Kong Yiji's Long Gown: Empirical Insights into the Impact of Educational Mismatch on Labor Force

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Abstract

This study employs the character Kong Yiji from Lu Xun's short story as a metaphor for the struggles faced by the over-educated in today's society. Through an analysis of the educational mismatch phenomenon, this paper explores its impact on individual career choices, re-employment, and job quality. Using data from China's National Bureau of Statistics, the study reflects on the structural inconsistencies between university graduates and the job market. The research finds that educational mismatch significantly affects job satisfaction, remuneration, and job quality. By utilizing data from the China Family Panel Studies (CFPS) and employing self-assessment methods to identify educational mismatch, this study applies least squares and instrumental variable estimation to analyze the impact. We found that The impact of educational over-qualification or under-qualification on job quality is not immediate but emerges over an extended period. Educational mismatch negatively affects the quality of employment. Re-employment through labor market mechanisms can mitigate the adverse effects of educational mismatches.

Keywords: Educational Mismatch, Career Choice, Re-employment

JEL classification: I2, J6, J24, J64, J68, Z1, Z13

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1. Introduction

Kong Yiji is a character from Lu Xun's short story, often depicted as a pedantic scholar who becomes a laughingstock due to his inability to adapt to societal changes. His long gown, a symbol of his scholarly status, becomes a burden as he fails to pass the Imperial Examinations and ends up in poverty. This character is frequently used to illustrate the struggles of over-educated individuals who feel have talent but no opportunity. Hence, 'wearing a long shirt' represents a scholar, and 'drinking while standing up' indicates that he is living a rather difficult life, where portray the image of the intellectual today. This image serves as a metaphor for the current situation of intellectuals: on the one hand, quality education encourages young people to pursue higher achievements; on the other hand, it also leads to dissatisfaction with their current status, as their job and salary do not align with their educational background. This dissatisfaction highlights the ongoing issue of educational mismatch in the job market.

The data provided by China's National Bureau of Statistics (NBS) indicates that in the year 2023, there were 1.015 million individuals who had completed postgraduate studies and 10.47 million who had completed general and vocational undergraduate studies. However, the rate of youth unemployment experienced a notable increase, rising from 17.3% in January 2023 to 21.3% in June 2023. In response to the limited job opportunities that align with their qualifications, some college graduates opt to delay entering the workforce by pursuing further education or seeking public office positions (Li et al., 2024). This decision, made in light of heightened job transition costs (Curtis et al., 2024), can result in two notable consequences. Firstly, it can contribute to a decline in the individual's earnings relative to the time and effort invested (Wu, 2022). Secondly, it may exacerbate the difficulty in finding employment and the structural mismatch between the availability of jobs and the pool of qualified applicants (Xiang et al., 2023). So, what are the consequences of this structural inconsistency for individual accessibility to the labour market? Which occupational categories are pursued by younger individuals, and which are created by government institutions to minimise the loss of well-being? How does the resolution of the issue of reemployment for unemployed youth impact individual well-being?

China's Higher Education Expansion Policy has resulted in a significant increase in the number of highly educated individuals entering the labour market, although it raises humamn capital, there has no balabala (e.g. Ma, 2021; Ou and Hou, 2019; Hsieh et al., 2019). However, despite this expansion, there has been no corresponding increase in demand for highly educated individuals. Moreover, following the NBS data we said before, the mismatch between educational attainment and labor market demand leads many to adjust their job requirements in response to the competitive nature of the labour market (Wu et al., 2020). Consequently leading to some adverse situation, for example, over-education has been identified as a significant barrier to social integration among migrant workers with higher education qualifications (Chen and Hu, 2023), and many highly educated individuals are compelled to accept jobs that require lower educational qualifications. Conversely, the skills and cost advantages of individuals with low educational attainment have facilitated their employment prospects, enabling them to compete with those with high educational attainment in certain roles (Duncan and Hoffman, 1981). Such mismatches in educational requirements will reduce productivity (Tsang, 1987), with adverse effects on individual returns in labour market, job satisfaction, and even political and social Consequences (e.g. Luksyte et al., 2011; Wiedner, 2021). This study confirms that over-education, defined as the pursuit of advanced degrees by individuals who perceive themselves to be "under-educated" in job markets that demands a higher level of qualification, has a detrimental impact on their financial remuneration and job satisfaction. The phenomenon of under-education, whereby individuals with low qualifications enter a job market that they perceive as requiring higher levels of expertise, has a welfare impact on their well-being. Education mismatch can give rise to a range of psychological issues, including feelings of imbalance, a perception of not being adequately rewarded for one's efforts, and a reduction in job satisfaction and motivation. It can be readily concluded that this is inimical to an individual's long-term personal growth and development.

This paper offers several key contributions to the academic discourse. Firstly, it adopts a holistic research perspective, moving beyond the traditional focus on the linkage between education and single aspects of employment to explore the nuanced, long-term implications of educational mismatch on various facets of job quality. Through rigorous empirical analysis of data from the China Family Panel Studies (CFPS), the study provides a comprehensive examination of educational mismatch in the Chinese context, encompassing both over-education and under-education. The paper extends its analytical scope to the multidimensional impact of educational mismatch, including its effects on job satisfaction, wages, job security, work environment, and career advancement opportunities. By applying a Difference-in-Differences (DID) approach, the research reveals the causal effects of re-employment on job quality among the educationally mismatched, enhancing our understanding of the labor market's dynamic adjustments to educational disparities. With profound policy implications, the findings advocate for targeted educational policies, structural adjustments in the education system, and enhanced labor market services to mitigate the negative externalities of educational mismatch. The study also provides critical insights for individuals contemplating educational investment and career development, highlighting the complex interplay between educational qualifications and labor market outcomes. Furthermore, this paper contributes to the existing literature by offering novel evidence on the relationship between educational mismatch and job quality within a non-Western and transitioning economy. It stimulates discussions on educational inequality and its broader social and economic ramifications, particularly in the context of economic transformation and the evolving demands of the labor market. Collectively, these contributions not only advance academic knowledge but also provide actionable insights for a range of stakeholders, including policymakers, educators, and individuals navigating the complex landscape of education and employment.

The following are the research implications of this paper. Firstly, education mismatch is the result of education lagging behind economic development, and this study can help to enrich education mismatch research and help government recognise the need for education policy improvement from the punitive effect. Secondly, this study can assist higher education institutions in adjusting the number of enrolment quotas in faculties and departments, as well as students in choosing professional study and career choices. Thirdly, during periods of economic transition, it assists the government in formulating re-employment promotion policies that align education policy with the operational law of the labour market and the requirements of economic development, thereby reducing the unemployment rate. Lastly, it identifies structural contradictions in the labour market from the perspective of educational development and economic progress in order to providing new ideas for maintaining social stability, promoting efficiency and equity, and narrowing the income gap.

The following outlines the structure of the article. The second section comprises a literature review, the third section addresses the data and methodology, the fourth section presents the results, the fifth section discusses the findings, and the sixth section offers a conclusion.

2. Literature Review

2.1. Improve the Alignment between Education Attainment and Employment

Education is the equalizer for social equity(Jin et al., 2018). To this extent, academic credentials should be combined with economic rewards for employers in a specialization society (Bourdieu, 1990). However, the mismatch of education in today's job market has been found and discussed in many researches. Teichler (2000) demonstrated that there is a presumingly artificial reward of degrees called 'credentialism' and the exp ansion of higher education had only limited impact on equality of opportunity. In the same vein, over-education has lower returns than required education (e.g. Bourdieu, 1990; Battu et al., 2000). Nevertheless, most studies support the mismatch between education and employment but raise the strategies for individuals during education or employment, such as desirable curricular setting (Harvey, 2000) , experience accumulated in job market (Groot and Maasen Van Den Brink, 1997) and further training (Bhorat et al., 2016). There are limited previous published studies focus on individual's career options before getting a job.

There have been a great number of studies about employment. According to experience, employment can be divided into one-time employment and re-employment. For instance, Brouwer et al. (2015) investgated which personal and situational factors affect reemployment success in persons in their first year of unemployment. The study carried by Riddell and Song (2011) particular focus on the extent to which education improves re-employment outcomes among unemployed workers and the results indicate that education significantly increases re-employment rates of the unemployed. However, since most researches merely focus on one-time employment or re-employment, there is a lack of continuous research on both employment and re-employment, which highlights the need for future research.

2.1.1. Limitation of Previous Research Perspective in Employment

Employment, a pivotal activity that spans various life stages, including job research, school-to-work transition, job loss and job change, has garnered substantial academic attention. Drawing upon empirical insights, employment dynamics can be systematically categorized into two fundamental dimensions: initial employment (e.g. Chen et al., 2021; Abelha et al., 2020) and re-employment (e.g. Brouwer et al., 2015; Hulshof et al., 2020; Vobemer and Schuck, 2015).

Initial employment, particularly pertinent to graduates, marks the crucial transition from education to work. This phase encompasses job search strategies, access to opportunities, and the negotiation of expectations between the individual and the labor market. The first work experience post-graduation significantly influences an individual's subsequent job expectations, work habits, and career trajectories. Therefore, understanding the intricacies of this initial phase is vital for designing interventions that can enhance the (re-) employability of graduates and foster a smooth transition into the workforce.

Re-employment, on the other hand, focuses on individuals returning to the labor market after a period of unemployment. This process involves skill upgrading, adaptation to evolving job demands, and overcoming barriers to reentry. Understanding the barriers of re-entering the labor market is crucial for developing effective interventions that can support individuals in transitioning back into employment and preventing the vicious cycle of recurrent unemployment.

However, the existing literature has often approached these two dimensions of employment dynamics in isolation, neglecting the job transfer process experienced by individuals across their careers. This narrow focus overlooks the holistic journey of professional growth and the dynamic interplay between education, employment, and re-employment. Therefore, there is a pressing need for continuous research that adopts a cohesive framework, integrating these various facets of employment dynamics to advance our overall understanding and inform more effective policy interventions.

To bridge this gap, future research should adopt a longitudinal perspective, tracking individuals over extended periods to capture the full extent of their labor market experiences (Monfort et al., 2015). This approach would not only enrich our understanding of employment dynamic interactions but also facilitate the design of tailored interventions that can effectively address the specific needs and challenges of individuals at different stages of their careers. In conclusion, the analysis presented highlights the need for a more comprehensive and integrated approach to studying employment . By expanding the scope of research and adopting a longitudinal perspective, we can enhance our understanding of the multifaceted nature of employment dynamics and inform more effective policy interventions that can support individuals across their entire career lifespan. Such an approach holds the promise of fostering more inclusive and resilient labor markets, ultimately contributing to sustained economic growth and societal well-being.

2.1.2. *Enhancing the Alignment Between Education and Employment*

According to Human Capital Theory (HCT), investment in human capital leads to greater economic outputs, implying that promoting education as a form of "investment" can yield returns to individuals in terms of pay and to the state in terms of economic growth (Schultz, 1961).

Education serves as a pivotal equalizer in fostering social equity, acting as a cornerstone in mitigating disparities and ensuring fair opportunities for all (Jin et al., 2018). In a society increasingly characterized by specialization, where occupations require specialized skills and knowledge, academic qualifications harmoniously align with economic incentives for employers, serving as a signal of productivity and competence (Bourdieu, 1990). This alignment underscores the instrumental value of education in the labor market. Riddell and Song (2011) investigated the significant and positive correlation between educational attainment and re-employment, underscoring the transformative power of education in the labor market.

However, the intricate correlation between educational attachment and job opportunities has garnered significant attention in numerous studies, prompting scholars to delve deeper into this issue. Teichler (2000) demonstrated the existence of 'credentialism', an artificial reward of degrees that confers advantages in the job market. This seemingly spurious elevation of degrees highlights a paradox: despite the expansion of higher education and the rising number of qualified individuals, there has been limited progress in advancing equality of opportunity. Similarly, research conducted by Hartog (2000) and Battu et al. (2000) posits that over-education, where individuals possess qualifications that exceed job requirements, yields diminished returns compared to tailored educational attainment. It means that while education is generally considered a pathway to better job prospects, an imbalance between the level of education and job demands can lead to underutilization of skills and subsequently, reduced job satisfaction and economic rewards.

While some studies acknowledge the mismatch between education and employment, they primarily focus on strategies that individuals can adopt during their educational journey or in the workforce to navigate these challenges. These strategies include optimizing curriculum design to ensure it remains relevant and responsive to industry needs (Harvey, 2000), accumulating job market experience to bridge the gap between theoretical knowledge and practical application (e.g. Groot and Maasen Van Den Brink, 1997; Sagen et al., 2000), and pursuing further training or specialization to enhance employability (Bhorat et al., 2016).

However, a notable gap in the extant literature is the limited focus on the career exploration and decision-making processes that individuals undertake before securing employment. Understanding these processes is crucial, as it can provide insights into how individuals navigate the complex interplay between educational choices, job market demands, and personal aspirations. By exploring this underexamined aspect, further studies need to uncover new avenues for promoting a more equitable and effective alignment between education and employment.

