056)	(0.056)	(0.056)
Retailing and wholesaling	0.218***	0.215***	0.196**	0.219***	0.217***
	(0.083)	(0.083)	(0.084)	(0.083)	(0.083)
First job	-0.070	-0.072*	-0.061	-0.071	-0.073*
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Literacy	0.012**	0.013**	0.017***	0.012**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Locus of control	0.048	0.054	0.054	0.048	0.055
	(0.038)	(0.038)	(0.039)	(0.038)	(0.039)
lambda	-0.199	-0.216	-0.260	-0.207	-0.229
	(0.249)	(0.248)	(0.256)	(0.248)	(0.247)
Constant	1.524*	1.560*	1.483*	1.553*	1.599**
	(0.839)	(0.830)	(0.842)	(0.808)	(0.801)
Occupations	Yes	Yes	Yes	Yes	Yes
Observations	870	870	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.2: Return to education qualities and subject groups using net wages, interactions added

	(1)	(2)
University	0.253***	
	(0.088)	
Key University		0.371***
		(0.140)
Ordinary University		0.212**
		(0.092)
University*STEM	-0.127	
	(0.111)	
University*STEM	-0.066	
	(0.103)	
Key University*STEM		-0.142
		(0.189)
Ordinary University*STEM		-0.114
		(0.119)
Key University*LEM		0.049
		(0.191)
Ordinary University*LEM		-0.092
		(0.113)
STEM	0.030	0.033
	(0.076)	(0.076)
LEM	0.015	0.020
	(0.074)	(0.074)
Minority	0.092	0.093
	(0.080)	(0.080)
Male	0.060	0.060
	(0.043)	(0.043)
Age	-0.029	-0.029
	(0.037)	(0.036)
Age square/100	0.025	0.028
	(0.046)	(0.047)
Marriage	0.111*	0.109*
	(0.062)	(0.062)
Urban residence	0.049	0.050
	(0.099)	(0.097)
Urban “Hukou”	0.245***	0.240***
	(0.072)	(0.071)
Northeast	0.130*	0.125*
	(0.069)	(0.069)
East	0.399***	0.388***
	(0.065)	(0.066)
Middle	0.028	0.018
	(0.062)	(0.062)
Public sector	-0.028	-0.024
	(0.050)	(0.049)
Raw materials	-0.071	-0.086
	(0.411)	(0.409)
Manufacturing	0.082	0.085
	(0.056)	(0.056)
Retailing and wholesaling	0.221***	0.218***
	(0.083)	(0.083)
First job	-0.071	-0.073*
	(0.044)	(0.044)

Table N.2: Continued

	(1)	(2)
Literacy	0.012**	0.013**
	(0.006)	(0.006)
Locus of control	0.048	0.054
	(0.039)	(0.039)
Lambda	-0.240	-0.243
	(0.247)	(0.241)
Constant	1.645**	1.635**
	(0.812)	(0.791)
Occupations	Yes	Yes
Observations	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.3: Return to education qualities and subject groups controlling for numeracy skills

