



Trends in income effects of education mismatch and skill mismatch among Chinese undergraduate graduates from 2018 to 2022

Genshu Lu^a, Xiaojuan Cheng^{b,*}

^a School of Humanities and Social Science & West China Higher Education Evaluation Center, Xi'an Jiaotong University, Xi'an, China

^b School of Humanities and Social Science, Xi'an Jiaotong University, Xi'an, China

ARTICLE INFO

Keywords:

Undergraduate graduates
Education mismatch
Skill mismatch
Income effects
Trends

ABSTRACT

As higher education expands, concerns about its value have arisen due to rising educational mismatches among undergraduate graduates. Using data from the Shaanxi University Graduates' Employment and Entrepreneurship Quality Tracking Survey from 2018 to 2022, this study employs multiple linear regression and Heckman's two-step method to analyze the distribution patterns, income effects, and trends associated with education and skill mismatches among Chinese undergraduate graduates. Key findings include: (1) The proportion of various education and skill mismatch combinations ranged from 47.86% to 53.87%, indicating that nearly half of undergraduate graduates face education or skill mismatch risks. (2) A weak but stable correlation exists between educational mismatch and skill mismatch in employment. (3) Different combinations of education and skill mismatch result in distinct income effects compared to the genuine educational match (the reference category). Specifically, compared to the reference category, the matched-in-education but overskilled category yields an income premium due to superior skill, consistent with human capital theory; the mismatch types related to overeducation impose an income penalty because these individuals are generally employed in lower-level positions, aligning with job competition theory. Over time, the earnings premium associated with combinations of education and skill mismatch tends to decrease, while the earnings penalty increases. Our findings are contextualized within China's economic development and higher education policies.

1. Introduction

Expanding higher education is pivotal for enhancing academic attainment, refining the human capital structure in the labor market, and fostering technological innovation and industrial transformation (Zhang et al., 2011). However, the expansion of higher education has also led to an oversupply of university graduates, making it challenging for them to secure jobs that match their qualifications (Freeman, 1976). Moreover, economic development dynamics closely intertwine with graduate employment prospects. In recent years, the slowdown in economic growth, exacerbated by the global COVID-19 pandemic, has constrained job opportunities, intensifying challenges for university graduates seeking employment (Lu et al., 2024). In this context, many graduates have to accept jobs that do not correspond to their qualifications, contributing to the prevalence of educational mismatch. The growing awareness of educational mismatch has sparked public doubt about the value of higher education, with some viewing it as less important.

According to human capital theory, educational investment enhances income potential. The extent to which educational mismatch contributes to the devaluation of higher education is assessed by estimating its impact on graduates' income. Some scholars have investigated the income effects of educational mismatches to address this question, yielding mixed results: while some studies indicate a devaluation of higher education in Greece in 1977 (Patrinos, 1997), in the United Kingdom in the late 1990s (Walker et al., 2005), in the United States from 2002 to 2016 (Kamis et al., 2022), others suggest that it confers an income premium in 1976 in the United States (Duncan et al., 1981), and in Portugal in the decade following 1982 (Hartog, 2000). The relationship between education mismatch and income may differ across socioeconomic and labour market conditions. China's higher education system has the largest enrollment in the world, making it a global leader. However, research on the value of higher education in China tends to mainly concentrate on the cognitive aspect, with limited empirical studies exploring the financial impact of educational mismatch.

Moreover, extensive research has examined the income effects of

* Correspondence to: School of Humanities and Social Science, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China.

E-mail address: ChengXJ@stu.xjtu.edu.cn (X. Cheng).

<https://doi.org/10.1016/j.ijedudev.2026.103592>

Received 7 February 2025; Received in revised form 4 May 2026; Accepted 10 May 2026

Available online 16 May 2026

0738-0593/© 2026 Elsevier Ltd. All rights reserved, including those for text and data mining, AI training, and similar technologies.

educational mismatch, indicating that educational attainment may not accurately reflect the education students actually receive and that skill levels are a more decisive factor in shaping educational outcomes (Chevalier, 2003; Flisi et al., 2017; Green et al., 1999; Mavromaras et al., 2013). Individuals with the same educational qualifications may exhibit varying skill levels, and overlooking this heterogeneity can introduce bias into estimates of the income effects of educational mismatch. Certain scholars have integrated educational and skill mismatches to categorize overeducation into apparent and genuine overeducation. The former refers to situations in which an employee's educational attainment exceeds job requirements, but their skills match the position. At the same time, the latter denotes cases in which both educational attainment and skills exceed the required level for the job. And these scholars have further explored the incidence and economic implications of these forms (Chevalier, 2003; Mavromaras et al., 2013).

Other researchers have also examined trends in incidence and financial outcomes associated with apparent and genuine overeducation, though their findings have often diverged (Chevalier et al., 2009; Green et al., 2010). Furthermore, these studies have predominantly focused on the relative distribution and wage effects of specific mismatch combinations involving overeducation or overskilling, while neglecting undereducation and underskilling.¹ This oversight leads to an incomplete understanding of the various education and skill mismatch scenarios workers may encounter.

We will address the limitations highlighted in previous research. The study aims to investigate the relationship between educational mismatch, skill mismatch, and income, as well as changes in these patterns from 2018 to 2022 among undergraduate graduates in Shaaxi Province, China. Accordingly, the research addresses the following questions: (1) What is the distribution structure of educational mismatch and skill mismatch among undergraduate graduates? (2) What is the relationship between educational mismatch and skill mismatch? (3) What are the income effects and their trends for different combinations of educational mismatch and skill mismatch?

The remainder of this paper proceeds as follows. 2 introduces the Nine-square Grid Model, which comprises nine distinct education-skill mismatch combinations, along with the theoretical framework. 3 describes the data and measurement of variables. 4 presents the results of descriptive statistics and regression analysis. 5 presents the discussion. 6 describes implications. 7 presents limitations. 8 describes future directions for research.

2. Literature review

2.1. Overview of educational mismatch

The concept of educational mismatch arose from the phenomenon of overeducation. In 1976, Freeman introduced the idea of overeducation in his book *The Overeducated American*. In 1981, Duncan and Hoffman classified education-occupation matching into three categories—overeducation, education-job matching, and undereducation—by assessing the variance between individuals' educational attainment and the educational requirements of their occupations. At the turn of the century, scholars like Green et al. (1999) and Chevalier (2003) argued that individuals with the same educational backgrounds do not necessarily have the same skill levels. They emphasized distinguishing the overeducated population based on skill utilization level or the extent of skill matching with job requirements (Green et al., 1999; Chevalier, 2003). From the evolution of the concept of educational mismatch, we can see that it encompasses mismatches in educational and skill levels.

2.2. Classification framework of educational mismatch

Educational mismatch and skill mismatch are recognized as distinct phenomena (Allen et al., 2001). The integration of these two concepts yields multiple forms of combined mismatches of education and skills. A review of the existing literature (as shown in Table 1) reveals that most empirical studies used self-reported measures to assess educational or skill mismatches, and that addressing the intersection of overeducation and skill mismatch employs diverse classification frameworks. Some researchers classify the education-job matching status into matched in education, apparent overeducation, and genuine overeducation (Chevalier, 2003). In contrast, others propose a fourfold taxonomy comprising apparent educational match, genuine educational match, apparent overeducation, and genuine overeducation (Pecoraro, 2014; Mavromaras et al., 2013). Specifically, an apparent educational match occurs when an individual's educational level meets job requirements, but their skills do not align with occupational demands. A genuine educational match refers to the educational background and abilities possessed by practitioners that are commensurate with the requirements of the job. Apparent overeducation occurs when an individual's education exceeds job requirements, yet their skills remain aligned with the

Table 1
Classifications of educational mismatch in previous research.

Authors	Measurement methods		Specific categories of education mismatch jointly consider educational level and skills.
	Education mismatch	Skill mismatch	
Chevalier, (2003); Chevalier et al., 2009	Roughly equivalent job analysis (JA)	Self-reported satisfaction with the match between education and job	Three categories: matched in education, apparent overeducation (graduate in nongraduate jobs and satisfied with the match), genuine overeducation (graduate in nongraduate jobs and unsatisfied with the match)
Mavromaras et al., 2013	Realized matches (RM): mode	Self-reported the degree of utilization of skills	Four categories: well-matched (matched in both education and skills), only overeducation (matched in skills and overeducation), only overskilling (matched in education and overskilling), overeducation and overskilling
Pecoraro (2014); Park et al., 2019	Work self-assessment (WA)	Self-reported match level between skills and jobs	Four categories: apparent match (adequate education and skills mismatch), genuine match (match in education and skills), apparent overeducation (overeducation and skills match), genuine overeducation (overeducation and skills mismatch)
McGuinness et al., (2017); Liu, (2018)	Work self-assessment (WA)	Self-reported match level between skills and jobs	Nine categories: crossed education mismatch (undereducation, match in education, overeducation) and skill mismatch (underskilling, match in skill, overskilling) to obtain nine matching categories

¹ The terms "underskilling" and "overskilling" are referenced from the studies by Mavromaras et al. (2010) and Castro et al. (2022).

role. Genuine overeducation refers to the educational background and abilities of practitioners that exceed the requirements of their jobs.