Overall, the analysis presented above suggests that while education is a powerful tool for fostering social equity and economic growth, its effectiveness is contingent upon a more nuanced understanding of the intricate relationship between educational attainment, job market demands, and individual career decision-making processes. Future research should aim to address this gap by investigating how individuals navigate the complex landscape of educational and career choices to foster a more equitable and effective alignment between education and employment opportunities.

2.2. Education Mismatch and the quality of employment

Over the past two decades, China has witnessed a tenfold expansion of its higher education sector (Zheng et al., 2021). Huertas and Raymond (2024) proposes that enhanced educational opportunities are positively correlated with improved employment prospects. The observed increase in the likelihood of attaining a high-skill occupation subsequent to the completion of an additional year of education is consistent with the human capital theory of economic growth. However, according to a recent survey, only 39.7% of Chinese employees of Chinese employees believe that their level of education meets the qualifications required for their current job (Annual Reporton China?s Macroeconomic Situation Analysis and Forecast [2020 - 2021]), and there is a growing problem of job mismatch in the labour market (Xu and Chen, 2024). The discrepancy in the skills of the labour force and the requirements of the labour market is a consequence of the expansion of higher education, which has resulted in a surplus of highly educated workers and a shortage of workers with lower levels of education. Consequently, there is a greater propensity for workers with lower levels of education to engage in mismatched employment(Wiedner, 2024).

Educational mismatch includes overeducation and undereducation(Duncan and Hoffman, 1981). Existing research mainly focuses on overeducation and for their negative influence on personal welfare, such as healthy (Zheng et al., 2024), wage penalties (Sevilla et al., 2021), but not focus on under-education the influence on the quality of employment. The majority of extant studies on the phenomenon of education mismatch originate from Western countries, such as the European Union (e.g. Wiedner, 2024; Pompei and Selezneva, 2021; Murillo et al., 2012). However, China's education system and labour market institutions are markedly distinct from those of Western countries. Consequently, it is imperative to construct a model that is tailored to the specific characteristics of the Chinese labour market.

The concept of ”decent work” was first introduced by the International Labour Organization in 1999 with the aim of measuring the quality of employment. However, the concept is subject to variation in interpretation and measurement across different countries (Burchell et al., 2013), and it remains a broad and open-ended concept to this day. Following (United Nations, 2015), we define the dimensions of quality of employment into 7 sections: Safety and ethics of employment,Income and benefits from employment, Working time and work-life balance, Security of employment and social protection, Social dialogue, Skills development and training, Employment-related relationships and work motivation.

First, the resolution of the International Conference of Labour Statisticians (ICLS) on occupational injury statistics states that protection against occupational injuries is an important part of the protection of workers against hazards and risks [1]. The risk of injury or death can exist in all types of employment, involving both work-related injuries and physical and mental health. Secondly, Income and benefits from employment should include salaries, bonuses, and all types of benefits or allowances in cash and in kind. Thirdly, the term 'working time' is used to describe the period of time spent on productive activities, as well as the manner in which this time is arranged during a specified reference period(e.g. night work, evening work, weekend work, flexible work schedules). The concept of 'work-life balance' encompasses not only measures that are closely related to decisions regarding paid or profit-driven work in the context of family or care responsibilities, but also attempts to quantify the time allocated to work and the time spent in private life (e.g. commuting time, child care use). Forth, The security of employment and social protection encompasses the evaluation of potential threats to employment security, as well as the assessment of the efficacy of existing measures and safety nets that can mitigate the risks associated with periods of unemployment or inactivity, health issues, and retirement (e.g. contract, insurance). Fifth, Social dialogue describes the extent to which workers are able to join organizations of their choice and engage in social dialogue with employers and government on a collective basis, which contributes to improved employment conditions. Examples include collective bargaining agreements that determine terms and conditions of employment, and collective bargaining agreements that contribute to fair and equitable employment. Sixth, empirical research demonstrates a robust correlation

[1] The resolution concerning statistics of occupational injuries (resulting from occupational accidents), adopted by the Sixteenth International Conference of Labour Statisticians (October 1998), is available for consultation at: `https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@dgreports/@stat/documents/normativeinstrument/wcms_087528.pdf`

between employability and well-being (Eurofound, 2012). However, low skill level is not the sole factor associated with inferior employment quality. In the event that an individual is unable to utilise the skills they have acquired in their role, this may result in diminished well-being and increased dissatisfaction (e.g. education). In fact, this aspect is strongly related to our dependent variable, education mismatch. Seventh, employment-related relationships and work motivation are important because they not only directly affect health and well-being, but are also key factors for achieving high levels of sustainability of work, including employment-related relationships and work motivation.

According to existing research, the quality of employment is negative for the overeducated but positive for the undereducated. For example, when workers assess the treatment they enjoy at work, by comparing themselves with the moderately educated, the overeducated develop a sense of deprivation and unfairness, which in turn affects employment satisfaction and leads to a decline in the quality of work (e.g. Erdogan and Bauer, 2009; Brown et al., 2012).

2.3. Options for Educational Mismatches

This study aims to measure the impact of educational mismatch on job quality using the Mincer equation and to further investigate whether re-employment mitigates educational mismatch and improves job quality.

In examining the trade-offs that job seekers make between occupational downgrading and rapid reemployment after unemployment, Buchs et al. (2017) have drawn upon search and matching theory during unemployment (Rogerson et al., 2005), human capital theory (Becker, 1964), and labour market segmentation theory (Blossfeld and Mayer, 1988). The degree of status downgrading at reemployment is largely contingent on the prospects of employment. Consequently, the unemployed may find themselves drawn into a downgraded form of reemployment when the demand for skills in the labour market is higher than in the ”best-fit” labour market. However, the quality of reemployment is not explained in terms of education mismatch.

Existing research reveals some aspects of the impact of educational mismatches on the quality of employment after re-entry. Based on previous research from scholars about those who are strongly mismatched earn less than those who are weakly mismatched (e.g. Rudakov et al., 2019; Bender and Roche, 2013), Jiang (2024) found that workers who were previously job mismatched due to job vacancies in related fields were more likely to engage in complex mobility, i.e., to change employers and jobs simultaneously, and to experience higher earnings growth than matched workers. However, the persistent heterogeneity in employment quality among mismatched workers has not been adequately studied. This study makes a contribution to the existing literature by examining the heterogeneity in the patterns of change in the quality of employment of different types of mismatched workers.

2.4. Assumption

From the preceding theoretical discussion we derive the following hypothesis to test:

Assumption 1: The impact of over-education or under-education on individual job quality does not manifest immediately but emerges over an extended period.

Assumption 2: Education mismatch has a negative effect on the quality of employment.

Assumption 3: The reemployment of individuals through the mechanisms of the labour market will serve to mitigate the adverse effects of educational mismatches.

3. Data and Methods

3.1. Data Source

The data employed in this study are derived from the China Family Panel Studies (CFPS). The CFPS project was officially inaugurated in 2010, with all individuals from the 2010 baseline survey designated as permanent subjects of longitudinal observation. Subsequent surveys were conducted in 2012, 2014, 2016, 2018 and 2020, allowing the application of panel estimation techniques to mitigate the impact of omitted variable bias.

The dataset comprises comprehensive data on individual educational levels, income, occupation, and regional and urban-rural characteristics, thereby providing reliable data for the investigation of the wage penalty effect of an educational mismatch. However, due to the existence of significant data gaps and the implementation of ongoing questionnaire revisions in 2012, the data from that year were not utilised.

To ensure the accuracy of the key indicators for years of overeducation and undereducation, this study focuses on employed individuals. During the selection process, samples that did not meet the labour force age criteria (16-55 years for females and 16-60 years for males) and those with missing or duplicate key variables were excluded. This resulted in a final effective sample size of 14,991 individuals.

3.2. Variables Selection

The core explanatory variable in this study is educational mismatch. There are three primary methods for estimating educational mismatch: job analysis, realized matches, and self-assessment(Capsada-Munsech, 2019). The job analysis method involves occupational analysts establishing the requisite educational level for each occupation in accordance with the demands and responsibilities of the role. Subsequently, the established standards are contrasted with the actual educational attainments of the workforce, thereby identifying any mismatch. The realised matches method employs observational data, whereby researchers delineate the requisite educational level for each occupation through measures such as the mode or standard deviation. Following this, the actual educational levels of individuals are contrasted with these standards to ascertain the existence of an educational mismatch. The self-assessment method is based on workers' self-reported perceptions of the educational level deemed necessary for their role, informed by their experience and job requirements. These self-reported educational levels are then compared with the workers' actual educational levels to identify any discrepancy.

This study employs the self-assessment method to determine overeducation, using a dummy variable(*overedu* and *underedu*). We selected two questions from the survey: the level of education that employees believe is required for their job and the actual level of education that employees have. If the required level of education is higher than the actual level, this indicates undereducation; if it is the same, it indicates adequate education; and if it is lower, it indicates overeducation. The self-assessment method is based on the question "What level of education do you think is necessary to be competent in this job? The answers are coded from 0 to 9, ranging from 'no education' to 'PhD'. The choice of the self-assessment method is based on several considerations: First, based on human capital theory, educational mismatches arise from the commodity nature of human capital and the functioning of the labour market, reflecting a mismatch between the supply and demand of skilled labour. In a perfectly competitive market, wage adjustments could resolve this mismatch, making it a short-term phenomenon. In reality, however, perfect competition does not exist and the levels of education required for similar jobs vary across regions and firms. Self-assessment can mitigate these differences. Second, according to the job competition theory, individuals signal their educational level to employers, who prefer to hire overqualified candidates in order to secure talent. The rigidity of occupational hierarchies contrasts with the rapid changes and intense competition within individual career paths. To secure jobs, individuals often over-invest in education to improve their signalling. As the requirements for the same job change over time, the self-assessment method better captures job search outcomes and reduces the impact of temporal changes. Finally, according to allocation theory, it is unclear whether educational mismatches are the result of voluntary or involuntary choices by workers and how labour market allocation works. The self-assessment method also reflects workers' 'mental accounts', taking into account their decision-making process. This approach ensures a comprehensive understanding of educational mismatch by incorporating workers' perspectives and contextual factors.

A total of ten variables were selected as dimensions of work, with due consideration given to the content of the CFPS questionnaire and the International Labour Organization (ILO) measure of 'decent work'. In order to gauge the level of job satisfaction(*satis*) amongst respondents, a questionnaire was devised which asked the question, 'How satisfied are you with this job?'. In this study, the term "income" refers to the total remuneration received by an individual over the past year, inclusive of salaries, bonuses, cash benefits, and in-kind allowances, exclusive of taxes and insurance premiums. This value is then taken as a natural logarithm and represented by *lnw*. We also chose working hours(*h*) as an explanatory variable. Additionally, the workers were asked to evaluate various aspects of their job in the questionnaire, including their satisfaction with income(*satis_w*), safety(*satis_security*), the working environment(*satis_environment*), working hours(*satis_h*), and job promotion satisfaction(*satis_promotion*). We also wanted to see the effect of educational mismatch on workers' values and chose two variables from the questionnaire: 'How serious do you think the employment problem is in our country?' and 'How serious do you think the education problem is in our country?

Referring to the existing literature, we classify the control variables into three categories, the first one is at the individual level, controlling for age(*age*), gender(*gender*), marriage((*marriage_last*), years of education(*sch*) and hukou(*hukou*),a term used to identify whether an individual is from a rural or urban area, military or not((*military*).A measure of work experience is not provided in the CFPS data, and this paper uses an age-6-years-of-education proxy. The second one is at the job level, controlling for employment contract(*labour*, work experience(*exp*), square of work experience(exp^2), insurance(*insure*), enterprise size(*coscale*) and type of job(*coiden*); and the third one is at the regional level, according to China's administrative planning and economic development, the situation of the eastern, central and western regions is significantly different, so we included the region they belong to as one of the control variables(*region_east*,*region_middle*). Table 1 describes all of the variables.

