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ABSTRACT

Returns to College Education of Chinese Manufacturing Employees: Who Benefits More?*

Using the China Employer-Employee Survey (CEES) data, this study examines the returns to college education for employees across China's manufacturing industry, most of them work in small and medium-sized enterprises (SME). Our baseline model finds that while the 1999 higher education (HE) expansion has no significant impact on college enrollment for male employees, it significantly increases college enrollment for female employees by 23.7% in the manufacturing sector. College education significantly increases the returns by 45.20% for males and 88.33% for females. Moreover, there is heterogeneity in the effects by potential gains: individuals who failed to attend college would have had a higher return compared to college graduates, indicating reverse selection into HE. Further analysis reveals that the effects are more pronounced among female managers, middle birth cohorts (born between 1984 and 1987), female vocation-track degree holders, and STEM graduates. Additionally, college education facilitates employment in roles requiring cognitive skills and reduces the likelihood of female employees performing physically demanding tasks.

JEL Classification: I23, I26, J31, L60, O14

Keywords: China employer-employee survey, manufacturing industry, marginal treatment effect, returns to college education

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1 Introduction

Investment in higher education (HE) has been demonstrated to impact the earnings and productivity of individuals in the labour market. A vast body of empirical literature has also focused on the expansion of HE in high-income countries such as the U.S. (Card and Lemieux, 2001; Goldin and Katz, 2008) and the U.K. (Blundell et al., 2000, 2016, 2022; Walker and Zhu, 2008) and has provided clear causal evidence of positive returns to HE (McKenzie et al., 2025).

In contrast, fewer studies have analyzed the consequences of attending college on labour market performance within middle- and low-income economies. Among middle-income economies, China has had the most substantial investment in HE, which has experienced dramatic growth over the past decades. Some recent studies evidence the impact of China's HE expansion on access to education, educational attainment, and returns to schooling (Liu and Zheng, 2019; Ou and Hou, 2019; Dai et al., 2022; Huang et al., 2022). In addition, China's unique *hukou* (household registration) system,[1] might limit college attendance among those residing in the rural areas. Despite the significant increase in educational attainment nationwide following the HE expansion, inequalities persist among the most socio-economically disadvantaged students, particularly those with rural *hukou* (Ou and Hou, 2019; Wu et al., 2020).

In 2019, China accounted for 28.7% of the global manufacturing output, overtaking the United States' leading position as the world's largest manufacturing industry.[2] The Chinese manufacturing sector has witnessed substantial growth, with Chinese products being available in many countries worldwide. As shown in Figure 1, employment in China's manufacturing industry constituted close to 30% of total employment among 19 industries from 2003 to 2019.[3] China's large pool of skilled labour at relatively low costs has been a key driver of its position as a leading global manufacturing hub (Hanson, 2020).

This abundant labour supply contributes to lower wages for Chinese manufacturing workers compared to their international counterparts, particularly as many are employed by small

[1] *Hukou* constitutes the household registration framework in China. For additional insights, refer to Chan (2009) for an examination of the historical development of the *hukou* system, and Meng (2012) for an analysis of *hukou*'s pivotal role in labour market reforms in China over recent decades.

[2] According to the United Nations Statistics Division, nearly 30 percent of the China's economy was based on manufacturing. Total value added by Chinese manufacturing in the year 2019 was almost $4 trillion. Source: `https://unstats.un.org/unsd/snaama/CountryProfile`

[3] We are constrained by the unavailability of statistics from the pre-HE expansion period in the 1990s or before China's 2001 WTO accession. The earliest statistics from the National Bureau of Statistics (China) dated back to 2003 only.