In this study, we integrated three forms of education-job matching status (undereducation, match in education, and overeducation) with three categories of skill-job matching status (underskilling, match in skill, and overskilling) to establish nine distinct statuses of education, skill, and job alignment (as shown in Table 2), which we called the Nine-square Grid Model. In this model, except for the category match in education and skill, which we used as a reference, the other eight categories are either education mismatches or skill mismatches.

Based on categories in existing research, the categories in Table 2 can be further delineated as follows: Category A reflects genuine undereducation, marked by both inadequate educational attainment and skill levels. Categories B and C represent apparent undereducation, where educational qualifications are below requirements despite skill levels that meet or exceed job demands. Categories D and F correspond to an apparent educational match; here, educational attainment aligns with job requirements, yet skill levels either fall short of or surpass those required. Category E exemplifies a genuine educational match, indicating alignment in both educational background and skill proficiency. Categories G and H constitute apparent overeducation, defined by educational attainment beyond job requirements, while skill levels meet or fall short of expectations. Finally, Category I reflects genuine overeducation, where both educational qualifications and skill levels exceed the demands of the position.

2.3. Theoretical framework

2.3.1. Human capital theory

Becker’s classical theory of human capital holds that individual characteristics determine income by enabling individuals to accumulate human capital, including education and skills. Higher education or skills result in higher pay, while lower levels correspond to lower income (Becker, 1964). For undergraduate graduates with the same educational attainment, variations in skill levels primarily account for income discrepancies. Accordingly, we can infer that the higher a graduate’s skill level, the higher their income.

Specifically, when compared with individuals with the same educational level who are a genuine educational match, a clear pattern emerges by skill level. Those experiencing underskilling—whether through insufficient education and skills, matched in education but underskilling, or overeducation accompanied by underskilling—tend to face income penalties due to their lower skill levels. This result is supported, for example, by findings that genuinely overeducated individuals earn less than those genuinely education-matched (Chevalier, 2003; Green et al., 2010). In contrast, mismatch types linked to overskilling—including undereducation but overskilling, matched education accompanied by overskilling, and excessive education and skills—typically exhibit higher skill levels and thus receive income premiums. Allen et al. (2013), for instance, explained this positive wage effect for individuals with limited education but advanced skills through the concept of “super-matching”. Similarly, for cases of matched skills—encompassing undereducation but matched skills and overeducation but matched skills—individuals possess skill levels equivalent to the reference category. Consequently, these groups display no significant income disparities. Hartog (2000), for example, found that undereducated individuals with elevated skill levels can meet job

requirements without an income penalty, while Pecoraro (2016) observed no significant income difference for overeducated individuals whose skills are matched.

2.3.2. Job competition theory

Thurow’s job competition theory states that income is affected by job characteristics, with higher-level positions yielding higher incomes (Thurow, 1975). The level of a job depends on educational attainment. For undergraduate graduates with the same bachelor’s degree, “matched” refers to jobs requiring that degree, “undereducation” refers to positions exceeding the bachelor’s level, and “overeducation” applies to positions below this level. In this context, we can make the following inferences:

Firstly, compared to individuals with the same educational level who are a genuine educational match, those mismatch types related to undereducation (including education and skill deficits, undereducation but matched skills, and undereducation but overskilling) occupy positions above the bachelor’s level and receive income premiums. For instance, Liu (2018) observed that individuals with undereducation often hold higher job levels than those with overeducation, leading to higher incomes for those with education and skill deficits than those with education and skill surpluses.

Secondly, mismatch types related to matched education—such as matched education but underskilling and matched education but overskilling—occupy positions at the bachelor’s degree level and generally show no significant income differences relative to the reference category. This point is supported, for example, by Mavromaras et al. (2013), who found that individuals with matched education but overskilling did not earn significant income premiums.

Thirdly, those associated with overeducation—including overeducation but underskilling, overeducation but matched skills, and both education and skill surpluses—occupy positions below the bachelor’s level, which typically leads to income penalties relative to the reference category. Research has shown that apparently overeducated individuals face income penalties precisely because they hold jobs below their educational level (Rumberger, 1987). Moreover, such lower-level positions may create a “ceiling effect,” further limiting income growth within these roles (Zhao et al., 2023).

2.3.3. Assignment theory

In 1993, Sattinger sought to reconcile human capital theory with job competition theory through assignment theory (Sattinger, 1993). According to the assignment theory, earnings are jointly determined by individual human capital characteristics and job characteristics (Caroleo et al., 2018). The match quality between workers’ education, skills, and job requirements is a key aspect of assignment theory (Nordin et al., 2010). This alignment significantly impacts income. When individuals effectively match their education and skills to job requirements, they increase productivity by using their skills more efficiently, resulting in higher revenue. On the contrary, a poor match reduces income, leading to underutilization of skills or skill gaps, which impede the translation of skills into productivity.

A clear gradation in income penalties emerges when different mismatch profiles are compared to genuinely matched individuals at the same educational level. First, four categories—those with undereducation but matched skills, matched education but underskilling, matched education but overskilling, and overeducation but matched

Table 2
The Nine-square Grid Model of educational mismatch.

Categories		Education-job matching status		
		Undereducation	Match in education	Overeducation
Skill-job matching status	Underskilling	A. Undereducation and underskilling	D. Match in education but underskilling	G. Overeducation but underskilling
	Match in skills	B. Undereducation but match in skills	E. Match in education and skills	H. Overeducation but match in skills
	Overskilling	C. Undereducation but overskilling	F. Match in education but overskilling	I. Overeducation and overskilling

skills—are expected to earn lower incomes due to a single mismatch dimension (either education or skills). In contrast, another four groups—individuals with both insufficient education and skills, undereducation but overskilling, overeducation but underskilling, and both excessive education and skills—are likely to face more substantial income penalties. This stronger effect arises from the compounded disadvantage of mismatches in both education and skills. These assumptions align with Pecoraro's (2016) research framework and are further supported by empirical evidence, the findings of Chevalier (2003) and Green et al. (2010), indicating that workers with genuine overeducation incur the most significant income penalties.

Table 3 summarizes the income effect hypotheses for eight combinations of education and skill mismatches based on human capital theory, job competition theory, and assignment theory. Only a small portion of these hypotheses have been empirically tested, while the vast majority remain untested.

Based on the analysis of the three theoretical mechanisms explaining the income effects of education mismatch and related research findings, we can find that while each theory emphasizes distinct factors influencing income, there is also some overlap. Human capital theory highlights the determinative role of human capital attributes in income; job competition theory focuses on the influence of job characteristics; and assignment theory emphasizes the combined effect of human capital and job characteristics on income. These varying emphases yield both consistencies and contradictions across theoretical analyses of the income effects of the same mismatch categories, necessitating further verification within the Chinese context.

In the current socioeconomic landscape of China—characterized by economic transformation centered on industrial upgrading and the transition from old to new growth drivers (Zheng et al., 2021), alongside an unprecedented and sustained expansion of higher education over the past two decades—the employment prospects for bachelor's degree holders are increasingly subject to significant structural pressures (Guo, 2022). According to classical human capital theory, investment in education enhances individuals' knowledge and skills, and their overall productivity, which should ultimately translate into higher labor-market returns. However, in reality, with the continuous implementation of

higher education expansion policies, the annual supply of bachelor's graduates has persistently outstripped effective labor demand for corresponding educational qualifications, resulting in diminishing marginal economic returns to academic credentials (Li et al., 2023). This phenomenon highlights the limitations of traditional human capital theory in explaining the income penalty observed in education-occupation mismatch scenarios.