3.3. Descriptive Statistics

Table 2 shows the descriptive statistics of the variables. We find that individuals with insufficient education make up 62% of our sample. Although this may seem counterintu-

Table 1: **Variable Description**

Explained variable	Job Satisfaction (satis)	'How satisfied are you with this job?' Very dissatisfied = 1, Not very satisfied = 2, Fair = 3, Quite satisfied = 4, Very satisfied = 5
	h	Work hours here means excluding lunch breaks but including overtime, whether paid or unpaid. How many hours per week did this job typically involve in the past 12 months.
	Income (lnw)	Logarithm of total income from work
	satis_w	Satisfaction with wage, Very dissatisfied = 1, Not very satisfied = 2, Fair = 3, Quite satisfied = 4, Very satisfied = 5
	satis_security	Satisfaction with job security, Very dissatisfied = 1, Not very satisfied = 2, Fair = 3, Quite satisfied = 4, Very satisfied = 5
	satis_environment	Satisfaction with job environment, Very dissatisfied = 1, Not very satisfied = 2, Fair = 3, Quite satisfied = 4, Very satisfied = 5
	satis_h	Satisfaction with work hours, Very dissatisfied = 1, Not very satisfied = 2, Fair = 3, Quite satisfied = 4, Very satisfied = 5
	satis_promotion	Job promotion satisfaction, Very dissatisfied = 1, Not very satisfied = 2, Fair = 3, Quite satisfied = 4, Very satisfied = 5, No promotion opportunities = 0
	employment_problem	How serious the employment problem is in society? On a scale of 0 to 10, with 0 being not serious and 10 being very serious.
	education_problem	How serious the eduction problem is in society? On a scale of 0 to 10, with 0 being not serious and 10 being very serious.
Core explanatory variables	overeducation(overedu)	overeducation = 1, other = 0
	undereducation (unedu)	undereducation = 1, other = 0
Control Variable	age	Unit: years
	gender	Female = 0, Male = 1
	marriage_last	Married = 1, not married = 0
	hukou	Agricultural households = 0, non-agricultural households = 1
	military	Yes = 1, No = 0
	sch	Unit: years
	exp	Age - years of education - 6 (or age - 18 if less than 12 years of education)
	exp2	Square term
	insurance	With work insurance = 1, without work insurance = 0
	labour	Yes = 1, No = 0
	coscale	Total number of employees in the workplace, in persons
	coiden	Including within the system (government departments/party and government organs/people's organisations, institutions, state-owned enterprises), outside the system (private enterprises/individual businessmen, foreign/Hong Kong, Macao and Taiwan enterprises, other types of enterprises, individuals/families, private non-enterprise organisations /associations /guilds /foundations /village committees). Work for himself/herself=1,Employed by another person/his family/organisation/unit/company=5
	region	Eastern region = 1, Central region = 2, Western region = 3

itive, it is reasonable given that the sample survey spans almost a decade during which China's economy has developed rapidly. The educational attainment or knowledge of individuals has not kept pace with the rapid economic changes. In particular, the average age of respondents in the sample is around 34, a period when educational qualifications are increasingly valued and individuals gradually acquire new skills on the job. In addition, the average number of years of education is 13 for the overeducated and 9 for the undereducated. According to the characteristics of educational stratification in China, the years of education for junior high school graduates is 9 years, for high school graduates 12 years, for vocational college graduates 15 years, and for university graduates 16 years. It can be inferred that most people with insufficient education have no experience of higher education. Regardless of the educational mismatch, it is evident that their average working hours exceed the legal limit of 40 hours per week, indicating the presence of overtime. Another notable difference is that the over-educated tend to work in larger enterprises.

3.4. Methods

3.4.1. Models

On the analysis of quantitative indicators such as income and job satisfaction, this paper adopts a research method that combines quantitative and qualitative analysis, constructs an econometric model based on the ORU model and Mincer's equation, and investigates whether educational mismatches have an impact on the quality of employment through the use of least squares and instrumental variable estimation.The traditional Mincer equation model is expressed as follows:

$$\ln w_i = \beta_0 + \beta_1 S_i + \beta_2 \exp_i + \beta_3 \exp_i^2 + \alpha_i x_i + u_i \tag{1}$$

where w_i represents personal income, S_i denotes the number of years of education actually received by the individual, exp_i denotes the individual's work experience in the labour market, x_i are the variables that define individual characteristics other than years of

Table 2: **Descriptive Statistics**

	Overeducation		Undereducation		Moderate education	
	mean	sd	mean	sd	mean	sd
satis	3.376	0.763	3.632	0.839	3.519	0.782
h	51.361	16.965	53.863	18.344	50.686	17.001
ln_w	9.908	1.013	9.926	1.008	10.005	1.003
satis_w	3.098	0.848	3.391	0.940	3.267	0.876
satis_security	3.604	0.905	3.839	0.905	3.750	0.874
satis_environment	3.440	0.897	3.665	0.955	3.614	0.872
satis_h	3.346	0.975	3.530	1.024	3.453	0.998
satis_promotion	2.391	1.485	2.174	1.798	2.384	1.592
employment_problem	7.075	2.123	6.560	2.596	6.889	2.206
education_problem	6.847	2.398	6.474	2.856	6.819	2.445
overdue	1.000	0.000	0.000	0.000	0.000	0.000
unedu	0.000	0.000	1.000	0.000	0.000	0.000
age	33.512	10.378	35.708	11.470	34.056	10.441
gender	0.662	0.789	1.235	1.545	0.821	1.096
marriage_last	1.599	1.090	1.408	1.993	1.550	1.385
hukou	1.906	1.076	1.641	1.252	1.876	1.163
military	0.009	0.096	0.009	0.095	0.009	0.092
sch	13.051	2.966	9.159	4.518	11.677	3.306
exp	13.736	11.054	17.141	11.890	14.895	10.944
exp_2	310.834	412.238	435.164	470.627	341.601	405.676
labour	0.512	0.500	0.429	0.495	0.541	0.498
coscale	978.839	11131.382	616.588	5291.579	908.670	9906.960
coiden	3.702	1.123	3.750	0.976	3.628	1.109
region	1.691	0.763	1.741	0.807	1.663	0.766
N	930		5287		2224	

education and work experience received, and u_i denotes the residual term. This formula reflects the market returns based on workers' personal information, which is entirely dependent on the supply side of the information obtained on education.

In this section of the paper, the model proposed by (Verdugo and Verdugo, 1989) for the study of educational mismatch is used to decompose the years of schooling (Ae) into the years required for work (Re), the years of over-education (Oe) and the years of under-education (Ue), as follows.

$$Ae_{i,t} = Re_{i,t} + Oe_{i,t} - Ue_{i,t} \tag{2}$$

$$Oe_{i,t} = \begin{cases} Ae_{i,t} - Re_{i,t} & \text{if } Ae_{i,t} > -Re_{i,t} \\ 0 & \text{if } Ae_{i,t} \leq Re_{i,t} \end{cases} \tag{3}$$

$$Ue_{i,t} = \begin{cases} Re_{i,t} - Ae_{i,t} & \text{if } Re_{i,t} > -Ae_{i,t} \\ 0 & \text{if } Re_{i,t} \leq Ae_{i,t} \end{cases} \tag{4}$$

Substituting into equation 1, we get,

$$\ln w_{it} = \mu + \beta_r Re_{it} + \beta_o \mathrm{Oe}_{it} + \beta_u \mathrm{Ue}_{it} + X_{it}\gamma + \varepsilon_{i,t} \tag{5}$$

where w_i represents personal income, $Ae_{i,t}$ the years of schooling, $Re_{i,t}$ denotes the years required for work, β_r denotes its coefficient, $Ue_{i,t}$ denotes the years of under-education, β_u denotes its coefficient, $Oe_{i,t}$ denotes the years of over-education, β_o denotes its coefficient, $X_{i,t}$ denotes other control variables (e.g., work experience, squared work experience, gender, and other variables), and γ denotes its coefficient. and ε_{it} denotes the residual term. This formula reflects the market returns based on workers' personal information, which is entirely dependent on the supply side of the information obtained on education.

3.4.2. Cross-period Characteristics

This study is grounded on a fundamental and pivotal assumption: the influence of education level on job quality is not instantaneously evident, but rather necessitates a substantial period of observation to be fully and clearly manifested. Recognizing the complexity and the delayed nature of this relationship, we have adopted a robust time series framework to conduct a thorough, comprehensive, and cross-period in-depth exploration of the research question at hand.

To facilitate this analysis, we have carefully selected four highly representative time points: 2014, 2016, 2018, and 2020. These time points allow us to track changes and trends over a significant span, providing valuable insights into the evolving relationship between education level and job quality. As the primary metric to assess job quality, we have chosen the logarithmic transformation of individual income. This transformation not only normalizes the data but also allows us to capture the multiplicative effects of income changes on job quality.

Furthermore, to gain a nuanced understanding of the role of education in shaping job quality, we have categorized education status into three distinct groups: insufficient education, appropriate education, and excessive education. This categorization is based on a comparison between individuals' actual education levels and their expected or desired education levels.

To provide a more generalized and comprehensive picture of the long-term impact of education status on work income, we have employed the advanced machine learning technique of k-means clustering analysis. The K-means algorithm represents a clustering analysis method rooted in iterative optimization strategies. Its core objective is to partition a dataset into k distinct clusters, ensuring that each data point is assigned to the nearest cluster, with the cluster center being determined by the average of all data points within that cluster. As a pivotal technique in the field of data mining, the K-means algorithm plays a significant role in uncovering potential relationships among data points within a dataset. Notably, clustering analysis differs fundamentally from classification methods, as it does not rely on any prior knowledge or predefined labels. Instead, it naturally divides data points into different categories based solely on their inherent characteristics and distributions. The objective function of the K-means algorithm is typically defined as the sum of squared distances between all data points within a cluster and their corresponding cluster center. By continuously iterating and optimizing, the algorithm strives to minimize this objective function, thereby achieving an optimal clustering effect. This method allows us to meticulously analyze the collected data and successfully divide the samples into the aforementioned three groups, as illustrated in the accompanying figure. Through this analysis, we aim to uncover the underlying patterns and trends that link education status to work income over time.

3.4.3. DID analysis

The following section will examine the influence of over- and under-education on job quality. The effects of educational mismatch on job quality are assessed using the Difference-in-Differences (DID) method. The DID design employs a matched control group to compare the reemployment observations with a control group. Reemployment is defined as an individual changing their occupation after 2016.

The year 2018 is taken as the point of departure for the classification of individuals into the treatment and control groups. Those who changed jobs in or after 2018 are assigned to the former, while those who did not are placed in the latter. A time variable is first established, with a value of 1 assigned to samples observed in 2018 and 2020, and 0 assigned to all other samples. Subsequently, a treatment variable is established, whereby individuals who changed occupations after 2018 are assigned a value of 1 and the remainder are assigned a value of 0. By estimating the interaction term coefficient (δ), the Average Treatment Effect (ATE) of educational mismatch on job quality can be identified. If (δ) is significantly positive, it indicates a positive impact of educational mismatch on job quality; if significantly negative, it indicates a negative impact.

Initially, there was some uncertainty regarding the comparability of the two groups in terms of job quality. Consequently, a Difference-in-Differences (DID) regression test was conducted to identify interpretable variables, followed by parallel trend tests and placebo tests. In the difference-in-differences (DID) model, placebo tests are employed to eliminate the influence of non-policy factors on the research results. This helps to circumvent any potential for subjective changes in the study subjects due to prior knowledge of the impending policy implementation, which could otherwise lead to errors in the estimation of the policy effect. The most common placebo test is the individual placebo test, which involves the plotting of a kernel density graph. In general, the closer the points are to the zero point on the horizontal axis, the more reliable the DID model's estimation of the policy effect is considered to be. The DID model identifies the causal impact of educational mismatch on job quality by comparing the changes in the treatment group and the control group before and after the intervention. The model is structured as follows:

$$Y_{it} = \alpha + \beta \cdot \text{Post}_t + \gamma \cdot \text{Treat}_i + \delta \cdot (\text{Post}_t \times \text{Treat}_i) + \mathbf{X}_{it} \cdot \theta + \epsilon_{it} \tag{6}$$

where Y_{it} denotes an indicator of employment quality for individual i at time t, Post_t is a time dummy variable (1 for 2018 and after, 0 before), Treat_i is a treatment group dummy variable (1 for the treatment group, 0 for the control group), $\text{Post}_t \times \text{Treat}_i$ is the interaction term, $\mathbf{X}_{it}$ is the control variable. β, γ, δ, θ are the coefficients respectively, and ϵ_{it} is the error term. This method effectively controls for temporal and individual heterogeneity, thereby providing a reliable estimate of the impact of educational mismatch on job quality.

4. Results

4.1. Delayed Impacts on Job Quality

The clustering analysis divides all samples into three distinct groups: the educationally progressive, the over-educated, and the educationally moderate (as shown in the first figure in 1). In the educationally progressive group, individuals exhibit a consistent upward trend in their educational attainment over time, reflecting their sustained pursuit and investment in education. The over-educated group, on the other hand, remains in a state of educational excess, which may be attributed to their excessive pursuit of higher education or the unequal distribution of educational resources. Lastly, the educationally moderate group tends towards an appropriate level of education amidst fluctuations, indicating their quest for a relative balance between educational investment and returns. To further explore the impact of different educational statuses on individual employment quality, this study uses income as a reference indicator to measure the cross-period characteristics of employment quality among different cluster groups (as shown the second figure in the Figure 1). The results show that the income of the educationally progressive group remains at a relatively high level, confirming the positive role of educational investment in improving individual employment quality and income levels. In contrast, the income of the educationally moderate group exhibits greater volatility. They experience a decline in income when pursuing over-education, but their income levels recover when education returns to an appropriate level. This finding suggests that appropriate educational investment is crucial for improving individual employment quality and income levels, while over-education may lead to resource wastage and income reduction. As for the over-educated group, their income remains at a relatively low level, further evidencing the negative impact of over-education on individual employment quality and income levels.