	(1)	(2)	(3)	(4)	(5)
University	0.196***			0.199***	
	(0.055)			(0.053)	
Key University		0.393***			0.401***
		(0.080)			(0.081)
Ordinary University		0.137**			0.139**
		(0.060)			(0.059)
STEM			0.057	0.064	0.073
			(0.069)	(0.066)	(0.066)
LEM			0.042	0.059	0.073
			(0.068)	(0.065)	(0.065)
Minority	0.050	0.048	0.053	0.051	0.048
	(0.085)	(0.085)	(0.088)	(0.085)	(0.086)
Male	0.051	0.051	0.054	0.043	0.041
	(0.045)	(0.045)	(0.047)	(0.045)	(0.046)
Age	-0.028	-0.030	-0.030	-0.031	-0.034
	(0.039)	(0.039)	(0.041)	(0.039)	(0.038)
Age square/100	0.021	0.023	0.028	0.028	0.018
	(0.038)	(0.039)	(0.039)	(0.039)	(0.039)
Marriage	0.116*	0.113*	0.114*	0.115*	0.112*
	(0.065)	(0.065)	(0.067)	(0.065)	(0.065)
Urban residence	0.026	0.021	0.039	0.019	0.012
	(0.104)	(0.103)	(0.110)	(0.104)	(0.104)
Urban “Hukou”	0.269***	0.267***	0.291***	0.265***	0.262***
	(0.077)	(0.076)	(0.078)	(0.077)	(0.077)
Northeast	0.112	0.107	0.139*	0.113	0.108
	(0.073)	(0.073)	(0.075)	(0.073)	(0.073)
East	0.438***	0.422***	0.450***	0.435***	0.417***
	(0.068)	(0.068)	(0.071)	(0.069)	(0.069)
Middle	0.044	0.032	0.056	0.041	0.027
	(0.064)	(0.065)	(0.067)	(0.065)	(0.065)
Public sector	-0.021	-0.017	-0.017	-0.018	-0.013
	(0.052)	(0.052)	(0.053)	(0.052)	(0.052)
Raw materials	-0.054	-0.070	-0.120	-0.054	-0.074
	(0.430)	(0.428)	(0.436)	(0.429)	(0.427)

Table N.3: Continued

	(1)	(2)	(3)	(4)	(5)
Manufacturing	0.095	0.098*	0.053	0.093	0.096*
	(0.058)	(0.058)	(0.059)	(0.058)	(0.058)
Retailing and wholesaling	0.184**	0.181**	0.156*	0.181**	0.178**
	(0.087)	(0.087)	(0.088)	(0.087)	(0.087)
First job	-0.095**	-0.098**	-0.087*	-0.095**	-0.098**
	(0.046)	(0.045)	(0.046)	(0.046)	(0.045)
Numeracy	0.012	0.012	0.015	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Locus of control	0.034	0.042	0.041	0.037	0.045
	(0.040)	(0.040)	(0.042)	(0.041)	(0.041)
Lambda	-0.287	-0.310	-0.380	-0.313	-0.343
	(0.262)	(0.261)	(0.272)	(0.262)	(0.261)
Constant	2.085**	2.139**	2.112**	2.117**	2.187**
	(0.878)	(0.870)	(0.904)	(0.857)	(0.851)
Occupations	Yes	Yes	Yes	Yes	Yes
Observations	870	870	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.
Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.4: Return to education qualities and subject groups controlling for numeracy skills,interactions added

	(1)	(2)
University	0.287***	
	(0.094)	
Key University		0.416***
		(0.150)
Ordinary University		0.243**
		(0.098)
University*STEM	-0.107	
	(0.118)	
University*STEM	-0.085	
	(0.111)	
Key University*STEM		-0.104
		(0.202)
Ordinary University*STEM		-0.089
		(0.127)
Key University*LEM		0.046
		(0.203)
Ordinary University*LEM		-0.132
		(0.121)
STEM	0.106	0.112
	(0.082)	(0.081)
LEM	0.145*	0.148*
	(0.079)	(0.079)
Minority	0.050	0.052
	(0.086)	(0.086)
Male	0.047	0.045
	(0.046)	(0.046)
Age	-0.037	-0.037
	(0.039)	(0.038)

Table N.4: Continued

	(1)	(2)
Age square/100	0.026	0.028
	(0.046)	(0.047)
Marriage	0.113*	0.110*
	(0.066)	(0.065)
Urban residence	0.004	0.006
	(0.105)	(0.102)
Urban “Hukou”	0.263***	0.256***
	(0.077)	(0.077)
Northeast	0.113	0.107
	(0.074)	(0.073)
East	0.436***	0.423***
	(0.069)	(0.070)
Middle	0.040	0.027
	(0.066)	(0.066)
Public sector	-0.019	-0.014
	(0.052)	(0.052)
Raw materials	-0.064	-0.082
	(0.428)	(0.425)
Manufacturing	0.088	0.093
	(0.058)	(0.058)
Retailing and wholesaling	0.184**	0.181**
	(0.087)	(0.087)
First job	-0.096**	-0.099**
	(0.046)	(0.045)
Numeracy	0.011	0.011
	(0.010)	(0.010)
Locus of control	0.037	0.044
	(0.041)	(0.041)
lambda	-0.353	-0.355
	(0.261)	(0.253)
Constant	2.229***	2.210***
	(0.864)	(0.839)
Occupations	Yes	Yes
Observations	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.5: Return to education qualities and subject units