Exacerbating this supply-demand mismatch are profound structural constraints within China's economy (Huang, 2024). On one hand, certain traditional industries experience sluggish upgrading, limiting their capacity to generate a substantial number of technical and managerial positions aligned with the knowledge profiles of bachelor's degree holders (Ding et al., 2018). On the other hand, although emerging strategic industries are growing rapidly, their talent demands tend to be highly specialized, creating skill gaps relative to the broadly educated bachelor graduates. Concurrently, positions commonly regarded as "ideal careers"—such as those in the public sector, leading technology firms, and core roles in financial institutions—often impose stringent requirements regarding educational credentials and alma mater prestige. This result has led to a massive number of undergraduate graduates fiercely competing for a limited number of high-quality positions. Empirical studies consistently demonstrate that access to these sectors, which are often characterized by institutional protection or technological premiums, decisively influences both starting salaries and long-term income trajectories (Li et al., 2011).

Within this context, the income-determination mechanism for university graduates exhibits a dual logic. On one hand, the accumulation of individual human capital—encompassing factors such as institutional prestige and professional expertise—remains fundamental to graduates' competitive advantage. On the other hand, the attributes of the positions they ultimately obtain—including structural determinants such as industry profitability, the ownership type of the employing entity, and the technical complexity and exclusivity of the role—frequently exert an equally critical, if not more decisive, influence. This income distribution paradigm, shaped by the interaction between human capital characteristics and job characteristics, closely aligns with the central tenets of assignment theory, which posit that income is governed not solely by individual productivity but also by job characteristics. Therefore, to fully comprehend the employment and income dynamics of contemporary Chinese undergraduate graduates, it is essential to examine these phenomena within a macro-level framework—one in which the intertwined forces of economic transformation and educational expansion interact and exert their combined influence.

2.4. Trends in income effects of different combinations of education and skill mismatch

A few scholars have examined the evolving income effects of various combinations of education and skill mismatches over time, though their findings remain inconsistent. Several studies have suggested that the income penalties associated with apparent overeducation and genuine overeducation have increased over time. They attribute this trend to a growing disparity in returns to higher education. The increasing income inequality between high- and low-income groups reflects the expanding gap in these returns, with overeducated individuals becoming more concentrated in the low-income category (Green et al., 2010). Conversely, other studies have reported that the income effects associated with apparent overeducation and genuine overeducation have remained stable. This stability may result from employers upgrading non-bachelor-level positions, fully utilizing overeducated workers' human capital (Chevalier et al., 2009).

Existing studies have explored changes in income effects associated with apparent and genuine overeducation from the perspectives of increased differentiation in returns to higher education and job structure upgrading. However, these studies have largely overlooked the role of economic conditions and national policies. In reality, prevailing

Table 3

Income effects hypotheses for the eight types of education-skill mismatch combinations based on three theories.

Eight types of education and skill mismatch combinations	Human capital theory	Job competition theory	Assignment theory
A. Undereducation and underskilling	(-)	(+) ★	(-)
B. Undereducation but match in skills	(No) ★	(+)	(-)
C. Undereducation but overskilling	(+) ★	(+)	(-)
D. Match in education but underskilling	(-)	(No)	(-)
F. Match in education but overskilling	(+)	(No) ★	(-)
G. Overeducation but underskilling	(-) ★	(-)	(-)
H. Overeducation but match in skills	(No) ★	(-) ★	(-)
I. Overeducation and overskilling	(+)	(-)	(-) ★

Note: a. When analyzing the income effect, take the match in the education and skill category as a reference category. b. The symbols +, -, and No indicate the direction of the income effects for the eight mismatch types derived from the three theories. Among these, "+" refers to a positive income effect, "-" refers to an adverse income effect, and "No" refers to no significant income effect. The number of symbols indicates the strength of the income effect; the more symbols there are, the stronger the corresponding income effect. c. "★" indicates previous research has empirically tested the corresponding category.

economic conditions and national policies promoting higher education expansion shape the income impact of education and skill mismatches among undergraduate graduates (Cabus et al., 2018; Sparreboom et al., 2017). During periods of rapid economic development, the growth rate of technical jobs exceeds that of higher education expansion, leading to higher returns to higher education (Peng, 2017). In contrast, when economic growth decelerates, the creation of technical jobs lags behind the expansion of higher education, leading to a decline in these returns (Park et al., 2019). This study examines graduates from 2018 to 2022, a period characterized by both phases of economic growth acceleration and slowdown in China. Simultaneously, China's higher education system continued to expand throughout this period. Therefore, the significant influence of economic conditions and the expansion of higher education must be acknowledged when analyzing the changing trends in income effects across different education-skill mismatch combinations.

3. Method

3.1. Participants and data collection

This study uses data from a large-scale online survey conducted in Shaanxi Province, an inland region of Northwest China. In 2022, the province had a resident population of 39.56 million and a gross domestic product (GDP) of RMB 3.28 trillion, with the secondary sector (industry) accounting for the largest share (48.6%) of its economy, and the initial employment rate for university graduates stands at 81.9%. The provincial capital, Xi'an, is a key hub for education and advanced manufacturing, underpinning a sizable and dynamic local labor market. The survey, which targeted all university graduates in the province, was commissioned by the Student Affairs Office of the Shaanxi Provincial Department of Education and implemented by the Western China Higher Education Evaluation Center of Xi'an Jiaotong University (hereafter referred to as the WCHEEC).

Operating as an independent entity directly under Xi'an Jiaotong University, the WCHEEC is guided by the principles of "scholarship first, open service; local roots, global perspective; based in Shaanxi, serving the nation". The university graduate survey was initiated in 2016 and has been conducted six times as of 2022, with a suspension in 2020 due to the COVID-19 pandemic.

The survey primarily uses the "Shaanxi College Graduate Employment and Entrepreneurship Tracking Questionnaire," developed independently by the WCHEEC. The questionnaire comprehensively covers graduates' personal and family backgrounds, employment status, employment quality, and learning experiences.

To address the research objectives, we used survey data from 2018, 2019, and 2022. In these respective years, the total graduate populations in Shaanxi Province were 340,000, 330,000, and 410,000, with 79,000,

63,000, and 40,000 questionnaires returned, yielding response rates of approximately 23%, 19%, and 10%, respectively. After excluding post-graduate students, vocational college students, flexible employment cases, students pursuing further postgraduate studies, and incomplete responses, the final analytical samples consisted of 6413 (2018), 4812 (2019), and 3443 (2022) four-year undergraduate graduates who had secured employment contracts, as summarized in Tables 4 and 5.

3.2. Measurement

3.2.1. Dependent variable

This study's dependent variable is undergraduate graduates' monthly income from 2018 to 2022. We removed samples at the 1st percentile and below, as well as at the 99th percentile and above, to mitigate the impact of outliers. Following this, we calculated the natural logarithm of income before incorporating it into the regression model.

3.2.2. Independent variables

Existing studies used work self-assessment (WA), job analysis (JA), and realized matches (RM) to measure education mismatch (Hartog, 2000). In this study, we adopted the work self-assessment method. We used the question "What education level do you think is suitable for your job?" to capture self-reported job education requirements. Then we subtract the job's required education level from the completed education level. A negative difference indicates undereducation, a zero difference suggests a match in education, and a positive difference indicates overeducation.

This study measures skill mismatch by comparing the match quality of the skills undergraduate graduates possess with those required for employment. The Programme for the International Assessment of Adult Competencies (PIAAC), a widely used database for skill-mismatch indicators (Perry et al., 2014), assesses only three foundational cognitive skills: literacy, numeracy, and problem-solving in technology-rich environments. However, it does not adequately capture higher-order cognitive skills, thereby limiting its comprehensiveness in assessing advanced cognitive competencies. Core skills and higher-order cognitive competencies represent the most critical forms of human capital for university graduates, serving as essential information-processing capacities transferable across diverse social and occupational contexts (OECD, 2013). These abilities also constitute a central mechanism through which formal education influences earnings, thereby playing an instrumental role in the relationship between schooling and income (Bowles et al., 2001). Accordingly, this study focuses on analyzing the mismatches of eight distinct core and higher-order cognitive competencies.

In the questionnaire, we asked undergraduate graduates about the match quality between the eight skills students possess (professional

Table 4
Participants' demographic data.