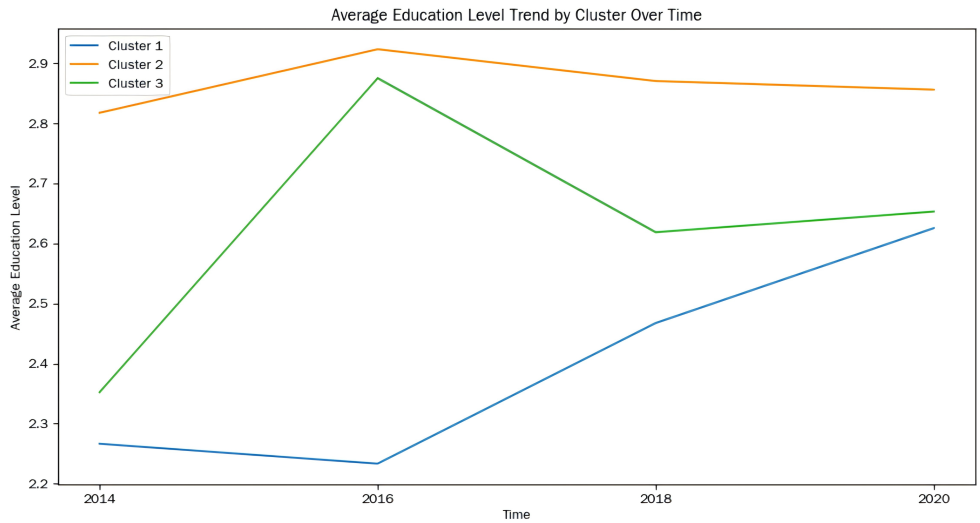
The time series distribution figure 2 of income based on educational status is shown below.This chart presents us with a more comprehensive perspective, showing the income trends over time for people with different educational backgrounds.

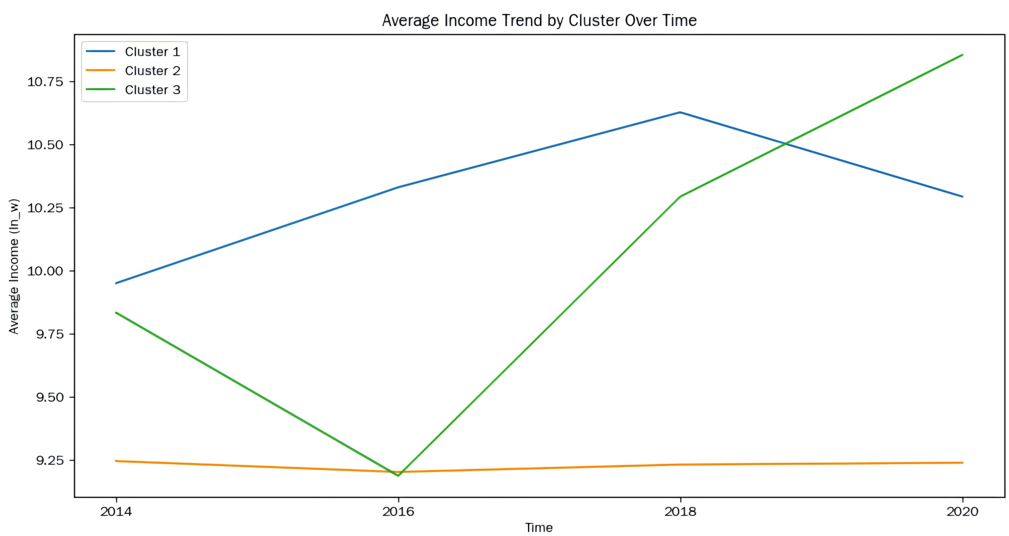
4.2. Punishment and Cake effect of Educational Mismatch

Our first research question examines the impact of educational mismatch on job quality. Individuals ultimately complete their educational journey by seeking employment, which marks the beginning of their efforts to earn a living and support their families. Em-

Figure 1: Impact of re-employment of over-educated Group

This group of charts analyzes individual income trends across different educational statuses using data from the CFPS database (2014, 2016, 2018, 2020) with 14,983 observations. Cluster analysis was applied to categorize the sample into three distinct groups. The first figure illustrate the disparities in income trends among these three groups, highlighting the impact of changes in educational status on individual income over time. The second figure depict the temporal changes in educational status among these three groups, serving as the basis for classification. The findings of this study contribute to understanding the differences among the three groups.



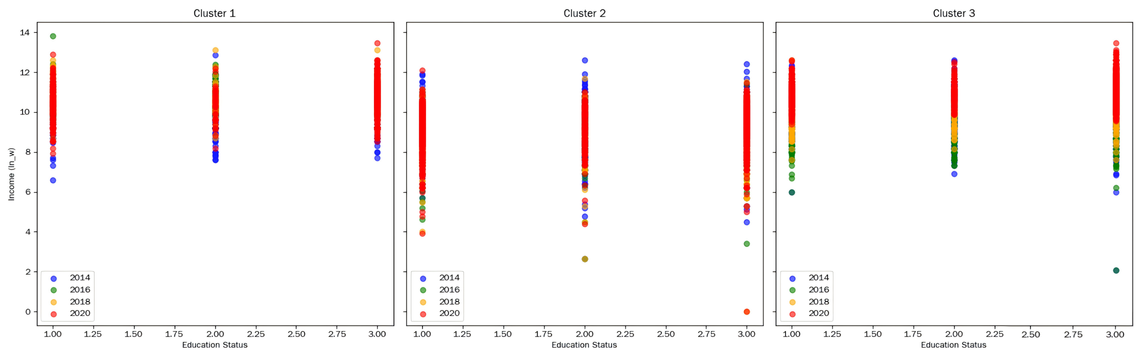


ployment is also an important part of life. The regression results of the empirical analyses are shown in Table 3 and 4.

Our first focus is on the impact of educational mismatch on job satisfaction. In the survey, respondents expressed their satisfaction with their jobs and their experiences at

Figure 2: Impact of re-employment of over-educated Group

This group of figures analyzes individual income trends across different educational statuses using data from the CFPS database (2014, 2016, 2018, 2020) with 14,983 observations. Clustering analysis was employed to categorize the sample into three groups. The charts depict the varying income trends among these clusters, emphasizing the impact of relative educational level on individual income over time. The findings contribute to a long-term understanding of the relationship between shifts in educational status and income.



work. In the first column of the table, we see that the effect of educational mismatch on job satisfaction is statistically significant and economically meaningful. Specifically, overeducation leads to an 11.36% decrease in job satisfaction, while undereducation leads to an 8.12% increase in job satisfaction. A plausible explanation is that individuals whose level of education exceeds the requirements of the job may feel underchallenged and undervalued, much like the character Kong Yiji in Lu Xun's writings, whose talents became a burden. This mismatch can lead to a sense of unfulfilled potential, boredom and a lack of achievement, thereby reducing enthusiasm for work. Conversely, those with inadequate training may feel fortunate to have secured their positions and may perceive greater opportunities for growth and development, thus fostering a sense of recognition and satisfaction with their work.

The second column shows the effect of educational mismatch on working hours. The effect of educational mismatch on working hours is statistically significant and economically meaningful. In particular, overeducated individuals have to work significantly longer hours, with this coefficient being almost four times higher than for undereducated individuals. A possible explanation for this is that overeducated individuals tend to have higher levels of skills and knowledge, leading employers to assign them more responsibilities and tasks. In contrast, under-educated individuals may be given simpler or more repetitive tasks. This is consistent with our choice of subjective assessment methods, as even within the same job, tasks may vary in complexity, which may not be captured by job analysis and reality matching methods. In addition, consistent with our empirical findings, overeducated individuals experience greater pressure for career advancement and promotion. They may work overtime and invest more time to demonstrate their skills and value in the hope of securing better career opportunities.

The third column examines the effect of educational mismatch on wage income, which is consistent with the results in the first column, as job satisfaction is significantly influenced by income. The effect of educational mismatch on wages is statistically significant and economically meaningful. Specifically, overeducation leads to a 13.38% reduction in job satisfaction, while undereducation leads to a 6.5% positive effect on job satisfaction, with the former being almost twice as large as the latter. Overeducated individuals clearly face a wage penalty, which contradicts the intuitive expectation that higher levels of education should correspond to higher earnings. In reality, they do not receive adequate compensation for their higher education. Conversely, under-educated individuals receive positive feedback in terms of wages. However, this does not imply that lower levels of education lead to higher earnings, as we have not accounted for 'survivorship bias'. In fact, it is not easy to get a job with "under-education". Furthermore, the signing of labour contracts has a significant positive impact on wage income, suggesting that such contracts increase job stability and provide additional benefits and subsidies. Moreover, enterprises that sign labour contracts tend to have more standardised requirements for talent, which is positively correlated with wage income. Both age and years of education also have a significant positive impact on wage income. In practice, as individuals age and their level of education increases, they tend to outperform 'newcomers' in terms of knowledge, skills and compliance. As a result, companies are more inclined to hire people with greater social and professional skills.

The following research focuses on employees' attitudes towards their jobs, examining five aspects: wages, job security, working environment, working hours and promotion opportunities. The fourth column of the table shows the effect of educational mismatch on wage satisfaction. The effect of the overeducation variable on wage satisfaction is significant at the 1% level, while the effect of the undereducation variable is significant at the 10% level. Specifically, each unit increase in the overeducation variable leads to a 12% decrease in wage satisfaction, while each unit increase in the undereducation variable leads to a 4% increase in wage satisfaction. The coefficient for overeducation is three times higher than that for undereducation, whereas we found earlier that the wage gap is twice as large. This suggests that overeducated individuals not only face an 'unfair' wage penalty, but also evaluate this 'unfairness' more negatively.

The fifth and sixth columns examine the impact of educational mismatch on job security and the working environment, focusing on occupational illnesses, necessary health and safety measures, and air quality and working conditions. Both the overeducation and educational mismatch variables are statistically significant and economically meaningful. This suggests that overeducated individuals have not found the comfortable jobs they had imagined and feel that their jobs do not match their qualifications. Their sense of entitlement is stronger and they may feel disadvantaged by their positions and wages. Consequently, they have higher expectations of comfort, which is reflected in the higher absolute values of the coefficients compared to those with insufficient education.

The seventh column examines the effect of educational mismatch on working hours. Each unit increase in the overeducation variable leads to a 9.48% decrease in wage satisfaction, while each unit increase in the undereducation variable leads to an 8% increase in wage satisfaction. The difference between the two is not significant. This finding is consistent with employees' perceptions of working time. Over-educated individuals, who face wage penalties, are reluctant to work overtime and seek psychological balance through other means, such as shorter working hours. This is illustrated by the widespread debate about China's 996 schedule (e.g. Dong et al., 2023; Chen et al., 2023). Conversely, the less educated tend to have lower expectations of comfort at work. Reflecting the characteristics of the East Asian Confucian cultural sphere, they are willing to sacrifice job comfort and work diligently to earn their wages.

The eighth column examines the effect of educational mismatch on career advancement satisfaction. Here we observe a reversal of the sign of the coefficients. The effect of the overeducation variable on promotion satisfaction is significant at the 5% level and positive, while the effect of the undereducation variable is significant at the 1% level and negative. Despite the stronger short-term 'penalty' for overeducated individuals compared to undereducated individuals, they are temporarily less satisfied but have better prospects for promotion. This suggests that overeducated individuals may not be reluctant to choose their jobs, but are willing to endure temporary 'penalties' in anticipation of better future opportunities. This also supports the conclusion from the third column that individuals with higher levels of education have a higher 'ceiling'. In the long run, this may not contradict the economic principle of a positive correlation between education and earnings.

We aimed to examine the relationship between educational mismatch and individuals' values, with a particular focus on education and employment issues related to the impact of educational mismatch on work. However, the empirical results did not provide evidence to support this hypothesis. This finding suggests that during periods of economic growth (as reflected in our sample period), individuals' expectations regarding employment and education are generally consistent.

4.3. The effect of Reemployment

Subsequently, the Difference-in-Differences (DID) method was employed for the purpose of investigating the impact of over-education and under-education on job quality. The initial step involved categorising the sample into two distinct groups: those who were

Table 3: **Emprical Results. Panel A**

This table analyzes the effect of panel data in work quality using CFPS dataset from 2014 to 2020. All of the variables are come from the investigation questionnaire. Panel A reports results of equation 5 using *satis*, *h*, *ln_w*, *satis_w*, *satis_security* to measure work quality. Variable *overdue* and *unedu* are served as core explanatory variables. Personal features, work characteristics and region are used as controls. Detailed definitions of variables can be found in Table 1. t-statistics are in parentheses. We also took time fixed effects and used robust clustering variance.