	(1)	(2)	(3)
University		0.171^{***}	
		(0.055)	
Key University			0.381^{***}
			(0.083)
Ordinary University			0.108^{*}
			(0.053)
Economics	0.456^{**}	0.449^{**}	0.464^{**}
	(0.190)	(0.182)	(0.182)
Law	0.396^{**}	0.354^{*}	0.372^{*}
	(0.199)	(0.191)	(0.192)
Education	0.298	0.306	0.308
	(0.202)	(0.194)	(0.194)
Literature	0.468^{**}	0.423^{**}	0.423^{**}
	(0.192)	(0.185)	(0.185)
Science	0.474^{**}	0.442^{**}	0.449^{**}
	(0.211)	(0.203)	(0.204)
Engineering	0.614^{***}	0.583^{***}	0.595^{***}
	(0.192)	(0.184)	(0.184)
Agriculture	0.151	0.148	0.157
	(0.237)	(0.227)	(0.228)
Medicine	0.296	0.283	0.291
	(0.198)	(0.190)	(0.190)
Management	0.487^{**}	0.478^{***}	0.492^{***}
	(0.189)	(0.182)	(0.182)
Minority	0.057	0.059	0.056
	(0.091)	(0.087)	(0.087)
Male	0.020	0.015	0.013
	(0.049)	(0.047)	(0.047)
Age	-0.057	-0.051	-0.054
	(0.041)	(0.040)	(0.039)
Age square/100	0.082^{***}	0.083^{***}	0.079^{***}
	(0.012)	(0.013)	(0.013)
Marriage	0.140^{**}	0.138^{**}	0.134^{**}
	(0.069)	(0.066)	(0.067)
Urban residence	-0.029	-0.027	-0.033
	(0.111)	(0.105)	(0.105)
Urban "Hukou"	0.281^{***}	0.262^{***}	0.258^{***}
	(0.079)	(0.076)	(0.077)
Northeast	0.130^{*}	0.109	0.104
	(0.077)	(0.075)	(0.075)
East	0.420^{***}	0.414^{***}	0.396^{***}
	(0.074)	(0.070)	(0.071)
Middle	0.039	0.034	0.020
	(0.070)	(0.067)	(0.067)
Public sector	-0.001	-0.002	0.003
	(0.052)	(0.052)	(0.051)
Raw materials	-0.096	-0.063	-0.083
	(0.425)	(0.422)	(0.419)
Manufacturing	0.017	0.056	0.058
	(0.059)	(0.059)	(0.058)
Retailing and wholesaling	0.134	0.157^{*}	0.154^{*}
	(0.087)	(0.086)	(0.085)

Table N.5: Continued

	(1)	(2)	(3)
First job	-0.073	-0.084*	-0.086*
	(0.046)	(0.045)	(0.045)
Literacy	0.014**	0.010*	0.011*
	(0.006)	(0.006)	(0.006)
Locus of control	0.067	0.056	0.064
	(0.044)	(0.042)	(0.042)
lambda	-0.526*	-0.420	-0.445*
	(0.271)	(0.262)	(0.261)
Constant	2.078**	2.016**	2.065**
	(0.952)	(0.905)	(0.897)
Occupations	Yes	Yes	Yes
Observations	870	870	870

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.6: Return to different education qualities under the larger sample size