Category	2018		2019		2022	
	Frequency	Rate (%)	Frequency	Rate (%)	Frequency	Rate (%)
Gender						
Male	3340	52.08	2467	51.27	1956	56.81
Female	3073	47.92	2345	48.73	1487	43.19
Home location						
Rural	3645	56.84	2541	52.81	2196	63.78
Urban	2768	43.16	2271	47.19	1247	36.22
Institution type						
Least selective	3413	53.22	2377	49.40	1934	56.17
Moderately selective	1808	28.19	1562	32.46	971	28.20
Most selective	1192	18.59	873	18.14	538	15.63
Field of study						
STEM	3271	51.00	2459	51.10	1945	56.49
Humanities sciences	1267	19.76	926	19.24	630	18.30
Social sciences	1875	29.24	1427	29.66	868	25.21
Total	6413	100	4812	100	3443	100

Table 5

Chi-square test results for education mismatch and skill mismatch from 2018 to 2022.

Year	Categories	Education mismatch			Total	χ^2	Cramer's V	
		Undereducation	Match in education	Overeducation				
2018	Skill mismatch	Underskilling	0.56	8.93	4.27	68.36***	0.073	
		Match in skills	2.00	46.13	17.92			
		Overskilling	0.70	11.69	7.80			
	Total	3.26	66.75	29.99	100.00			
2019	Skill mismatch	Underskilling	0.83	8.50	3.47	44.80***	0.068	
		Match in skills	2.43	52.14	14.84			69.41
		Overskilling	0.62	11.93	5.24			17.79
	Total	3.88	72.57	23.55	100.00			
2022	Skill mismatch	Underskilling	0.99	6.16	3.63	76.58***	0.106	
		Match in skills	3.54	52.02	18.30			73.86
		Overskilling	0.87	8.31	6.19			15.36
	Total	5.40	66.48	28.12	100.00			

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, same as below.

qualifications, reading comprehension, oral expression, written expression, mathematical ability, logical reasoning, on-the-job learning, and problem-solving) and the skills required for employment. Each skill was coded as: -1 if the graduate reported their skill level was below the job requirements; 0 if it met the requirements; and 1 if it exceeded the requirements. We then summed the scores for all eight skills. A total score across the eight skills of below zero, zero, or above zero indicates underskilling, matched skills, or overskilling, respectively. As with any method for measuring skill mismatches (Quintini, 2011), this method presents both advantages and limitations. Although it enables the estimation of overall cognitive skill mismatch and simplifies regression analyses, it lacks the capacity to identify mismatches at the individual skill level and to assess their respective impacts on income.

Cross-combinations of the matches between education and jobs and between skills and employment can yield the nine combinations shown in Table 2. Except for the genuine educational match, the other eight categories are either education mismatches or skill mismatches. In the regression equation, we focus on the wage effects of the eight mismatch categories, with the genuine educational match category as the reference.

3.2.3. Control variables

Control variables of this study include gender, home location, institution type, field of study, occupation type, and non-cognitive abilities. Gender comprises male and female; home location includes rural and urban areas. Regarding the institution type, we adopt the classification of universities proposed by Johnson et al. (2018). According to Johnson et al. (2018), institutional selectivity serves as a criterion for classifying universities. The most selective university corresponds to the most or highly competitive category, characterized by the most extensive learning resources and highest teaching quality; the moderately selective university aligns with the competitive category; and the least selective university corresponds to less competitive or noncompetitive institutions, which typically exhibit the most constrained learning resources and lowest instructional quality. Field of study comprises STEM (refers to science, technology, engineering, and mathematics), humanities sciences, and social sciences; occupational type includes office personnel, professional and technical personnel, commercial service personnel, production and transportation personnel, and other occupations; non-cognitive abilities include social communication ability, social adaptability, and teamwork ability, which are crucial in the job market but have been overlooked in prior research.

3.3. Regression models

A standard approach for estimating the returns to education is the Mincer Earnings Equation. Duncan and Hoffman (1981) extended the Mincer Earnings Equation by decomposing total schooling into three

components: years of education required for the job, years of overeducation, and years of undereducation, thereby establishing the Duncan-Hoffman (D-H) model. The D-H model uses colleagues in the same occupation with matched education as the reference group, estimating wage effects of surplus or deficit years relative to the job's required educational years. Verdugo et al. (1989) subsequently refined the D-H model in two key ways: first, by including acquired years of schooling as a control variable in the earnings equation, and second, by using dummy variables to represent overeducation and undereducation, giving rise to the Verdugo-Verdugo (V-V) model. The V-V model selects individuals with the same education level and match in education as the reference category.

This study focuses on undergraduate graduates, with the reference group defined as individuals possessing the same level of education and being well-matched in their jobs—a specification consistent with the V-V model. Therefore, we employ the V-V model to estimate wage effects of various combinations of education and skill mismatch.

Furthermore, we use undergraduate graduates who have signed employment contracts as our research sample, which may not accurately reflect the employment status of all undergraduate graduates and may introduce sample selection bias. It's necessary to use Heckman's two-step method to address this bias, with the specific procedure as follows:

In the first step, we estimate the selection equation using a Probit model. Based on a full sample of undergraduate graduates, with employment contract status as the dependent variable and academic ranking within the student's major, parental education level, parental occupation type, and other relevant variables as independent variables, the probability of obtaining an employment contract is estimated. The inverse Mills ratio is calculated based on the probability that undergraduate graduates will secure employment contracts. In the second step, incorporate the inverse Mills ratio obtained in the first step as a control variable into the multiple linear regression model.

Inspired by the study of Allen et al. (2001), the conduct of this study is as follows. We conducted a series of fundamental multiple linear regression analyses in the initial step. This process involved the following stages: (1) incorporating only the control variables into the model; (2) adding the undereducation and overeducation variables to the model established in (1); (3) including the underskilling and overskilling variables in addition to those in (1); (4) integrating both the undereducation, overeducation, underskilling, and overskilling variables on top of the model from (1); and (5) introducing various categories of education and skill mismatch combinations on top of the model established in (1). Heckman's two-step method is used in the second step to adjust the five equations derived in the first step.

4. Results

4.1. Distribution and trends of educational mismatch and skill mismatch

From Fig. 1, when analyzing education mismatch or skill mismatch separately, the proportions range from 27.43% to 33.51% and from 26.14% to 33.95%, respectively. From 2018–2022, the educational mismatch incidence rate initially decreased before rising, whereas the skills mismatch incidence rate declined. In 2018 and 2019, the incidence rate of skills mismatch surpassed that of educational mismatch, whereas from 2020 to 2022, the incidence rate of skills mismatch consistently remained lower than that of educational mismatch.

As for educational mismatch, the proportion of undereducation ranged from 3.26% to 5.40%, whereas the proportion of overeducation spanned from 23.55% to 29.99%. Over the examined period, the incidence rates of overeducation initially declined, then rose, with 2019 as a pivotal turning point. The incidence rate of undereducation has been steadily increasing.

As for skill mismatch, the proportion of underskilling ranged from 10.78% to 13.76%, whereas the proportion of overskilling ranged from 15.37% to 20.19%. Across the period under scrutiny, there was a decreasing trend in the incidence rates of underskilling and overskilling.

From Fig. 2, when combining education and skill mismatches, the proportion of combinations ranged from 47.86 to 53.87%, and the incidence rates and trends of the various types of mismatches differed. Specifically, the four categories of combined education and skill mismatches, which account for about 40% of the total, in descending order of incidence rate, include overeducation with matched skills (also apparent overeducation), matched education with overskilling (also apparent education match), matched education with underskilling (also apparent education match), and excessive education and skills (also genuine overeducation). This finding reflects that most graduates are either apparently overeducated or apparently educationally matched, with only a minority being genuinely overeducated.

The remaining four categories of combined education and skill mismatches, representing less than 10% of the overall population, include overeducation with a skill deficit (also apparent overeducation), undereducation with skill match (also apparent undereducation), concurrent deficits in education and skills (also genuine undereducation), and undereducation accompanied by overskilling (also apparent undereducation). Many cases within these categories exhibit

mismatches in both education and skills. Furthermore, the incidence rates associated with these mismatch types have remained relatively consistent.

The trends in the incidence rates of these eight mismatch combinations vary significantly, as outlined below: Firstly, individuals with overeducation but matched skills and those with excessive education and skills experience an initial decrease before a subsequent rise. Secondly, individuals with matched education but underskilling and those with matched education but overskilling show a consistent downward trend. Finally, those with overeducation but underskilling, individuals with undereducation but matched skills, graduates with insufficient education and skills, and those with undereducation but overskilling demonstrate stable incidence rates.