	(1) satis	(2) h	(3) ln_w	(4) satis_w	(5) satis_security
overdue	-0.1136***	2.3111***	-0.1338***	-0.1213***	-0.1459***
	(-3.7172)	(5.8038)	(-5.8285)	(-3.5492)	(-4.1167)
unedu	0.0812***	-0.5958*	0.0650***	0.0484*	0.1061***
	(3.7046)	(-1.7372)	(3.3369)	(1.9527)	(4.4491)
age	0.0069	-1.2278***	0.0875***	0.0153*	0.0370***
	(0.9083)	(-9.9068)	(11.9115)	(1.7517)	(4.4861)
gender	0.0153**	-0.3343**	0.0014	-0.0086	0.0276***
	(2.1051)	(-2.4631)	(0.1819)	(-1.0421)	(3.5464)
exp	-0.0179**	1.2695***	-0.0312***	-0.0208**	-0.0480***
	(-2.4071)	(10.2177)	(-4.2498)	(-2.4183)	(-5.8513)
exp_2	0.0003***	-0.0029**	-0.0012***	0.0002*	0.0002***
	(4.1154)	(-2.4115)	(-18.8262)	(1.8561)	(2.8471)
sch	0.0035	-0.4845***	0.0196***	-0.0002	0.0080**
	(1.1352)	(-8.3203)	(6.5595)	(-0.0466)	(2.3599)
labour	0.0864***	-0.3122	0.2578***	0.0413*	0.0414*
	(4.0707)	(-0.9518)	(13.9067)	(1.7233)	(1.8013)
region_east	-0.0168	-1.0748***	0.1736***	-0.0034	0.0539**
	(-0.7323)	(-2.8500)	(8.4281)	(-0.1318)	(2.1308)
region_middle	-0.0080	-0.5555	-0.0015	-0.0454	0.0502*
	(-0.3205)	(-1.3334)	(-0.0652)	(-1.5928)	(1.8232)
hukou	-0.0057	-1.1136***	-0.0083	-0.0177**	0.0209***
	(-0.8067)	(-8.9632)	(-1.1423)	(-2.1282)	(2.8187)
coiden1	0.1082***	-4.0807***	-0.0642***	-0.0126	0.0094
	(4.6250)	(-11.8829)	(-3.3377)	(-0.4564)	(0.3620)
coscale	-0.0000***	0.0000**	0.0000***	-0.0000	-0.0000
	(-2.8784)	(2.0707)	(3.0846)	(-0.5012)	(-0.7276)
marriage_last	-0.0059	-0.1092	-0.0187***	-0.0024	-0.0089*
	(-1.2598)	(-1.1292)	(-3.7950)	(-0.4753)	(-1.8656)
military	0.0001	0.0086	0.0096***	-0.0010	-0.0075
	(0.0183)	(0.1539)	(3.2755)	(-0.1440)	(-1.1429)
insure	0.0406*	-2.5047***	0.2656***	0.0396	0.0828***
	(1.6728)	(-7.1166)	(12.9956)	(1.4088)	(3.1271)
_cons	3.3589***	86.3076***	7.4666***	3.0704***	2.8236***
	(23.2560)	(40.0124)	(57.1554)	(18.4589)	(18.2909)
Time Fixed	Yes	Yes	Yes	Yes	Yes
N	8274	14991	14991	8274	8274
adj. R^2	0.038	0.109	0.145	0.036	0.051

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

Table 4: **Emprical Results.Panel B**

This table analyzes the effect of panel data in work quality using CFPS dataset from 2014 to 2020. All of the variables are come from the investigation questionnaire. Panel B reports results of equation 5 using *satis_environment*, *satis_h*, *satis_promotion*, *employment_problem*, *education_problem* to measure work quality. Variable *overdue* and *unedu* are served as core explanatory variables. Personal features, work characteristics and region are used as controls. Detailed definitions of variables can be found in Table 1. t-statistics are in parentheses. We also took time fixed effects and used robust clustering variance.

	(6)	(7)	(8)	(9)	(10)
	satis_environment	satis_h	satis_promotion	employment_problem	education_problem
overdue	-0.1724***	-0.0948**	2.2819**	0.1016	-0.0255
	(-4.9080)	(-2.4204)	(1.9765)	(0.8922)	(-0.1956)
unedu	0.0683***	0.0830***	-3.4165***	-0.0442	-0.1453
	(2.7820)	(2.9679)	(-3.9769)	(-0.4508)	(-1.3017)
age	0.0317***	0.0111	-1.7266***	-0.0833	0.0073
	(3.6467)	(1.1499)	(-6.2808)	(-0.7506)	(0.0576)
gender	0.0325***	0.0308***	0.1736	0.0226	0.0564*
	(3.9386)	(3.4547)	(0.6083)	(0.7630)	(1.7415)
exp	-0.0481***	-0.0174*	2.5807***	-0.0638	-0.0265
	(-5.6148)	(-1.8323)	(9.4035)	(-0.6601)	(-0.2462)
exp_2	0.0004***	0.0002**	-0.0013	0.0022**	0.0007
	(4.4648)	(2.3334)	(-0.4370)	(2.4199)	(0.6449)
sch	0.0071**	0.0135***	-0.4553***	-0.0053	-0.0353
	(2.0164)	(3.5198)	(-3.9105)	(-0.2683)	(-1.3791)
labour	0.0718***	0.0032	-5.9409***	-0.0117	0.0401
	(2.9842)	(0.1199)	(-7.1630)	(-0.1156)	(0.3569)
region_east	0.0655**	0.0811***	-0.1576	-0.4444	0.0240
	(2.5161)	(2.8225)	(-0.1766)	(-1.1268)	(0.0593)
region_middle	0.0299	0.0383	-0.0250	-0.6721	-0.3378
	(1.0409)	(1.2205)	(-0.0254)	(-1.5072)	(-0.7284)
hukou	0.0102	0.0000	-0.1931	0.0791*	0.0684
	(1.2607)	(0.0025)	(-0.7435)	(1.7987)	(1.3396)
coiden1	0.0608**	0.1121***	-0.0554	0.2805**	0.1107
	(2.2293)	(3.7862)	(-0.0641)	(2.4080)	(0.8712)
coscale	-0.0000***	-0.0000***	-0.0001**	0.0000	0.0000
	(-3.2595)	(-2.6619)	(-2.2861)	(0.8391)	(0.0193)
marriage_last	-0.0071	-0.0061	-0.3632**	0.0038	0.0517
	(-1.4246)	(-1.1242)	(-2.0262)	(0.0861)	(1.1334)
military	0.0045	0.0125	0.3217	-0.0287	0.0208
	(0.6481)	(1.6223)	(1.2896)	(-1.4081)	(0.8731)
insure	0.0406	0.1098***	-7.4554***	-0.1497	0.1491
	(1.4217)	(3.5389)	(-8.3043)	(-1.3908)	(1.2449)
_cons	2.9216***	3.0741***	62.9329***	9.9425***	7.0515**
	(17.7361)	(16.7533)	(11.7153)	(3.6821)	(2.2630)
Time Fixed	Yes	Yes	Yes	Yes	Yes
N	8274	8274	8274	5805	5805
adj. R^2	0.043	0.028	0.215	0.194	0.210

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

overeducated and those who were undereducated. The subsequent section, presented in Table 5 and Table 6, comprises a series of t-tests that examine the impact of job changes on individual job quality.

Table 5 focus on the over-educated group and reveal that, with the exception of income, no significant effects were observed. However, it is notable that income levels for over-educated individuals declined significantly following 2018. Figures 3 and 4 illustrate the parallel trend test and the placebo test, respectively. Left of figure 3 depicts a time trend graph, which illustrates that prior to the shock in 2018, the income trends of the treatment and control groups were largely parallel. However, during the period spanning 2018 to 2020, the trends of the target variables in the two groups exhibited a divergence. Subsequent to 2014, the income of the control group exhibited a slight increase, whereas the income of the treatment group demonstrated a downward trajectory, with a notable decline in 2020. It can therefore be posited that the time trend assumption between the two groups prior to the shock in 2018 is largely satisfied, and that the divergence in trend lines observed subsequent to this can be attributed to educational mismatch. Right of figure 4 illustrates that the majority of points are situated around the zero point on the horizontal axis, which serves to reinforce the robustness of the DID model results. This indicates that during the period from 2018 to 2020, China experienced the conclusion of a phase of accelerated growth, characterised by a notable decline in the returns for those with excess qualifications. As economic growth decelerated, the labour market's demand for highly educated talent failed to keep pace, resulting in many highly educated individuals facing the dilemma of possessing high abilities but occupying low positions. This phenomenon had significant implications for the overall quality and equity of the labour force, affecting not only individual career development and income levels. The discrepancy between the educational qualifications of the labour force and the requirements of the labour market forced many highly educated individuals to accept positions that were below their capabilities and educational levels. This resulted in a reduction in the return on educational investment. The characteristics of the labour market during this period reflect the contradictions and challenges between the education system and the labour market during economic restructuring and industrial upgrading. The lack of effective alignment between educational resources and the labour market affected overall labour productivity and equity. These issues will be further analysed in the subsequent Discussion in 6.

We found that, unlike in Table 5 where only the wage column showed significant interaction terms, Table 6 presents statistical significance across four variables: job satisfaction($satis$), working hours(h), perceptions of job issues($employment\_problem$), and income(w). Specifically, the interaction term in the job satisfaction regression is statistically significant at the 5% level with a negative coefficient, while in the working hours regression, the interaction term is statistically significant at the 1% level with a positive coefficient. This indicates that the 'cake effect' for under-educated individuals diminished after 2018. In the regression for perceptions of job issues, the interaction term is statistically significant at the 1% level with a negative coefficient, and in the income regression, the interaction term is also statistically significant at the 1% level with a negative coefficient. This suggests that their perceptions of employment issues lag behind the actual changes in wages impacted by the shock. However, upon examining Figure 4, we regretfully did not obtain the expected results. The four graphs show parallel trend tests and placebo tests for each of these four variables. The parallel trend test and placebo test seem to contradict the t-test results. Although the t-tests demonstrated statistical significance, the results from the parallel trend tests and placebo tests were less robust. Despite these limitations, we can still draw several important conclusions. Firstly, as the overall level of education increases, the 'survivor bias' for under-educated individuals diminishes. This bias, reflected in terms of salary and job satisfaction, indicates that under-educated individuals who remain employed tend to experience lower wages and reduced job satisfaction over time. Secondly, under-educated individuals perceive employment issues to be more severe, as they are more significantly impacted by the increasing educational standards in the labor market. This heightened perception of employment challenges is likely due to the greater difficulty they face in securing and retaining jobs that match their skills and qualifications. Consequently, the mismatch between their educational attainment and job requirements becomes more pronounced, exacerbating their employment difficulties. These findings underscore the need for targeted policies to address educational mismatches and support under-educated individuals in the labor market.

Table 5: **DID Analysis. Panel A**

This table analyzes the effect of panel data in work quality using CFPS dataset from 2014 to 2020. All of the variables are come from the investigation questionnaire. Panel A reports results of equation 6 for over-education group using *satis*, *h*, $employment\_problem$,$education\_problem$,$satis_w$,$satis_security$, $satis_environment$, $satis_h$, $satis_promotion$, ln_w to find how re-employment in over-education group affects work quality. Variable *did* and *unedu* are served as core variable. Personal features, work characteristics and region are used as controls. Detailed definitions of varibles can be found in 1. t-statistics are in parentheses. We also took time fixed effects and used robust clustering variance. The significance level is labelled as: * p <0.1, ** p <0.05, *** p <0.01