	(1)	(2)	(3)	(4)
University	0.238***	0.228***		
	(0.037)	(0.037)		
Key University			0.385***	0.373***
			(0.059)	(0.059)
Ordinary University			0.169***	0.161***
			(0.040)	(0.041)
Minority	0.089	0.088	0.090	0.089
	(0.077)	(0.077)	(0.077)	(0.077)
Male	0.081	0.080	0.082	0.081
	(0.136)	(0.136)	(0.136)	(0.136)
Age	0.012	0.009	0.012	0.010
	(0.017)	(0.017)	(0.017)	(0.017)
Age square/100	-0.023	-0.022	-0.019	-0.018
	(0.045)	(0.045)	(0.048)	(0.047)
Marriage status	0.083	0.088*	0.083	0.088*
	(0.052)	(0.052)	(0.052)	(0.052)
Urban residence	0.174***	0.183***	0.171***	0.180***
	(0.058)	(0.059)	(0.058)	(0.059)
Urban “Hukou”	0.032	0.025	0.031	0.026
	(0.058)	(0.058)	(0.058)	(0.058)
Northeast	0.074	0.070	0.076	0.072
	(0.061)	(0.061)	(0.061)	(0.061)
East	0.607***	0.601***	0.598***	0.593***
	(0.054)	(0.054)	(0.054)	(0.054)
Middle	0.015	0.008	0.014	0.007
	(0.056)	(0.056)	(0.056)	(0.056)
Public sector	0.057	0.053	0.058	0.054
	(0.042)	(0.042)	(0.042)	(0.042)
Raw materials	-0.055	-0.060	-0.086	-0.090
	(0.332)	(0.332)	(0.331)	(0.331)

Table N.6: Continued

	(1)	(2)	(3)	(4)
Manufacturing	0.199***	0.198***	0.195***	0.194***
	(0.051)	(0.051)	(0.051)	(0.051)
Retailing and wholesaling	0.258***	0.258***	0.253***	0.253***
	(0.050)	(0.050)	(0.050)	(0.050)
First job	-0.192	-0.191	-0.175	-0.175
	(0.136)	(0.136)	(0.136)	(0.136)
Literacy		0.017***		0.016***
		(0.005)		(0.005)
Locus of Control		0.032		0.040
		(0.041)		(0.041)
Lambda	-0.468	-0.445	-0.487	-0.467
	(0.355)	(0.355)	(0.356)	(0.356)
Constant	1.334***	1.183***	1.345***	1.208***
	(0.356)	(0.376)	(0.355)	(0.376)
Occupation	Yes	Yes	Yes	Yes
N	1392	1392	1392	1392

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.7: Return to different subjects under the larger sample size

	(1)	(2)
STEM	0.044	0.048
	(0.049)	(0.049)
LEM	0.021	0.028
	(0.048)	(0.048)
Minority	0.096	0.095
	(0.078)	(0.078)
Male	0.056	0.052
	(0.127)	(0.127)
Age	0.025	0.021
	(0.018)	(0.018)
Age square/100	-0.021	-0.019
	(0.045)	(0.045)
Marriage status	0.067	0.077
	(0.053)	(0.053)
Urban residence	0.189***	0.203***
	(0.060)	(0.060)
Urban “Hukou”	0.034	0.029
	(0.059)	(0.059)
Northeast	0.092	0.086
	(0.062)	(0.062)
East	0.636***	0.625***
	(0.055)	(0.055)
Middle	0.028	0.018
	(0.058)	(0.058)
Public sector	0.059	0.054
	(0.043)	(0.043)
Raw materials	-0.099	-0.077
	(0.338)	(0.338)

Table N.7: Continued

	(1)	(2)
Manufacturing	0.152***	0.153***
	(0.053)	(0.053)
Retailing and wholesaling	0.217***	0.221***
	(0.052)	(0.052)
First job	-0.167	-0.165
	(0.139)	(0.139)
Literacy		0.013***
		(0.005)
Locus of Control		0.042
		(0.038)
Lambda	-0.489	-0.493
	(0.423)	(0.435)
Constant	1.153***	0.868**
	(0.365)	(0.384)
Occupation	Yes	Yes
N	1392	1392