Note: a. Mismatch categories are defined as presented in Table 2: A, Undereducation and underskilling; B, Undereducation but match in skills; C, Undereducation but overskilling; D, Match in education but underskilling; E, Match in education and skills; F, Match in education but overskilling; G, Overeducation but underskilling; H, Overeducation but match in skills; I, Overeducation and overskilling. b. Fig. 2 presents the eight categories of education or skill mismatch, excluding the matched in education and skills category (Category E), which are employed as the key variables in the regression analysis. c. Categories marked with the symbol ‘●’ on the solid line denote those associated with undereducation (A-C); categories marked with the symbol ‘■’ on the solid line represent those matched education (D, F); and categories marked with the symbol ‘▲’ on the solid line correspond to overeducation (G-I). Simultaneously, the color gradient of the solid line transitions from light to dark, representing underskilling, match in skill, and overskilling, respectively.

4.2. The correlation between educational mismatch and skills mismatch

The Chi-square test results show that Cramer’s V coefficients for education mismatch and skills mismatch range from 0.068 to 0.106, suggesting a weak association despite the significance. This finding indicates that education mismatch and skill mismatch are distinct phenomena in the Chinese context, consistent with previous studies (Green et al., 2007).

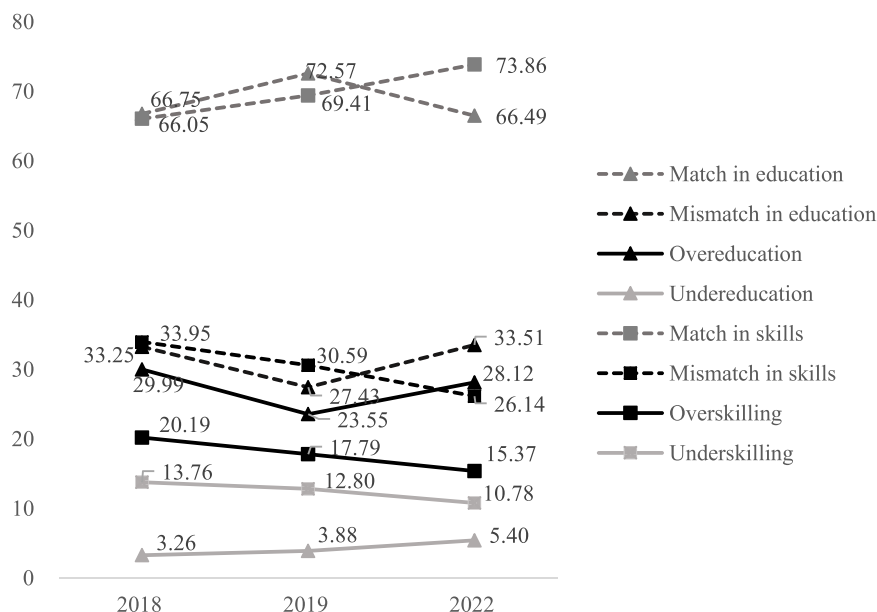


Fig. 1. Trends in educational and skill mismatch incidence rates from 2018 to 2022.

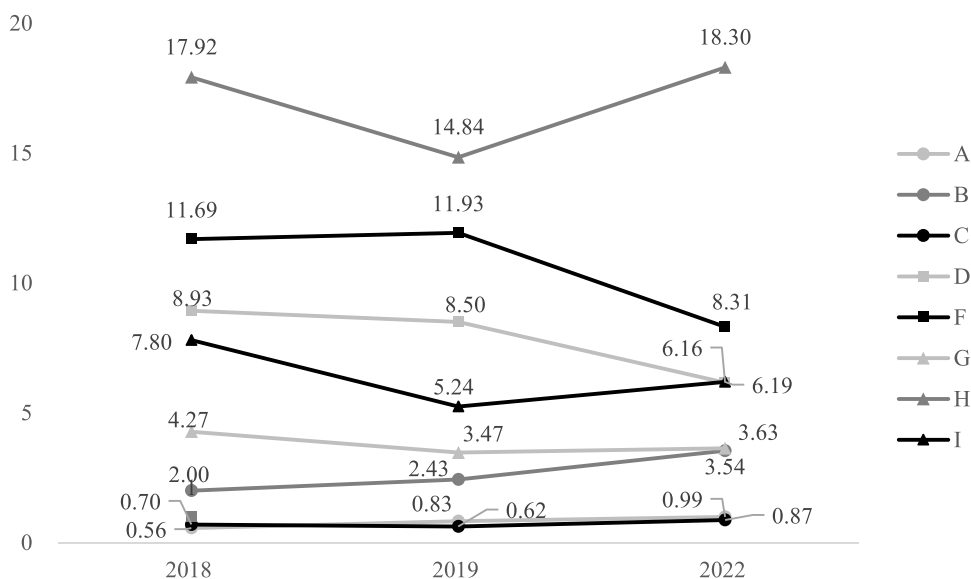


Fig. 2. Trends in the incidence rates of various education and skill mismatch combinations from 2018 to 2022.

4.3. Trends in the income effects of education mismatch and skill mismatch

Tables 6–8 report estimates of the income effects of education and skill mismatches for 2018, 2019, and 2022. Models 1–5 for ordinary multiple linear regression results, whereas Models 6–10 for Heckman’s two-step procedure to correct for sample selection bias. The statistically significant inverse Mills ratio in the latter Models supports the use of the Heckman correction.

4.3.1. Trends in the income effect of education mismatch or skill mismatch

According to Models 6–9 in Tables 6–8, when the income effect of

education mismatch or skill mismatch is analyzed individually, we can find that:

By controlling for skill mismatch and comparing outcomes with appropriately educated individuals at the same level of education, several trends emerge. Education mismatch exhibits a clear temporal pattern: overeducated individuals face an increasing income penalty, rising from 11.8% in 2018–12.6% in 2019 and reaching 15.5% in 2022. In contrast, the income benefits of undereducation have strengthened over time. Specifically, undereducation did not significantly affect income in 2018 and 2019, but it led to a notable 7.7% income premium in 2022.

When education mismatch is controlled for, a different dynamic is

Table 6

Regression analysis results on the income effects of education and skill mismatches in 2018.

	Dependent variable: natural logarithm of monthly income in 2018									
	Multiple linear regression model					Heckman’s two-step method				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Independent variables										
Education mismatch (Well-matched education as reference)										
Undereducation		-0.003		-0.003			-0.005		-0.006	
Overeducation		-0.116***		-0.122***			-0.112***		-0.118***	
Skill mismatch (Well-matched skill as reference)										
Underskilling			-0.006	-0.007				-0.008	-0.008	
Overskilling			0.036**	0.053***				0.034**	0.051***	
Education mismatch or skill mismatch (match in education and skills as reference)										
Undereducation and underskilling					0.077					0.075
Undereducation but match in skills					-0.048					-0.051
Undereducation but overskilling					0.107					0.102**
Match in education but underskilling					-0.022					-0.024
Match in education but overskilling					0.067***					0.063***
Overeducation but underskilling					-0.106***					-0.105***
Overeducation but match in skills					-0.116***					-0.114***
Overeducation and overskilling					-0.094***					-0.090***
IMR						0.247***	0.233***	0.246***	0.231***	0.229***
_cons	8.048***	8.143***	8.068***	8.175***	8.175***	7.940***	8.038***	7.960***	8.070***	8.071***
Observations	6413	6413	6413	6413	6413	6413	6413	6413	6413	6413
Adjusted R2	0.177	0.193	0.178	0.195	0.196	0.186	0.201	0.187	0.203	0.204

Note: The control variables include gender, home location, institution type, field of study, occupation type, and non-cognitive abilities, same as below.

Table 7
Regression analysis results on the income effects of education and skill mismatches in 2019.

	Dependent variable: natural logarithm of monthly income in 2019									
	Multiple linear regression model					Heckman's two-step method				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Independent variables										
Education mismatch (Well-matched education as reference)										
Undereducation		0.030		0.030			0.026		0.026	
Overeducation		-0.123***		-0.126***			-0.123***		-0.126***	
Skill mismatch (Well-matched skill as reference)										
Underskilling			0.009	0.012				0.007	0.011	
Overskilling			0.022	0.036*				0.022	0.036*	
Education mismatch or skill mismatch (match in education and skills as reference)										
Undereducation and underskilling					0.096					0.086
Undereducation but match in skills					0.019					0.018
Undereducation but overskilling					0.043					0.034
Match in education but underskilling					0.003					0.003
Match in education but overskilling					0.049**					0.051**
Overeducation but underskilling					-0.102***					-0.101***
Overeducation but match in skills					-0.119***					-0.117***
Overeducation and overskilling					-0.113***					-0.115***
IMR						0.206***	0.202***	0.206***	0.202***	0.203***
_cons	8.112***	8.198***	8.114***	8.206***	8.204***	7.992***	8.081***	7.995***	8.089***	8.086***
Observations	4812	4812	4812	4812	4812	4812	4812	4812	4812	4812
Adjusted R2	0.188	0.206	0.189	0.207	0.207	0.194	0.212	0.195	0.212	0.212

Table 8
Regression analysis results on the income effects of education and skill mismatches in 2022.