	(1) satis	(2) h	(3) employment_problem	(4) education_problem	(5) satis_w	(6) satis_security	(7) satis_environment	(8) satis_h	(9) satis_promotion	(10) ln_w
did	-0.0586	-2.5963	-0.4326	-0.4625	-0.1277	0.0228	-0.1410	0.0850	-3.6653	-0.7196***
	(-0.4083)	(-0.9290)	(-1.4147)	(-1.2731)	(-0.7757)	(0.1438)	(-0.9089)	(0.5212)	(-0.6872)	(-4.1454)
age	-0.0087	-1.1816***	0.0101	0.0795	-0.0415	-0.0113	0.0517	0.0881*	-0.4831	0.1197***
	(-0.2540)	(-3.1563)	(0.1970)	(1.4472)	(-1.0996)	(-0.2651)	(1.2430)	(1.9480)	(-0.3098)	(6.0607)
gender	0.0182	0.7529	-0.0692	-0.1668**	0.0586*	-0.0293	-0.0131	0.0502	0.0159	0.1737***
	(0.5961)	(1.5547)	(-1.1724)	(-2.3854)	(1.6584)	(-0.8808)	(-0.3804)	(1.3967)	(0.0137)	(5.9660)
exp	0.0139	1.1271***	-0.0525	-0.1105*	0.0450	-0.0082	-0.0514	-0.0726	1.0208	-0.0603***
	(0.3863)	(2.9048)	(-0.9764)	(-1.9199)	(1.1317)	(-0.1849)	(-1.1906)	(-1.5513)	(0.6358)	(-2.9347)
exp_2	-0.0000	0.0007	0.0006	0.0000	0.0001	0.0004	0.0002	-0.0002	0.0021	-0.0013***
	(-0.1112)	(0.2241)	(1.5120)	(0.0234)	(0.3188)	(1.5820)	(0.7299)	(-0.6858)	(0.2181)	(-7.5148)
sch	0.0338	-0.3582	0.0522	0.0228	0.0474	0.0414	0.0192	-0.0033	-1.5389	-0.0191*
	(1.2494)	(-1.4091)	(1.4331)	(0.6195)	(1.5903)	(1.2013)	(0.6044)	(-0.0954)	(-1.1946)	(-1.6549)
labour	0.0811	1.1544	-0.0660	0.0600	0.0630	-0.0316	0.0576	-0.0870	-4.6217**	0.2413***
	(1.3362)	(1.4790)	(-0.6346)	(0.4985)	(0.9177)	(-0.4321)	(0.8074)	(-1.1295)	(-1.9805)	(5.6836)
region_east	-0.0076	-2.8694***	-0.2659**	0.0070	0.0817	0.0738	0.1109	0.0959	-3.0585	0.2793***
	(-0.1161)	(-2.9561)	(-2.2433)	(0.0534)	(1.1131)	(0.9572)	(1.4012)	(1.1307)	(-1.2187)	(5.1273)
region_middle	-0.0574	-1.8841*	-0.0163	0.1394	-0.0338	0.0571	0.0923	-0.0035	-1.3350	0.0713
	(-0.8188)	(-1.8317)	(-0.1300)	(0.9955)	(-0.4267)	(0.6875)	(1.1069)	(-0.0392)	(-0.4977)	(1.2409)
hukou	-0.0034	-0.9249***	0.1182***	0.1528***	-0.0045	0.0307	-0.0060	0.0001	0.5897	-0.0172
	(-0.1376)	(-2.7876)	(2.7026)	(3.1956)	(-0.1474)	(1.1959)	(-0.2193)	(0.0031)	(0.6988)	(-0.8722)
coiden1	0.0686	-3.9349***	0.2354**	0.2819**	-0.1017	-0.0730	0.0270	0.0466	2.2961	-0.0080
	(0.9703)	(-4.8957)	(2.2864)	(2.3126)	(-1.2544)	(-0.8504)	(0.3294)	(0.5184)	(0.9448)	(-0.1788)
coscale	-0.0000***	0.0000***	0.0000	-0.0000	0.0000***	0.0000	-0.0000**	-0.0000***	-0.0000	0.0000***
	(-3.8243)	(3.2765)	(0.4102)	(-0.5407)	(2.7558)	(0.1206)	(-2.0211)	(-4.5047)	(-1.4928)	(2.7125)
marriage_last	-0.0331**	0.8133*	0.0059	0.0650	0.0030	0.0094	-0.0173	-0.0380*	-1.7147**	-0.0134
	(-2.0805)	(1.8040)	(0.1363)	(1.1256)	(0.1157)	(0.3782)	(-0.7394)	(-1.7013)	(-2.3321)	(-0.6494)
military	-0.0027	0.1487	0.0079	0.0148	-0.0041	-0.0198	-0.0057	0.0051	0.6332	0.0122
	(-0.2207)	(1.1136)	(0.4853)	(0.7840)	(-0.3304)	(-1.4866)	(-0.3961)	(0.3441)	(1.4111)	(1.6409)
insure	0.0829	-4.1265***	-0.0764	-0.0124	0.0588	0.1352	0.0399	0.0160	-6.9173***	0.3207***
	(1.1802)	(-5.0015)	(-0.6854)	(-0.0961)	(0.7317)	(1.6328)	(0.4671)	(0.1737)	(-3.0205)	(7.1457)
_Itime_2016	0.0000	2.3881**	-0.1661	-0.2710*	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0234
	(.)	(2.3272)	(-1.2170)	(-1.7197)	(.)	(.)	(.)	(.)	(.)	(-0.3589)
_Itime_2018	-0.0358	6.9234**	-0.0297	0.6391**	0.1684	0.0822	0.1860	-0.1215	15.4810***	0.2226*
	(-0.2718)	(2.4555)	(-0.1099)	(2.1561)	(1.2456)	(0.5660)	(1.2892)	(-0.8004)	(3.5008)	(1.8018)
_Itime_2020	0.2163	9.4197***	-0.6136*	-0.3237	0.3840**	0.1840	0.3901**	-0.1616	16.1084***	0.7961***
	(1.3460)	(2.7260)	(-1.6524)	(-0.7517)	(2.0529)	(1.0327)	(2.1875)	(-0.8409)	(2.7085)	(3.9150)
_cons	2.9811***	83.2158***	6.7030***	5.1234***	3.0328***	3.0758***	1.9169***	1.5631***	50.6597***	6.9734***
	(7.2991)	(15.6665)	(9.8044)	(6.7297)	(6.5463)	(6.3118)	(3.7437)	(2.8658)	(3.0253)	(23.1963)
N	925	2552	2552	2552	925	925	925	925	925	2552
adj. R^2	0.027	0.114	0.042	0.054	0.026	0.028	0.040	0.025	0.146	0.184

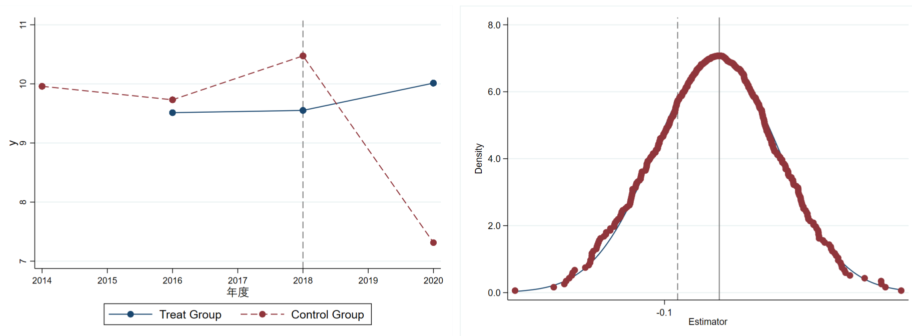
Table 6: **DID Analysis. Panel B**

This table analyzes the effect of panel data in work quality using CFPS dataset from 2014 to 2020. All of the variables are come from the investigation questionnaire. Panel 6 reports results of equation 6 for under-education group using $satis$, h, $employment\_problem$,$education\_problem$,$satis_{w}$,$satis_{s}ecurity$, $satis_{e}nvironment$, $satis_{h}$, $satis_{p}romotion$, ln_w to find how re-employment in under-education group affects work quality. Variable did and $unedu$ are served as core variable. Personal features, work characteristics and region are used as controls. Detailed definitions of varibles can be found in 1. t-statistics are in parentheses. We also took time fixed effects and used robust clustering variance. The significance level is labelled as: * p <0.1, ** p <0.05, *** p <0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	satis	h	employment_ problem	education_ problem	satis_w	satis_security	satis_ environment	satis_h	satis_promotion	ln_w
did	-0.0807**	2.0969***	-0.2469**	-0.1558	-0.0460	0.0419	-0.0169	-0.0162	0.7473	-0.6627***
	(-2.3047)	(3.0425)	(-2.3205)	(-1.3317)	(-1.1844)	(1.1096)	(-0.4251)	(-0.3811)	(0.5532)	(-18.3666)
age	-0.0010	-1.4539***	-0.0008	-0.0361	0.0145	0.0401***	0.0267**	-0.0224	-2.2294***	0.0925***
	(-0.0919)	(-7.4671)	(-0.0268)	(-1.0566)	(1.1798)	(3.6077)	(2.1652)	(-1.6374)	(-5.8866)	(7.7687)
gender	0.0124	-0.5979***	-0.0046	0.0322	-0.0183*	0.0394***	0.0424***	0.0312***	0.0635	-0.0453***
	(1.4563)	(-3.6390)	(-0.1783)	(1.1327)	(-1.8867)	(4.3436)	(4.3645)	(2.9906)	(0.1899)	(-5.1914)
exp	-0.0101	1.4749***	0.0039	0.0610*	-0.0209*	-0.0478***	-0.0433***	0.0154	3.3427***	-0.0431***
	(-0.9969)	(7.8156)	(0.1249)	(1.8095)	(-1.7347)	(-4.3860)	(-3.6113)	(1.1528)	(8.9912)	(-3.7209)
exp_2	0.0003***	-0.0023	-0.0004*	-0.0011***	0.0001	0.0001	0.0003***	0.0002	-0.0061*	-0.0011***
	(2.8924)	(-1.3406)	(-1.6455)	(-4.1628)	(1.2448)	(1.3797)	(3.2535)	(1.6320)	(-1.7446)	(-13.0106)
sch	0.0005	-0.3807***	0.0497***	0.0487***	-0.0041	0.0060	0.0042	0.0106**	-0.3125**	0.0174***
	(0.1466)	(-5.6666)	(4.7737)	(4.3822)	(-1.0870)	(1.6185)	(1.0741)	(2.5602)	(-2.5382)	(5.3961)
labour	0.0841***	-0.3784	-0.0731	0.0133	0.0661**	0.0409	0.0905***	0.0702**	-6.0538***	0.2813***
	(3.0332)	(-0.7838)	(-1.0030)	(0.1667)	(2.1046)	(1.3839)	(2.8524)	(2.0791)	(-5.5681)	(10.8612)
region_east	-0.0186	-1.1546**	-0.3321***	-0.1096	-0.0098	0.0490	0.0416	0.0549	-0.4978	0.1666***
	(-0.6335)	(-2.1925)	(-4.2935)	(-1.2827)	(-0.2997)	(1.5462)	(1.2525)	(1.5143)	(-0.4360)	(6.0547)
region_middle	-0.0122	-0.9976*	-0.1640**	0.0373	-0.0794**	0.0072	-0.0128	0.0307	-0.2777	-0.0365
	(-0.3746)	(-1.6815)	(-2.0050)	(0.4070)	(-2.1503)	(0.2060)	(-0.3461)	(0.7653)	(-0.2187)	(-1.2127)
hukou	-0.0023	-1.0769***	0.0902***	0.0786***	-0.0200*	0.0152*	0.0053	0.0064	0.1852	-0.0045
	(-0.2639)	(-6.5815)	(3.5606)	(2.7822)	(-1.9150)	(1.6631)	(0.5158)	(0.5838)	(0.5666)	(-0.4824)
coiden1	0.1134***	-4.7007***	0.2604***	0.1566*	0.0065	0.0421	0.0586	0.1197***	-0.4750	-0.0856***
	(3.7364)	(-9.0520)	(3.2717)	(1.7645)	(0.1814)	(1.2826)	(1.6271)	(3.1084)	(-0.4116)	(-3.0352)
coscale	-0.0000*	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0001*	0.0000*
	(-1.6949)	(0.9197)	(0.2078)	(-0.0788)	(-1.0771)	(-0.6643)	(-1.9404)	(-1.6322)	(-1.7117)	(1.7565)
marriage_last	0.0017	-0.2032*	0.0703***	0.0704***	0.0025	-0.0076	-0.0025	0.0022	-0.4031*	-0.0212***
	(0.2935)	(-1.7757)	(3.2953)	(3.1618)	(0.4315)	(-1.3804)	(-0.4212)	(0.3464)	(-1.9015)	(-3.6617)
military	-0.0107	-0.1351	0.0129	0.0362**	-0.0161	-0.0071	0.0024	0.0028	-0.3223	0.0071
	(-0.9687)	(-1.4428)	(0.9929)	(2.5052)	(-1.2799)	(-0.6714)	(0.2016)	(0.2092)	(-0.7597)	(1.5672)
insure	0.0550*	-2.7257***	-0.0921	0.1200	0.0591	0.1061***	0.0797**	0.1497***	-8.1477***	0.2618***
	(1.7330)	(-5.1623)	(-1.0870)	(1.3018)	(1.6024)	(3.0583)	(2.1263)	(3.7414)	(-6.7881)	(8.8324)
_Itime_2016	0.0000	1.4585*	-0.2463**	0.0091	0.0000	0.0000	0.0000	0.0000	0.0000	-0.1720***
	(.)	(1.6950)	(-2.1951)	(0.0732)	(.)	(.)	(.)	(.)	(.)	(-4.0221)
_Itime_2018	0.2457***	2.0281**	-0.0295	0.4046***	0.3641***	0.0772*	0.1045**	0.1754***	20.6254***	0.4444***
	(5.8344)	(2.4052)	(-0.2400)	(2.8920)	(7.8502)	(1.6601)	(2.1231)	(3.3872)	(12.6432)	(11.6613)
_Itime_2020	0.3670***	0.9618	-0.2951**	0.0770	0.4014***	0.1848***	0.2418***	0.2804***	16.9842***	0.6806***
	(7.6139)	(0.9677)	(-2.0478)	(0.4848)	(7.5988)	(3.5322)	(4.4169)	(4.7734)	(9.0537)	(13.7492)
_cons	3.3551***	87.5977***	6.5357***	6.6436***	2.8378***	2.7576***	2.9910***	3.5498***	46.7656***	7.5629***
	(16.5081)	(25.2459)	(11.9187)	(11.0088)	(11.8632)	(12.8306)	(12.5624)	(13.4401)	(6.2660)	(35.1422)
N	5147	7395	7395	7395	5147	5147	5147	5147	5147	7395
adj. R^2	0.029	0.090	0.027	0.028	0.026	0.044	0.039	0.027	0.220	0.182

Figure 3: Impact of re-employment of over-educated Group

This figure shows the parallel trend test (left) and the kernel density plot for the placebo test (right) in the study of whether re-employment affects job quality for the over-educated. We set 2018 as the shock period, with 2014 and 2016 representing the pre-shock period and 2020 the post-shock period and dataset is come from CFPS. Using 2018 as the cut-off point, individuals who changed jobs in or after 2018 are assigned to the treatment group, while those who did not change jobs are assigned to the control group. We first set a time variable, assigning a value of 1 to samples observed in 2018 and 2020, and 0 to others. We then establish a treatment variable, assigning a value of 1 to individuals who changed occupation after 2018, and 0 to others.In the Table 5, we found that only the variable ln_w passed the t-test. Therefore, we calculated the mean of the variable ln_w for both groups and plotted the results as shown below.