Lambda is the inverse Mills ratio for correction of self-selection.
Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table N.8: Return to different education qualities and subjects under the larger sample size

	(1)	(2)	(3)	(4)
University	0.245***	0.232***		
	(0.037)	(0.038)		
Key University			0.395***	0.393***
			(0.059)	(0.060)
Ordinary University			0.178***	0.156***
			(0.040)	(0.041)
STEM	0.010	0.010	0.007	0.007
	(0.048)	(0.048)	(0.048)	(0.048)
LEM	-0.012	-0.012	-0.009	-0.009
	(0.047)	(0.047)	(0.047)	(0.047)
Minority	0.090	0.089	0.091	0.090
	(0.077)	(0.077)	(0.077)	(0.077)
Male	0.079**	0.078**	0.080**	0.079**
	(0.037)	(0.037)	(0.037)	(0.037)
Age	0.013	0.010	0.013	0.011
	(0.017)	(0.017)	(0.017)	(0.017)
Age square/100	-0.018	-0.016	-0.017	-0.016
	(0.035)	(0.034)	(0.028)	(0.027)
Marriage status	0.083	0.089*	0.083	0.088*
	(0.052)	(0.052)	(0.052)	(0.052)
Urban residence	0.174***	0.183***	0.171***	0.180***
	(0.059)	(0.059)	(0.058)	(0.059)
Urban “Hukou”	0.032	0.025	0.032	0.026
	(0.058)	(0.059)	(0.058)	(0.058)
Northeast	0.074	0.071	0.076	0.073
	(0.061)	(0.061)	(0.061)	(0.061)

Table N.8: Continued

	(1)	(2)	(3)	(4)
East	0.609***	0.603***	0.600***	0.595***
	(0.054)	(0.054)	(0.054)	(0.054)
Middle	0.016	0.010	0.015	0.009
	(0.056)	(0.057)	(0.056)	(0.057)
Public sector	0.057	0.053	0.059	0.055
	(0.042)	(0.042)	(0.042)	(0.042)
Raw materials	-0.055	-0.060	-0.086	-0.090
	(0.332)	(0.332)	(0.332)	(0.332)
Manufacturing	0.198***	0.196***	0.194***	0.192***
	(0.052)	(0.052)	(0.052)	(0.052)
Retailing and wholesaling	0.261***	0.261***	0.256***	0.255***
	(0.051)	(0.051)	(0.051)	(0.051)
First job	-0.190	-0.189	-0.173	-0.173
	(0.136)	(0.136)	(0.136)	(0.136)
Literacy		0.017***		0.016***
		(0.005)		(0.005)
Locus of Control		0.038		0.044
		(0.043)		(0.043)
Lambda	-0.478	-0.454	-0.495	-0.476
	(0.358)	(0.358)	(0.358)	(0.358)
Constant	1.315***	1.163***	1.331***	1.194***
	(0.359)	(0.379)	(0.358)	(0.379)
Occupation	Yes	Yes	Yes	Yes
N	1392	1392	1392	1392

Lambda is the inverse Mills ratio for correction of self-selection.

Corrected standard errors from the Heckman method reported in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix O: Heckman First Stage Results for Return to Education Qualities and Subjects