	Dependent variable: natural logarithm of monthly income in 2022									
	Multiple linear regression model					Heckman's two-step method				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Independent variables										
Education mismatch (Well-matched education as reference)										
Undereducation		0.076*		0.078**			0.075*		0.077**	
Overeducation		-0.152***		-0.155***			-0.152***		-0.155***	
Skill mismatch (Well-matched skill as reference)										
Underskilling			-0.041	-0.034				-0.041	-0.035	
Overskilling			0.011	0.038*				0.009	0.036	
Education mismatch or skill mismatch (match in education and skills as reference)										
Undereducation and underskilling					-0.125					-0.125
Undereducation but match in skills					0.085*					0.084*
Undereducation but overskilling					0.305***					0.298***
Match in education but underskilling					-0.008					-0.010
Match in education but overskilling					0.052*					0.051*
Overeducation but underskilling					-0.176***					-0.174***
Overeducation but match in skills					-0.139***					-0.139***
Overeducation and overskilling					-0.152***					-0.154***
IMR						0.287**	0.281**	0.286**	0.276**	0.271**
_cons	8.211***	8.326***	8.228***	8.348***	8.349***	7.971***	8.090***	7.988***	8.116***	8.122***
Observations	3443	3443	3443	3443	3443	3443	3443	3443	3443	3443
Adjusted R2	0.205	0.232	0.206	0.233	0.236	0.207	0.233	0.208	0.235	0.238

observed relative to matched-skill individuals. The income premium for over-skilled workers gradually diminishes over time, declining from 5.1% in 2018–3.6% in 2019 before disappearing entirely by 2022. Meanwhile, under-skilled individuals show no significant income effect across all years analyzed.

Overall, educational mismatch consistently plays a more pivotal role in income differentials than skill mismatch, and its importance has grown over time. This point is reflected in the models' adjusted R-squared values, which indicate the models' explanatory power. Including educational mismatch in the base model significantly

increases the adjusted R-squared compared to skill mismatch. Specifically, our calculations reveal that the effect of educational mismatch on income differences for undergraduate graduates rose from 1.5% in 2018–1.8% in 2019, reaching 2.6% in 2022.

4.3.2. Trends in income effects of different types of education and skill mismatch combinations

Based on the regression coefficients from Models 10 in 2018, 2019, and 2022 (as presented in Tables 6–8), we can draw the following points.

First, from 2018 to 2022, individuals with matched education but overskilling (also apparent education match) consistently attained considerably higher incomes than those with a genuine educational match within the same educational level. This finding suggests a continuous income advantage for overskilling. However, we noted a downward trajectory in this reward, shrinking from 6.3% in 2018–5.1% in 2019 and 2022.

Second, from 2018 to 2022, individuals experiencing overeducation coupled with underskilling (also apparent overeducation), those with overeducation and matched skills (also apparent overeducation), and those with overeducation and overskilling (also genuine overeducation), persistently reported lower incomes than their counterparts with a genuine educational match within the same educational level, underscoring consistent income penalties for these mismatches. The trend of income penalties for these mismatch types has been increasing. Specifically, the pay penalty associated with overeducation and underskilling escalated from roughly 10.0% in 2018 and 2019–17.4% in 2022; for overeducation with matching skills, the pay penalty rose from 11.4% in 2018–11.7% in 2019, then further to 13.9% in 2022. The pay penalty linked to overeducation and overskilling increased from 9.0% in 2018–11.5% in 2019 and 15.4% in 2022.

Furthermore, the relative magnitudes of these pay penalties vary across years. Specifically, in 2018, the most severe pay penalties were for individuals with overeducation and matched skills, followed by those with overeducation but underskilling, and finally, those with overeducation and overskilling. In 2019, the order changed, with the most severe penalties for individuals with overeducation and matched skills, followed by those with overeducation and overskilling, and finally, those with overeducation and underskilling. By 2022, the order also changed, with the highest penalties for individuals with overeducation and underskilling, followed by those with overeducation and overskilling, and finally, those with overeducation and matched skills.

Third, from 2018 to 2022, specific years witnessed higher incomes for individuals experiencing undereducation yet possessing matched skills (also apparent undereducation) and those with undereducation but overskilling (also apparent undereducation), compared to the reference group. Conversely, incomes were not significantly different between these mismatched categories and the reference group in other years. Specifically, in 2022, both mismatched categories were associated with significant income gains; however, in 2018 or 2019, at least one mismatch type showed no significant effect on income.

Finally, from 2018 to 2022, we found no significant income differences of individuals with undereducation and underskilling (also genuine undereducation) or those with matched education but underskilling (also apparent education match) compared to the reference group. This observation highlights that these two types of mismatches did not result in increased or decreased income.

5. Discussion

5.1. Greater risk related to education and skill mismatches in employment

From 2018–2022, undergraduate graduates in China faced a higher risk of an education or skills mismatch. When we combined educational mismatch and skill mismatch, the proportion of educational and skill mismatch combinations ranged from 47.86 to 53.87%, and the

incidence rates and trends of the various mismatch types differed.

The four categories of combined education and skill mismatches, which account for about 40% of the total, include apparent overeducation, apparent education match, and genuine overeducation. This finding indicates that few graduates experience both educational mismatch and skills mismatch simultaneously, suggesting that only a tiny proportion of undergraduates face a genuine education mismatch in the Chinese context. This result is consistent with the findings of Chevalier (2003) and Pecoraro (2016).

From 2018–2022, the trends associated with the four categories of mismatches above evolved as follows: the incidence rates of mismatch types related to overeducation (overeducation with skill match, overeducation with overskilling) fluctuated, initially decreasing before increasing, with 2019 as a turning point. On the other hand, the incidence rates of mismatches involving education match (education match with underskilling, education match with overskilling) showed a consistent decline, with the decrease notably accelerating after 2019.

5.2. Significantly weak correlation between education mismatch and skill mismatch

As mentioned above, most undergraduates are either education-mismatched or skill-mismatched, and only a small number are both education- and skill-mismatched, indicating that there is no one-to-one correspondence between education mismatch and skill mismatch. At the same time, the chi-square test results indicate a weak but significant correlation between education mismatch and skill mismatch in the employment of Chinese undergraduate graduates, indicating that educational mismatch and skill mismatch are distinct phenomena, consistent with the findings of Allen et al. (2001). This result suggests future studies should consider both in estimating the wage effects of educational mismatch.

5.3. Trends in the income effects of education and skill mismatch

When the income effects of education mismatch or skill mismatch are examined independently, a key finding emerges: throughout 2018–2022, education mismatch has persistently been identified as the primary contributor to income disparities, overshadowing the effect of skill mismatch. The reasons are as follows: first, based on the theory of skill heterogeneity, individuals with the same educational attainment possess different skill endowments. Individuals experiencing educational mismatch often possess skill levels that are either below or above their attained educational level. Consequently, they may be engaged in lower- or higher-level jobs, leading to income penalties or premiums that drive income disparities (Korpi et al., 2009). Second, as match theory indicates, educational mismatch—particularly overeducation—may reflect a genuine misalignment between workers' productive potential and the productivity ceiling of their jobs (Budría et al., 2014). Third, income is influenced by structural factors such as institutions, independent of individual performance (Groot et al., 2000).

Furthermore, the role of educational mismatch in shaping income differentials among undergraduate graduates has grown increasingly prominent, underscoring the need to address this issue as it becomes a significant driver of income inequality in China. This conclusion aligns with Capsada-Munsech's (2017) argument that educational mismatch contributes to income inequality.

When we estimate the income effects of education and skill mismatch combinations, the income effects and trends differ across various combinations, which can be summarized into the following four categories:

The first category concerns declining income rewards. Individuals with matched education but overskilling—referred to as an apparent education match—consistently receive income rewards, though these rewards are diminishing. This positive effect aligns with human capital theory (Becker, 1964), as overskilling in this context reflects proficiency in eight core and advanced cognitive skills that exceed job requirements,

a trait typically rewarded by employers. The observed decline, however, signals a gradual reduction in the income premium for higher-order cognitive skills among bachelor's degree holders in education-matched roles.