5. Robust Test

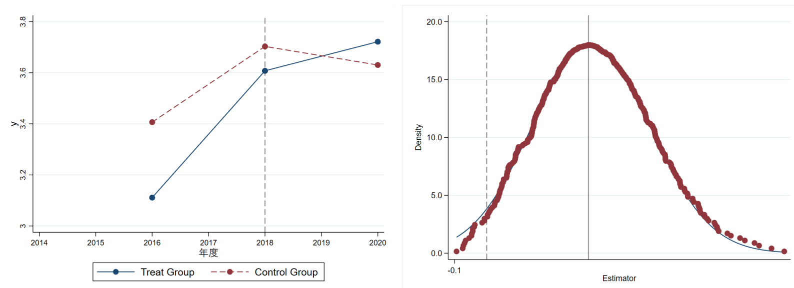
For regression in punishment and cake effect, given the differing employment values among individuals with varying educational levels, for example, lower-educated individuals tend to prioritise income, while higher-educated individuals place greater importance on job value-the sample was categorised into three groups based on educational attainment: highly educated, moderately educated, and lowly educated individuals. In particular, the term 'low education' is used to describe those with a high school education or below, while 'high education' refers to individuals with a degree above high school. This categorisation allows us to examine the impact of educational mismatch on income across different educational groups. The regression results are presented in 7 and 8, with Table 7 representing the low education sample, Table 8 the high education sample.

A review of the data in Table 7 reveals that the majority of results are consistent with previous conclusions. However, there are two exceptions. Firstly, within the low-education group, it is evident that the satisfaction with wages among both overeducated and under-educated individuals is not statistically significant. However, in Table 8, a significant re-

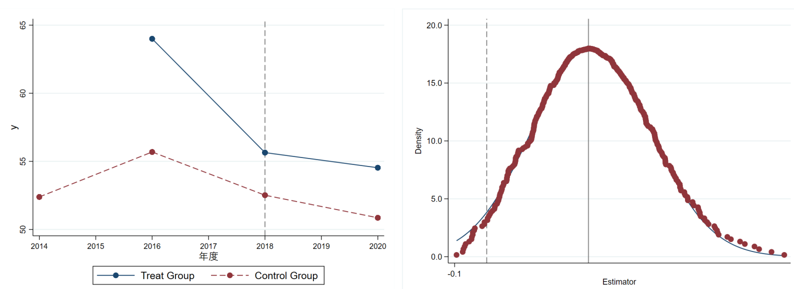
Figure 4: Impact of re-employment of under-educated Group

This figure shows the parallel trend test (left) and the kernel density plot for the placebo test (right) in the study of whether re-employment affects job quality for the under-educated. We set 2018 as the shock period, with 2014 and 2016 representing the pre-shock period and 2020 the post-shock period and dataset is come from CFPS. Using 2018 as the cut-off point, individuals who changed jobs in or after 2018 are assigned to the treatment group, while those who did not change jobs are assigned to the control group. We first set a time variable, assigning a value of 1 to samples observed in 2018 and 2020, and 0 to others. We then establish a treatment variable, assigning a value of 1 to individuals who changed occupation after 2018, and 0 to others.In the Table 6, we found that only the variable h, $satis$, $employment\_problem$, ln_w passed the t-test. Therefore, we calculated the mean of the variable h, $satis$, $employment\_problem$, ln_w for both groups and plotted the results as shown below.

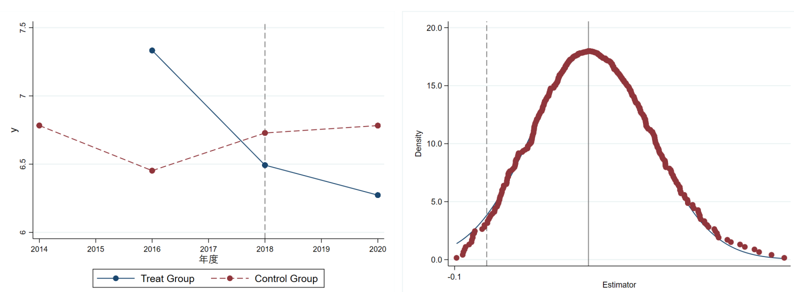
(a) h



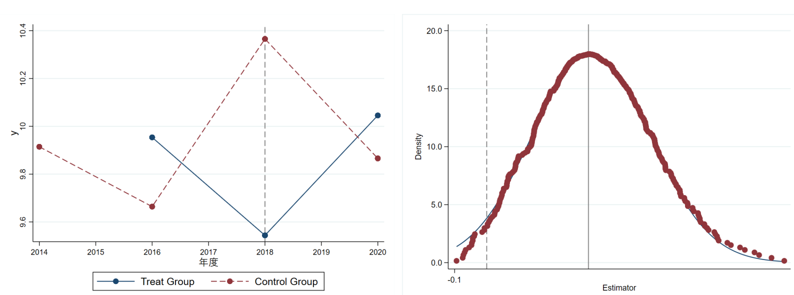
(b) satis



(c) employment_problem



(d) ln_w



lationship is observed between satisfaction with wages(see column(4)) and education for the high-education group. This indicates that individuals with lower levels of education are less responsive to wage incentives and do not have atypical expectations regarding their remuneration. Moreover, the satisfaction with job promotion is not statistically significant in both the low-education and high-education groups, but it is significant in the overall sample. One potential explanation for this is the existence of heterogeneous effects. It is possible that individuals with different levels of education may respond in different ways to job promotion satisfaction. For example, individuals with higher levels of education may have more ambitious career aspirations, which may result in a lower level of satisfaction even when promotions do occur. Conversely, those with lower levels of education may have lower expectations regarding promotions, which consequently has a minimal impact on their satisfaction. Table 8 also reveals two further anomalies. The satisfaction with working hours among those with lower education is not statistically significant, indicating low sensitivity. It may be that those with lower education are engaged in jobs with more fixed or less flexible working hours, resulting in minimal changes in their satisfaction with working hours. This is consistent with the statistically significant negative coefficient for job promotion satisfaction at the 1% level, suggesting fewer promotion opportunities.

Table 7: **Robust Test.A**

This table is a robust test to analyze the effect of panel data in work quality using CFPS dataset from 2014 to 2020. All of the variables are come from the investigation questionnaire. This table reports results of equation 5 using $satis$, h, $satis_w$, ln_w, $satis_security$, $satis_environment$, $satis_h$, $satis_promotion$, $employment\_problem$,$education\_problem$ to measure work quality of low-education group. Variable *overdue* and *unedu* are served as core explanatory variables. Personal features, work characteristics and region are used as controls. Detailed definitions of variables can be found in Table 1. t-statistics are in parentheses. We also took time fixed effects and used robust clustering variance. The significance level is labelled as: * p <0.1, ** p <0.05, *** p <0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	satis	h	ln_w	satis_w	satis_security	satis_environment	satis_h	satis_promotion	employment_ problem	education_problem
overdue	-0.1234***	2.1360***	-0.1330***	-0.0757	-0.1054**	-0.2163***	-0.1065*	2.5987	-0.0087	-0.2081
	(-2.5932)	(3.6435)	(-4.3602)	(-1.4448)	(-2.0404)	(-4.0038)	(-1.8483)	(1.3386)	(-0.0489)	(-1.0591)
unedu	0.0850***	-0.8795**	0.0469**	0.0327	0.1081***	0.0562*	0.1225***	-3.1224***	-0.0835	-0.1775
	(3.0411)	(-2.1026)	(2.1549)	(1.0643)	(3.5657)	(1.7718)	(3.6235)	(-2.7399)	(-0.6786)	(-1.3083)
age	-0.0236	-2.2693***	-0.1654***	-0.1012***	-0.0151	0.0107	-0.0092	-1.8093	0.3780	0.1789
	(-0.7082)	(-3.8977)	(-5.4605)	(-2.7600)	(-0.4158)	(0.2834)	(-0.2291)	(-1.3305)	(0.8772)	(0.3764)
gender	0.0238***	-0.4105**	0.0070	-0.0009	0.0421***	0.0476***	0.0431***	0.1934	0.0081	0.0618
	(2.7533)	(-2.3446)	(0.7716)	(-0.0940)	(4.4936)	(4.8622)	(4.1236)	(0.5493)	(0.2102)	(1.4560)
exp	0.0061	2.2703***	0.2086***	0.0875**	0.0026	-0.0315	0.0010	2.8984**	-0.5789	-0.0397
	(0.1856)	(3.9407)	(6.9586)	(2.4193)	(0.0737)	(-0.8444)	(0.0239)	(2.1615)	(-1.4773)	(-0.0918)
exp_2	0.0005***	-0.0019	-0.0009***	0.0003***	0.0003***	0.0005***	0.0003**	-0.0073**	0.0019*	0.0001
	(5.2561)	(-1.3864)	(-13.0113)	(3.4488)	(2.7602)	(4.7291)	(2.4086)	(-2.0647)	(1.7721)	(0.0580)
sch	0.0051	-0.5023***	0.0250***	-0.0014	0.0075**	0.0063*	0.0151***	-0.5166***	-0.0194	-0.0496
	(1.5235)	(-8.4196)	(8.0424)	(-0.3887)	(2.0731)	(1.6644)	(3.7301)	(-3.7883)	(-0.6654)	(-1.5453)
labour	0.0814***	-0.0878	0.2746***	0.0758***	0.0503*	0.0958***	0.0422	-6.4445***	-0.0325	0.0240
	(3.1946)	(-0.2121)	(12.7468)	(2.7007)	(1.8164)	(3.3120)	(1.3692)	(-6.1971)	(-0.2577)	(0.1722)
region_east	-0.0390	-0.8805*	0.1620***	-0.0244	0.0044	0.0098	0.0468	-0.0371	-0.6740	0.3318
	(-1.4210)	(-1.9491)	(6.8927)	(-0.8074)	(0.1460)	(0.3152)	(1.4089)	(-0.0332)	(-1.5049)	(0.6717)
region_middle	-0.0138	-0.3520	-0.0107	-0.0339	0.0037	-0.0035	0.0314	0.7578	-0.8409	-0.0846
	(-0.4588)	(-0.7178)	(-0.4176)	(-1.0211)	(0.1117)	(-0.1033)	(0.8618)	(0.6166)	(-1.6086)	(-0.1468)
hukou	-0.0120	-1.4709***	-0.0296***	-0.0322***	0.0115	0.0059	0.0058	0.4935	0.1100	0.1084
	(-1.2490)	(-8.6623)	(-3.3535)	(-3.0484)	(1.1056)	(0.5404)	(0.5038)	(1.2622)	(1.5625)	(1.3970)
coiden1	0.0878***	-4.8672***	-0.0629**	-0.0100	0.0543	0.0628*	0.1235***	0.2369	0.3507**	0.1884
	(2.7176)	(-10.1525)	(-2.5205)	(-0.2805)	(1.5492)	(1.7123)	(3.1608)	(0.1798)	(2.1673)	(1.0555)
coscale	-0.0000	0.0000	0.0000*	-0.0000	-0.0000	-0.0000	-0.0000	-0.0001	0.0000	0.0000
	(-1.2917)	(0.6462)	(1.8647)	(-1.2552)	(-1.0173)	(-1.5166)	(-0.9710)	(-1.1562)	(0.2613)	(0.2731)
marriage_last	0.0024	-0.1723	-0.0162***	0.0024	-0.0077	-0.0000	-0.0022	-0.4686**	0.0034	0.0449
	(0.4658)	(-1.6032)	(-2.8967)	(0.4303)	(-1.3818)	(-0.0013)	(-0.3588)	(-2.2288)	(0.0657)	(0.7897)
military	0.0006	0.0141	0.0119***	-0.0003	-0.0058	0.0011	0.0090	0.4416	-0.0380	0.0150
	(0.0797)	(0.2051)	(3.3306)	(-0.0291)	(-0.6777)	(0.1221)	(0.9368)	(1.3633)	(-1.5985)	(0.5713)
insure	0.0628*	-2.8734***	0.2177***	0.0246	0.1081***	0.0595	0.1218***	-9.1520***	0.0498	0.3033*
	(1.8830)	(-5.7119)	(8.3145)	(0.6716)	(2.9884)	(1.5718)	(3.0203)	(-6.7310)	(0.3178)	(1.7539)
_cons	3.9437***	106.5048***	12.1454***	5.2641***	3.8032***	3.3238***	3.3520***	63.4482**	2.9265	1.1280
	(6.5313)	(10.1554)	(22.2528)	(7.9222)	(5.8016)	(4.8491)	(4.5870)	(2.5759)	(0.3055)	(0.1068)
N	5877	10941	10941	5877	5877	5877	5877	5877	4019	4019
adj. R^2	0.037	0.067	0.091	0.036	0.030	0.028	0.026	0.168	0.154	0.195