Table O.1: Heckman first stage results: Education qualities

	(1)	(2)	(3)	(4)
University	0.301***	0.298***		
	(0.095)	(0.096)		
Key University			0.170	0.158
			(0.164)	(0.166)
Ordinary University			0.344***	0.345***
			(0.106)	(0.107)
Minority	0.011	0.012	0.013	0.014
	(0.169)	(0.169)	(0.169)	(0.169)
Male	0.019	0.022	0.022	0.025
	(0.087)	(0.087)	(0.087)	(0.087)
Age	0.285***	0.283***	0.284***	0.282***
	(0.038)	(0.038)	(0.038)	(0.038)
Age square/100	-0.423***	-0.428***	-0.435***	-0.437***
	(0.087)	(0.086)	(0.092)	(0.094)
Marriage	0.194	0.194	0.200	0.200
	(0.140)	(0.141)	(0.140)	(0.141)
Urban residence	0.517***	0.512***	0.515***	0.509***
	(0.123)	(0.123)	(0.123)	(0.123)
Urban “Hukou”	-0.085	-0.090	-0.081	-0.087
	(0.135)	(0.136)	(0.135)	(0.136)
Northeast	-0.206	-0.205	-0.203	-0.201
	(0.144)	(0.144)	(0.144)	(0.144)
East	0.144	0.144	0.154	0.155
	(0.131)	(0.132)	(0.132)	(0.132)
Middle	-0.026	-0.028	-0.019	-0.021
	(0.130)	(0.131)	(0.131)	(0.131)
Young children	-0.307***	-0.306***	-0.309***	-0.307***
	(0.082)	(0.082)	(0.082)	(0.082)
Old people	0.166*	0.166*	0.163*	0.163*
	(0.094)	(0.094)	(0.094)	(0.094)
Literacy		0.000		-0.000
		(0.012)		(0.012)
Locus of control		-0.054		-0.062
		(0.081)		(0.081)
Constant	-4.911***	-4.692***	-4.902***	-4.645***
	(0.653)	(0.792)	(0.654)	(0.793)
N	1161	1161	1161	1161
Pseudo R^2	0.15	0.21	0.16	0.24

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table O.2: Heckman first stage results: Subjects

	(1)	(2)
STEM	-0.278**	-0.280**
	(0.122)	(0.123)
LEM	-0.299***	-0.303***
	(0.116)	(0.117)
Minority	0.032	0.033
	(0.169)	(0.169)
Male	0.065	0.069
	(0.089)	(0.089)
Age	0.295***	0.291***
	(0.038)	(0.038)
Age square/100	-0.445***	-0.428***
	(0.098)	(0.099)
Marriage	0.196	0.201
	(0.140)	(0.140)
Urban residence	0.564***	0.554***
	(0.122)	(0.123)
Urban "Hukou"	-0.054	-0.059
	(0.136)	(0.137)
Northeast	-0.188	-0.188
	(0.143)	(0.143)
East	0.170	0.167
	(0.131)	(0.131)
Middle	0.006	0.001
	(0.130)	(0.131)
Young children	-0.322***	-0.319***
	(0.082)	(0.083)
Old people	0.150	0.150
	(0.094)	(0.094)
Literacy		0.003
		(0.011)
Locus of control		-0.075
		(0.080)
Constant	-4.814***	-4.575***
	(0.661)	(0.800)
N	1161	1161
Pseudo R^2	0.22	0.25

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table O.3: Heckman first stage results: Education qualities and subjects

	(1)	(2)	(3)	(4)
University	0.277***	0.277***		
	(0.096)	(0.097)		
Key University			0.150	0.138
			(0.166)	(0.167)
Ordinary University			0.318***	0.322***
			(0.107)	(0.108)
STEM	-0.256**	-0.262**	-0.256**	-0.262**
	(0.123)	(0.123)	(0.123)	(0.123)
LEM	-0.259**	-0.268**	-0.257**	-0.266**
	(0.117)	(0.118)	(0.117)	(0.118)
Minority	0.000	0.002	0.002	0.004
	(0.170)	(0.170)	(0.170)	(0.170)
Male	0.056	0.060	0.059	0.064
	(0.089)	(0.089)	(0.089)	(0.089)
Age	0.288***	0.286***	0.286***	0.285***
	(0.038)	(0.039)	(0.038)	(0.039)
Age square/100	-0.423***	-0.429***	-0.445***	-0.435***
	(0.087)	(0.086)	(0.092)	(0.094)
Marriage	0.203	0.201	0.209	0.207
	(0.140)	(0.141)	(0.140)	(0.141)
Urban residence	0.518***	0.514***	0.516***	0.511***
	(0.123)	(0.124)	(0.123)	(0.124)
Urban “Hukou”	-0.067	-0.073	-0.063	-0.070
	(0.136)	(0.137)	(0.137)	(0.137)
Northeast	-0.210	-0.208	-0.206	-0.204
	(0.144)	(0.144)	(0.144)	(0.144)
East	0.152	0.154	0.162	0.164
	(0.132)	(0.132)	(0.132)	(0.133)
Middle	-0.015	-0.015	-0.008	-0.009
	(0.131)	(0.131)	(0.131)	(0.131)
Young children	-0.315***	-0.312***	-0.316***	-0.314***
	(0.083)	(0.083)	(0.083)	(0.083)
Old people	0.162*	0.162*	0.159*	0.159*
	(0.094)	(0.094)	(0.095)	(0.095)
Literacy		-0.003		-0.003
		(0.012)		(0.012)
Locus of control		-0.068		-0.075
		(0.081)		(0.081)
Constant	-4.764***	-4.424***	-4.754***	-4.379***
	(0.662)	(0.804)	(0.663)	(0.805)
N	1161	1161	1161	1161
Pseudo R2	0.21	0.25	0.24	0.28