Conversely, a second category is characterized by increasing pay penalties. The three categories of overeducation—underskilling (also apparent overeducation), matched skills (also apparent overeducation), and overskilling (also genuine overeducation)—inevitably lead to income penalties. The possible reason for this outcome is that individuals experiencing such mismatches are generally employed in lower-level positions, resulting in lower income, which aligns with the assumptions of the aforementioned job competition theory (Thurrow, 1975). This result indicates that job characteristics indeed play a crucial role in explaining income disparities across different types of educational mismatches. Furthermore, in 2022 specifically, the income penalty for those mismatched in both education and skills was greater than that for individuals mismatched solely in education level, consistent with the “matching quality” hypothesis of allocation theory.

However, the relative magnitudes of these pay penalties exhibit variation across different periods. In some instances, the pay penalty associated with apparent overeducation exceeds that of genuine overeducation; in others, at least one form of apparent overeducation incurs less wage penalty than genuine overeducation. This pattern suggests that, in the former case, the higher skill levels of genuinely overeducated individuals may partially offset the wage penalty typically associated with overeducation (Mateos-Romero et al., 2017); Conversely, in the latter case, it may be attributed to constraints on job roles that limit the application of higher-level skills, thereby reducing their compensatory effect on earnings (Zhao et al., 2023). Overall, the mechanisms underlying the income effects of overeducation-related mismatch types are multifaceted.

Meanwhile, the trend of income penalties for all three mismatch types has been increasing, consistent with the findings of Green et al. (2010). This finding suggests that the negative income effects tied to overeducation-related mismatches are intensifying, with a pronounced rise after 2019. This shift may be attributable to the deceleration of economic growth in China following the COVID-19 pandemic and to the persistent expansion of higher education, which has created a surplus of undergraduate graduates in the labour market and reduced the economic returns to higher education (Lu et al., 2024).

A third pattern involves variable income effects for undereducation-related mismatches, including undereducation with matched skills and undereducation with overskilling. These effects fluctuate across years, which may be explained by the low and sharply rising incidence of undereducation between 2018 and 2022. Small sample sizes in earlier years may yield statistically insignificant results, whereas observed income gains in certain years may stem from individuals' high skill levels despite educational shortfalls (Hartog, 2000).

Lastly, a fourth category shows statistically insignificant income effects for two mismatch types: undereducation with underskilling (genuine undereducation) and matched education with underskilling. Neither income rewards nor penalties are observed, even though overeducation with underskilling—another underskilling-related type—incurs a pronounced penalty. This contrast underscores the primary influence of job characteristics on income, consistent with job competition theory (Thurrow, 1975).

6. Implications

Based on the above analysis, it can be observed that higher education in western China has indeed experienced a certain degree of devaluation. In addressing this issue, policy interventions should prioritize two interrelated domains, as informed by the current findings. Firstly, greater attention must be directed toward educational mismatch among undergraduate graduates. Given its central role in explaining income disparities and its increasing explanatory power over time, targeted

efforts should concentrate on mitigating overeducation, which remains prevalent and consistently linked to income penalties. Such strategies may include enhancing the quality of higher education to strengthen graduates' cognitive competencies, alongside expanding employment opportunities that align with their qualifications. Secondly, at the employer level, there exists substantial potential to optimize the utilization of graduates' broad skill sets. This suggestion can be operationalized through upgrading existing occupational structures to better utilise these competencies, thereby augmenting the income premiums associated with such skills and alleviating the devaluation of educational credentials.

The empirical patterns observed in western China both align with and extend current global understandings. The documented devaluation of higher education, coupled with significant income penalties faced by overeducated individuals, reflects trends observed across numerous economies undergoing mass educational expansion, thereby reinforcing the broad applicability of job competition theory and assignment theories. However, the pronounced intensification of such penalties since 2019 indicates a context-specific acceleration, likely attributable to China's post-pandemic economic growth slowdown alongside sustained growth in higher education enrollment. This case thereby illustrates how macroeconomic shocks can exacerbate underlying structural mismatches. Moreover, the observed decline in returns to overskilling among adequately matched in education graduates suggests a potential erosion of skill premiums in an increasingly saturated regional labor market, adding a nuanced layer to international comparative analyses. Consequently, while the fundamental mechanisms are widely shared, the scale and trajectory of these phenomena in western China offer critical insights for other regions navigating similar rapid higher education expansion amid economic transformation.

7. Limitations

This study has several limitations. First, the relatively low response rate to the graduate survey may introduce non-response bias, potentially affecting the generalizability of the findings. Second, key variables, such as educational and skill mismatches, are measured using self-reported instruments, which are subject to perceptual inaccuracies. Finally, the analysis relies on repeated cross-sectional data. While such data reveal trends, they do not allow tracking of individual-level changes over time, thereby limiting causal inference.

8. Future directions for research

Future research should address several limitations of the present study. First, to minimise response bias in data collection, a mixed-methods approach—for instance, combining online questionnaires with telephone interviews—could be adopted, along with targeted incentives to improve response rates and sample representativeness. Second, subjective and objective measurement methods (e.g., job analysis and realised matches) should be used jointly to assess educational and skills mismatches, thereby overcoming the limitations inherent in relying solely on self-reported measures. Third, the constraints on causal inference imposed by repeated cross-sectional data could be alleviated by conducting panel studies that track the same cohort over time. Such longitudinal designs are essential for establishing causal relationships between educational mismatches and labour market outcomes.

CRedit authorship contribution statement

Genshu Lu: Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **XiaoJuan Cheng:** Writing – review & editing, Writing – original draft, Visualization.

Funding

This work was supported by the National Education Science Planning Project: [Grant Number BIA240161].

Declaration of Competing Interest

No potential conflict of interest was reported by the author(s).