Table 8: **Robust Test.B**

This table is a robust test to analyze the effect of panel data in work quality using CFPS dataset from 2014 to 2020. All of the variables are come from the investigation questionnaire. This table reports results of equation 5 using $satis$, h, $satis_w$, ln_w, $satis_security$, $satis_environment$, $satis_h$, $satis_promotion$, $employment\_problem$,$education\_problem$ to measure work quality of high-education group. Variable *overdue* and *unedu* are served as core explanatory variables. Personal features, work characteristics and region are used as controls. Detailed definitions of variables can be found in Table 1. t-statistics are in parentheses. We also took time fixed effects and used robust clustering variance. The significance level is labelled as: * p <0.1, ** p <0.05, *** p <0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	satis	h	ln_w	satis_w	satis_security	satis_environment	satis_h	satis_promotion	employment_ problem	education_problem
overdue	-0.1241***	2.8723***	-0.1336***	-0.1747***	-0.1918***	-0.1372***	-0.1296**	1.6988	0.0402	0.0109
	(-2.9098)	(5.7148)	(-3.7536)	(-3.4942)	(-4.0643)	(-2.8572)	(-2.2694)	(1.3232)	(0.5207)	(0.1275)
unedu	0.0928**	-0.2925	0.2110***	0.1169***	0.1191***	0.0936**	0.0247	-3.7211***	0.0716	-0.0309
	(2.4824)	(-0.5140)	(5.2336)	(2.6670)	(2.8783)	(2.2220)	(0.4932)	(-3.3060)	(0.8195)	(-0.3196)
age	0.0155	-0.8851***	0.1963***	0.0513**	0.0606***	0.0252	0.0066	-1.2279**	-0.0086	0.0233
	(0.8222)	(-3.1945)	(10.0007)	(2.3209)	(2.9055)	(1.1888)	(0.2599)	(-2.1644)	(-0.2011)	(0.4955)
gender	-0.0071	-0.0834	-0.0119	-0.0247*	-0.0068	-0.0045	0.0004	0.1715	-0.0130	-0.0151
	(-0.5710)	(-0.4024)	(-0.8111)	(-1.6895)	(-0.4960)	(-0.3169)	(0.0237)	(0.4569)	(-0.4094)	(-0.4289)
exp	-0.0132	0.8094***	-0.1161***	-0.0470**	-0.0738***	-0.0364*	-0.0125	1.4493**	-0.0154	0.0288
	(-0.6781)	(2.8689)	(-5.8111)	(-2.0519)	(-3.4167)	(-1.6548)	(-0.4788)	(2.4651)	(-0.3544)	(0.6014)
exp_2	0.0000	0.0006	-0.0016***	0.0001	0.0004	0.0004	0.0003	0.0132*	0.0005	-0.0019***
	(0.1417)	(0.2230)	(-8.8941)	(0.4239)	(1.5678)	(1.3693)	(1.0805)	(1.8447)	(1.2946)	(-4.2611)
sch	-0.0048	-0.1590*	-0.0068	0.0029	0.0103	0.0082	0.0028	0.1314	0.0468***	0.0235
	(-0.7820)	(-1.6653)	(-0.9998)	(0.4035)	(1.5044)	(1.1793)	(0.3420)	(0.7041)	(3.1900)	(1.4510)
labour	0.1004**	0.0842	0.2475***	-0.0519	-0.0046	-0.0129	-0.1444***	-3.5142***	-0.1202	-0.0255
	(2.5223)	(0.1582)	(6.5614)	(-1.1121)	(-0.1042)	(-0.2877)	(-2.7091)	(-2.9330)	(-1.4695)	(-0.2818)
region_east	0.0360	-1.4317**	0.2017***	0.0583	0.1786***	0.2170***	0.1613***	-0.7001	-0.2127**	-0.2347**
	(0.8887)	(-2.5389)	(5.0485)	(1.2274)	(3.9857)	(4.7567)	(2.9748)	(-0.5743)	(-2.4560)	(-2.4518)
region_middle	0.0089	-0.8756	0.0281	-0.0637	0.1686***	0.1268**	0.0383	-2.0531	0.0373	0.0641
	(0.1997)	(-1.4392)	(0.6521)	(-1.2256)	(3.4373)	(2.5392)	(0.6451)	(-1.5384)	(0.3991)	(0.6206)
hukou	-0.0022	-0.4796***	0.0116	-0.0086	0.0298***	0.0104	-0.0076	-0.7673**	-0.0116	0.0243
	(-0.2266)	(-3.0096)	(1.0267)	(-0.7377)	(2.7146)	(0.9320)	(-0.5691)	(-2.5704)	(-0.4744)	(0.8993)
coiden1	0.1399***	-2.8370***	-0.0909***	-0.0257	-0.0467	0.0763*	0.0840*	-0.5674	0.2391***	0.0649
	(3.9718)	(-6.1309)	(-2.7744)	(-0.6235)	(-1.1975)	(1.9239)	(1.7805)	(-0.5352)	(3.3644)	(0.8261)
coscale	-0.0000*	0.0001***	0.0000**	0.0000	0.0000	-0.0000**	-0.0000***	-0.0000	0.0000	-0.0000
	(-1.7487)	(2.7152)	(2.5126)	(0.4097)	(0.1212)	(-2.5420)	(-3.4347)	(-0.8734)	(0.4925)	(-0.5980)
marriage_last	-0.0277***	0.2425*	-0.0109	-0.0059	-0.0105	-0.0281***	-0.0191*	0.0030	0.0039	-0.0340
	(-3.2385)	(1.6501)	(-1.0497)	(-0.5883)	(-1.1056)	(-2.9109)	(-1.6686)	(0.0115)	(0.1739)	(-1.3631)
military	-0.0050	-0.0897	0.0086	-0.0061	-0.0127	0.0099	0.0174	0.0550	0.0111	0.0171
	(-0.4814)	(-0.8552)	(1.1594)	(-0.4989)	(-1.1089)	(0.8518)	(1.2541)	(0.1765)	(0.6865)	(0.9592)
insure	-0.0032	-1.5612***	0.3392***	0.0594	0.0476	0.0228	0.1167**	-5.1544***	-0.2597***	-0.0146
	(-0.0833)	(-3.0188)	(9.2598)	(1.3203)	(1.1189)	(0.5274)	(2.2683)	(-4.4574)	(-3.2693)	(-0.1659)
_cons	3.2246***	70.4034***	5.2342***	2.1744***	2.2541***	3.0783***	3.5479***	43.0915***	7.0589***	6.2762***
	(8.3102)	(13.2205)	(13.8753)	(4.7804)	(5.2496)	(7.0421)	(6.8271)	(3.6883)	(8.6308)	(6.9419)
N	2397	4050	4050	2397	2397	2397	2397	2397	4050	4050
adj. R2	0.039	0.058	0.197	0.048	0.061	0.048	0.020	0.082	0.047	0.035

6. Discussion

The principal contribution of our study is its comprehensive approach to measuring job quality across ten dimensions, which distinguishes it from other literature that typically focuses on income and job satisfaction alone. In addition to examining the effects of over-education, our study addresses the phenomenon of the ”survivorship bias” associated with under-education. Our sample reveals a higher proportion of under-educated individuals, indicating that the span of working age (typically 18-60 years) is considerably broader than the span of educational age (typically before 22 years). Consequently, we have reason to believe that our empirical findings remain valid even during periods of economic change. Furthermore, educational status has a long-term impact on individual job quality. Therefore, when making educational investments, individuals should consider their actual circumstances and societal demands, avoiding the blind pursuit of higher education and over-education, in order to optimize the returns on their educational investments.

In March 2023, the All-China Federation of Trade Unions (ACFTU) published the Ninth National Workforce Survey (the ”ACFTU survey”), a quinquennial labour survey. In recent years, China has witnessed a decline in the creation of new employment opportunities, while the number of new university graduates has continued to rise. Many young people have adopted the term ”modern-day Kong Yiji” as a humorous reference to their situation, likening their academic qualifications to the long gown of Kong Yiji, which they perceive as a burden, much like the gown itself. This metaphor suggests that these individuals are reluctant to accept low-paying, menial jobs, yet unable to secure respectable employment. On social media platforms and **?**, netizens have commented that a degree is not only a stepping stone but also a pedestal from which one cannot descend, much like Kong Yiji was unable to get out of his scholar’s robes. They have also stated that if they had not attended school, they would be willing to work in a factory, but that this is not a hypothetical situation.

The results of our empirical analysis lead us to conclude that: Over-education has a detrimental impact on job satisfaction and remuneration, with the benefits received by those with less education being significantly less. Those who are over-educated are dissatisfied with various aspects of their employment, including job security, the work environment and working hours. They perceive a discrepancy between their qualifications and the nature of their roles. However, one positive aspect for those who are over-educated is that, despite their temporary dissatisfaction, they have better prospects for job promotion. This reflects their perspective when choosing jobs, which may not be out of necessity but rather a more forward-looking approach. It can therefore be inferred that, upon entering the labour market, those who are over-educated are characterised as 'high ability, low position', while those who are under-educated are characterised as 'low position, high ability'.

The findings of our research indicate that individuals experiencing an educational mismatch have two primary demands regarding their employment. Firstly, they seek positions that enable them to apply their education effectively, requiring tasks that are substantial and meaningful, and ensuring a high level of workplace comfort. This is typically reflected in technical and managerial roles. Secondly, they desire compensation that aligns with the effort and resources they invested in their education. Ideally, they aim for "unequal pay for equal work," where they receive higher-than-average returns. Nevertheless, the number of managerial positions is constrained, and not all individuals are suited to management roles, as this necessitates a larger number of individuals in subordinate positions. Consequently, the strategy of increasing managerial positions to alleviate social pressure is only effective in contexts where the educated population is scarce. Once education becomes more widely available, this strategy will become less viable. Conversely, concentrating on technical roles is a more viable option. The empowerment of young people to operate a greater number of machines and to acquire distinctive skills can serve to supplant inefficient manual labour, engender greater economic prosperity and facilitate the attainment of higher wages. China is currently experiencing a shortage of technical positions and difficulties in determining the optimal direction for investment. A significant proportion of the accumulated wealth from the previous economic cycle has been invested in speculative assets and symbols of political achievements, rather than being channelled into productive tools for the current young workforce. This has not resulted in enhanced productivity or integration into an efficient division of labour, leading to widespread dissatisfaction among workers. Consequently, many workers are compelled to accept less suitable positions, seeking roles where they can leverage their skills to make a living, much like Kong Yiji's inability to shed his long gown. In the long run, the only way to address Kong Yiji's long gown is to expand effective investment.

In the near term, it is imperative that we concentrate on the character of the employment opportunities made available by businesses. For example, companies should implement equal pay for equal work policies and legally protect the labour remuneration rights of those experiencing an educational mismatch. It is imperative that the government prioritises public service projects that significantly enhance the sense of social equity among the workforce, thereby mitigating the negative impact of educational mismatch on well-being. Educational mismatch not only affects the happiness and income of the workforce but also potentially leads to further segmentation and inequality in the labour market. Therefore, it is of the utmost importance that effective measures are taken to reduce educational mismatch and improve the alignment between education and occupation, in order to promote social equity and enhance the quality of the labour force.

7. Conclusions

Our findings validate the fundamental theory of "education enhancing income" in the field of economics of education, which posits a positive correlation between educational attainment and income.

The stability and variation in educational attainment and income across different clustered groups provide crucial insights for education policymakers, facilitating the implementation of more precise strategies for education and income enhancement. The positive impact of education on income is long-lasting, and sustained investment in education will lay a solid foundation for socioeconomic development, promoting the overall economic level. For groups with lower educational attainment and limited income, increased educational investment and enhanced educational quality are necessary to facilitate their income growth. Meanwhile, individuals with a certain educational foundation should be encouraged to pursue further studies to further enhance their economic capabilities. However, our research also reveals the long-term effects of overeducation on income, which cannot be overlooked in individuals' career decisions.

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