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table O.4: Heckman first stage results: interaction effect of Education qualities and subjects

	(1)	(2)	(3)	(4)
University	0.406**	0.406**		
	(0.203)	(0.204)		
Key University			0.935*	0.913*
			(0.491)	(0.489)
Ordinary University			0.305	0.309
			(0.215)	(0.215)
University*STEM	-0.249	-0.252		
	(0.255)	(0.255)		
University*LEM	-0.089	-0.087		
	(0.251)	(0.251)		
Key University*STEM			-0.742	-0.740
			(0.566)	(0.562)
Ordinary University*STEM			-0.160	-0.162
			(0.272)	(0.272)
Key University*LEM			-1.103**	-1.086**
			(0.547)	(0.544)
Ordinary University*LEM			0.218	0.218
			(0.277)	(0.277)
STEM	-0.172	-0.178	-0.179	-0.184
	(0.150)	(0.150)	(0.150)	(0.150)
LEM	-0.222	-0.231	-0.225	-0.234*
	(0.141)	(0.142)	(0.141)	(0.142)
Minority	0.003	0.005	0.000	0.002
	(0.170)	(0.170)	(0.171)	(0.171)
Male	0.058	0.062	0.067	0.071
	(0.089)	(0.089)	(0.090)	(0.090)
Age	0.288***	0.287***	0.287***	0.285***
	(0.038)	(0.039)	(0.038)	(0.039)
Age square/100	-0.423***	-0.428***	-0.435***	-0.437***
	(0.087)	(0.086)	(0.092)	(0.094)
Marriage	0.195	0.192	0.217	0.215
	(0.141)	(0.142)	(0.141)	(0.142)
Urban residence	0.521***	0.517***	0.517***	0.513***
	(0.123)	(0.124)	(0.123)	(0.124)
Northeast	-0.205	-0.203	-0.208	-0.206
	(0.144)	(0.144)	(0.145)	(0.145)
East	0.160	0.161	0.165	0.167
	(0.132)	(0.132)	(0.133)	(0.133)
Middle	-0.013	-0.014	-0.010	-0.010
	(0.131)	(0.131)	(0.132)	(0.132)
Young Children	-0.318***	-0.315***	-0.331***	-0.329***
	(0.083)	(0.083)	(0.084)	(0.084)
Old People	0.161*	0.161*	0.153	0.153
	(0.095)	(0.095)	(0.095)	(0.095)
Numeracy		-0.002		-0.002
		(0.012)		(0.012)
Locus of control		-0.070		-0.070
		(0.081)		(0.082)
Constant	-4.823***	-4.479***	-4.786***	-4.442***
	(0.667)	(0.808)	(0.668)	(0.811)
N	1161	1161	1161	1161
Pseudo R2	0.32	0.34	0.29	0.31

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.00$