References

- Allen, J., van der Velden, R., 2001. Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search. *Oxf. Econ. Pap.* 53 (3), 434–452. <https://doi.org/10.1093/oeq/53.3.434>.
- Allen, J.P., Levels, M., & van der Velden, R.K.W. (2013). Skill mismatch and use in developed countries: Evidence from the PIAAC Study. Maastricht University, Graduate School of Business and Economics. GSBE Research Memoranda No. 061.
- Becker, G.S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education. The University of Chicago Press.
- Bowles, S., Gintis, H., Osborne, M., 2001. The determinants of earnings: a behavioral approach. *J. Econ. Lit.* 39 (4), 1137–1176. <https://doi.org/10.1257/jel.39.4.1137>.
- Budría, S., Moro-Egido, A., 2014. Overqualification, skill mismatches and wages in private sector employment in Europe. *Technol. Econ. Dev. Econ.* 20 (3), 457–483. <https://doi.org/10.3846/20294913.2014.883341>.
- Cabus, S.J., Somers, M.A., 2018. Mismatch between education and the labour market in the Netherlands: is it a reality or a myth? the employers' perspective. *Stud. High. Educ.* 43 (11), 1854–1867. <https://doi.org/10.1080/03075079.2017.1284195>.
- Capsada-Munsech, Q., 2017. Overeducation: concept, theories, and empirical evidence. *Sociol. Compass* 11 (10), e12518. <https://doi.org/10.1111/soc4.12518>.
- Caroleo, F.E., Pastore, F., 2018. Overeducation at a glance. Determinants and wage effects of the educational mismatch based on AlmaLaurea data. *Soc. Indic. Res.* 137 (3), 999–1032. <https://doi.org/10.1007/s11205-017-1641-1>.
- Castro, J.F., Ortega, L., Yamada, G., & Mata, D. (2022). The magnitude and predictors of Overeducation and Overskilling in Latin America: Evidence from PIAAC (No. 15143). IZA discussion papers.
- Chevalier, A., 2003. Measuring over-education. *Economica* 70 (279), 509–531. <https://doi.org/10.1111/1468-0335.t01-1-00296>.
- Chevalier, A., Lindley, J., 2009. Overeducation and the skills of UK graduates. *J. R. Stat. Soc. Ser. A Stat. Soc.* 172 (2), 307–337. <https://doi.org/10.1111/j.1467-985X.2008.00578.x>.
- Ding, Z., Kong, C., 2018. An analysis of the causes of “employment difficulties” among university graduates and countermeasures: A review and prospect (in Chinese). *Educ. Econ.* (02), 54–61.
- Duncan, G.J., Hoffman, S.D., 1981. The incidence and wage effects of overeducation. *Econ. Educ. Rev.* 1 (1), 75–86. [https://doi.org/10.1016/0272-7757\(81\)90028-5](https://doi.org/10.1016/0272-7757(81)90028-5).
- Flisi, S., Goglio, V., Meroni, E.C., Rodrigues, M., Vera-Toscano, E., 2017. Measuring occupational mismatch: overeducation and overskill in Europe—evidence from PIAAC. *Soc. Indic. Res.* 131 (3), 1211–1249. <https://doi.org/10.1007/s11205-016-1292-7>.
- Freeman, R. (1976). *The Overeducated American*. Academic Press, New York, 4.
- Green, F., McIntosh, S., 2007. Is there a genuine under-utilization of skills amongst the over-qualified? *Appl. Econ.* 39 (4), 427–439. <https://doi.org/10.1080/00036840500427700>.
- Green, F., Zhu, Y., 2010. Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxf. Econ. Pap.* 62 (4), 740–763. <https://doi.org/10.1093/oeq/gpq002>.
- Green, F., McIntosh, S., Vignoles, A., 1999. Overeducation and skills-clarifying the concepts (No. dp0435). Centre for Economic Performance. LSE, pp. 1–59.
- Groot, W., Van Den Brink, H.M., 2000. overeducation in the labor market: a meta-analysis. *Econ. Educ. Rev.* 19 (2), 149–158. [https://doi.org/10.1016/S0272-7757\(99\)00057-6](https://doi.org/10.1016/S0272-7757(99)00057-6).
- Guo, B., 2022. Labor supply and structural employment contradictions: Characteristics, impacts, and alleviation (in Chinese). *Contemp. Econ. Manag.* 44 (12), 73–80.
- Hartog, J., 2000. Over-education and earnings: where are we, where should we go? *Econ. Educ. Rev.* 19 (2), 131–147. [https://doi.org/10.1016/S0272-7757\(99\)00050-3](https://doi.org/10.1016/S0272-7757(99)00050-3).
- Huang, M., 2024. The practical manifestations and response strategies of structural employment contradictions: An analysis of the employment supply-demand imbalance characterized by the coexistence of “jobs available but no workers” and “workers available but no jobs” (in Chinese). *People's Forum* (12), 28–31.
- Johnson, S.R., Stage, F.K., 2018. Academic engagement and student success: Do high-impact practices mean higher graduation rates? *J. High. Educ.* 89 (5), 753–781. <https://doi.org/10.1080/00221546.2018.1441107>.
- Kamis, A., Habibi, N., 2022. Impact of earnings and self-employment opportunities on overeducation: evidence from occupations in the United States labor market 2002–2016. *J. Educ. Work* 35 (5), 540–558. <https://doi.org/10.1080/13639080.2022.2092605>.
- Korpi, T., Tählin, M., 2009. Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974–2000. *Labour Econ.* 16 (2), 183–193. <https://doi.org/10.1016/j.labeco.2008.08.004>.
- Li, J., Gu, Y., 2011. Hukou Stratification in the Urban Labor Market in China (in Chinese). *Sociol. Stud.* 25 (02), 48–77. +244.
- Li, X., Lu, Y., Wu, X., 2023. Educational mismatch among highly educated workers (in Chinese). *Educ. Res.* 44 (06), 122–137.
- Liu, Y., 2018. Research progress and implications of labor skill mismatch (in Chinese). *China Vocat. Tech. Educ.* (30), 5–10.
- Lu, G., Cheng, X., 2024. The impact of the mismatch between education and skills on the income of undergraduate graduates: An analysis based on the survey data of college graduates in Shaanxi Province (in Chinese). *Jiangsu High. Educ.* 08, 34–45.
- Mateos-Romero, L., Salinas-Jiménez, M.D.M., 2017. Skills heterogeneity among graduate workers: real and apparent overeducation in the Spanish labor market. *Soc. Indic. Res.* 132 (3), 1247–1264. <https://doi.org/10.1007/s11205-016-1338-x>.
- Mavromaras, K., McGuinness, S., O’leary, N., Sloane, P., Fok, Y.K., 2010. The problem of overskilling in Australia and Britain. *Manch. Sch.* 78 (3), 219–241. [https://doi.org/10.1016/S0272-7757\(99\)00050-3](https://doi.org/10.1016/S0272-7757(99)00050-3).
- Mavromaras, K., McGuinness, S., O’leary, N., Sloane, P., Wei, Z., 2013. Job mismatches and labor market outcomes: panel evidence on university graduates. *Econ. Rec.* 89 (286), 382–395. <https://doi.org/10.1111/1475-4932.12054>.
- Mavromaras, K., Mahuteau, S., Sloane, P., Wei, Z., 2013. The effect of overskilling dynamics on wages. *Econ. Educ. Rev.* 21 (3), 281–303. <https://doi.org/10.1080/09645292.2013.797382>.
- McGuinness, S., Pouliakas, K., Redmond, P., 2017. How useful is the concept of skills mismatch. IZA Discussion Papers, No. 10786. Institute of Labor Economics (IZA), Bonn, pp. 1–30.
- Nordin, M., Persson, I., Rooth, D.O., 2010. Education–occupation mismatch: is there an income penalty? *Econ. Educ. Rev.* 29 (6), 1047–1059. <https://doi.org/10.1016/j.econedurev.2010.05.005>.
- OECD. (2013). OECD skills outlook 2013: First results from the survey of adult skills. doi: (10.1787/9789264204256-en).
- Park, K., Jang, D., 2019. The wage effects of over-education among young STEM graduates. *Singap. Econ. Rev.* 64 (05), 1351–1370. <https://doi.org/10.1142/S0217590817500059>.
- Patrinos, H.A., 1997. Overeducation in Greece. *Int. Rev. Educ.* 43 (2), 203–223. <https://doi.org/10.1023/A:1002981301802>.
- Pecoraro, M., 2014. Is There still a wage penalty for being overeducated but well-matched in skills? a panel data analysis of a Swiss Graduate Cohort. *Labour* 28 (3), 309–337. <https://doi.org/10.1111/labr.12031>.
- Pecoraro, M., 2016. The incidence and wage effects of overeducation using the vertical and horizontal mismatch in skills: evidence from Switzerland. *Int. J. Manpow.* 37 (3), 536–555. <https://doi.org/10.1108/IJM-10-2014-0207>.
- Peng, S., 2017. A study on the evolutionary causes of university wage premium in China (in Chinese). *Educ. Econ.* 03, 42–51.
- Perry, A., Wiederhold, S., Ackermann-Piek, D., 2014. How can skill mismatch be measured? New approaches with PIAAC. *methods. data Anal.* 8 (2), 38. <https://doi.org/10.12758/mda.2014.006>.
- Quintini, G., 2011. Right for the Job: Over-qualified or Under-skilled? OECD Social, Employment and Migration Working Papers, No. 121. OECD Publishing. <https://doi.org/10.1787/5kg58j9d7b6d-en>.
- Rumberger, R.W., 1987. The impact of surplus schooling on productivity and earnings. *J. Hum. Resour.* 22 (1), 24–50. (<https://www.jstor.org/stable/145865>).
- Sattinger, M., 1993. Assignment models of the distribution of earnings. *J. Econ. Lit.* 31 (2), 831–880. (<http://www.jstor.org/stable/2728516>).
- Sparreboom, T., Tarvid, A., 2017. Skills mismatch of natives and immigrants in Europe. International Labour Office, Conditions of Work and Equality Department. ILO, Switzerland: Geneva, pp. 1–48.
- Thurow, L.C. (1975). *Generating inequality: Mechanisms of distribution in the U.S. economy*. Basic Books.
- Verdugo, R.R., Verdugo, N.T., 1989. The impact of surplus schooling on earnings: Some additional findings. *J. Hum. Resour.* 24 (4), 629–643. (<https://www.jstor.org/stable/145998>).
- Walker, I., & Zhu, Y. (2005). The college wage premium, overeducation, and the expansion of higher education in Britain. Institute for the Study of Labor (IZA), Discussion Paper Series, 1627.
- Zhang, G., Wen, J., Tang, X., 2011. Human capital, human capital structure, and industrial structure upgrading in China. *China Population (in Chinese)*. *Resour. Environ.* 21 (10), 138–146.
- Zhao, X., Jiang, W., 2023. Overeducation among migrant workers and its income effects: An exploration from the perspective of skill matching. *J. Agric. Technol. Econ.* 02, 94–110.
- Zheng, J., Zhang, R., Chen, Y., 2021. How digital transformation facilitates the construction of a new development pattern: a perspective based on the conversion of old and new growth drivers (in Chinese). *China Econ.* 16 (03), 2–23.