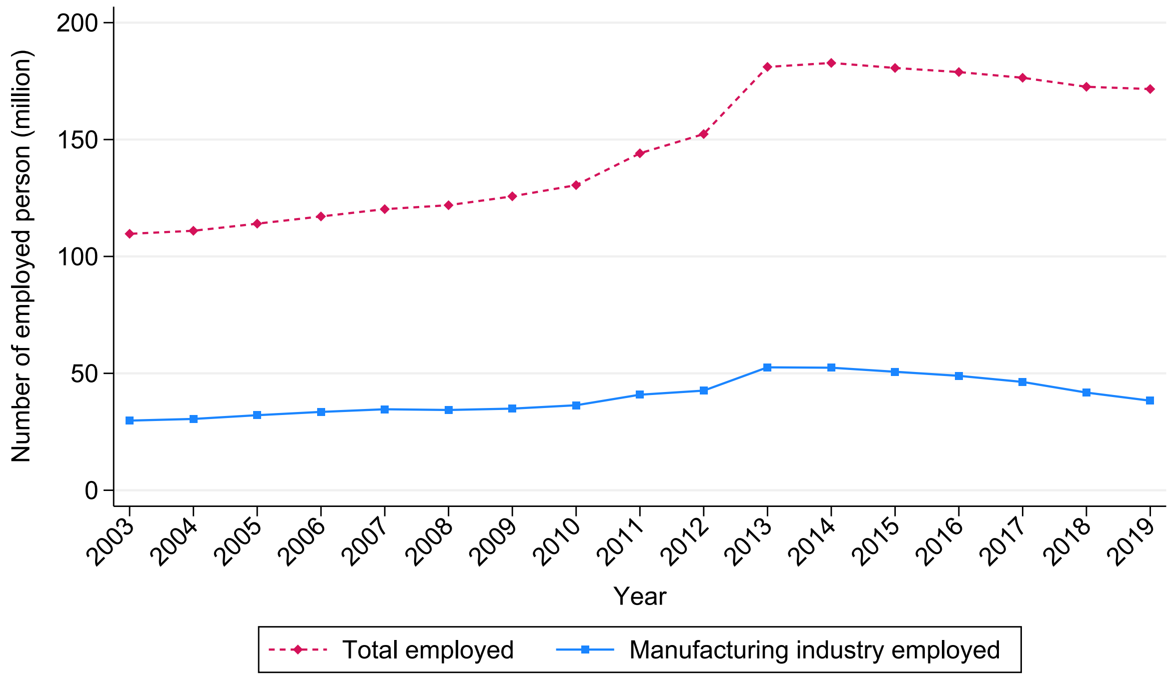

Figure 1. Employment trend in China.
Source: National Bureau of Statistics (China).
Notes: The total employment figure encompasses 19 industries within urban units of China. These industries are: *Agriculture, forestry, animal husbandry and fishery*; *Mining*; *Manufacturing*; *Production and supply of electricity, heat, gas and water*; *Construction*; *Transport, storage and post*; *Information transmission, software and information technology*; *Wholesale and retail trades*; *Hotels and catering services*; *Financial intermediation*; *Real estate*; *Leasing and business services*; *Scientific research and technical services*; *Management of water conservancy, environment*; *Services to households, repair and other services*; *Education*; *Health and social service*; *Culture, sports and entertainment*; *Public management, social security and social organization.*

and medium-sized enterprises (SMEs).[4] In 2020, China had more than 140 million SMEs, which represented 98.5% of all registered businesses. Together, these enterprises contributed over 60% of the country's gross domestic product, generated 50% of total tax revenue, and accounted for 79% of all employment (OECD, 2022). However, the self-selection of manufacturing employees into college education and their returns to education, especially within SMEs, remain underexplored, highlighting a critical gap for further research.

This paper addresses two key research questions: (1) What is the causal effect of obtaining a college degree on the returns to education for employees in SMEs in China's manufacturing industry? (2) Who benefits the most from attending college among Chinese manufacturing

[4]The SME is one of the boosters for China's economy. By the end of 2018, there are 18.07 million registered SMEs, creating over 233 million jobs. Source from National Bureau of Statistics (in Chinese): https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900574.html

SME employees? To explore these questions, we use data from the China Employer-Employee Survey (CEES) and employ a Two-Stage Least Squares (2SLS) framework for empirical analysis. In the first stage, we show that the significant and unexpected expansion of HE enrolment in 1999 led to a marked increase in college enrolment among female manufacturing workers in the post-1980 birth cohorts. In the second stage, we estimate the returns to college education for SME employees in the Chinese manufacturing sector. Thereafter, we estimate the Marginal Treatment Effect (MTE) to explicitly account for self-selection bias caused by unobserved factors influencing the decision to pursue HE. Compared to conventional 2SLS estimates, the MTE provides insights into the distributional effects of HE expansion, offering valuable implications for policy design.

Our benchmark Ordinary Least Squares (OLS) estimates indicate that the returns to college education, after controlling for birth cohort and regional fixed effects, are 26.62% for male and 27.25% female employees. However, addressing the potential endogeneity of college attendance using an instrumental variable (IV) approach raises the 2SLS estimates to 45.20% for males and 88.33% for females. These 2SLS estimates represent the Local Average Treatment Effect (LATE), capturing the returns for marginal individuals who enrolled in college primarily due to the HE expansion. Decomposing the IV-OLS coefficients, as proposed by Ishimaru (2024), reveals that the OLS estimates are downwardly biased. This bias stems from differences in marginal effects, driven by substantial endogeneity or omitted-variable bias. Beyond the LATE point estimates, our analysis explores the distributional effects for marginal individuals. The heterogeneity in effects is consistent with *reverse selection on gains*, as described by Cornelissen et al. (2016), where non-graduates would have experienced higher returns than those who attended college, conditional on pre-HE educational attainment and other relevant control variables. Further examination shows that the effects are particularly significant among female middle birth cohorts, vocational-track degree holders, and STEM graduates. College education also increases opportunities for employment in cognitively demanding roles and reduces the likelihood of female employees engaging in physically intensive tasks.

We acknowledge that Cheng et al. (2020) also use the CEES to estimate the returns to education among employees in the manufacturing industry. However, this study is the first to specifically examine the returns to college education from the perspective of SMEs within China's manufacturing industry. This work contributes to the literature on education returns in China in several important ways. First, it employs an identification strategy that addresses unobserved factors influencing college attendance decisions, which is particularly relevant for employees in SMEs. Second, it examines patterns of selection on gains by gender and explores underlying mechanisms using detailed employer-employee matched data, which allows for insights from the employer's perspective. Third, it enhances the robustness of the analysis by including controls for two-digit industry fixed effects and firm-level employment characteristics. We conduct a comprehensive analysis on different effects of firm's labour structure, birth cohort, degree type, subject type and non-monetary returns. By focusing on employees who would be at the margin of participating in HE, who are disproportionately from lower socioeconomic backgrounds, this study addresses critical gaps in the literature on college education returns in China.

The remainder of the paper is organized as follows. We review the relevant literature in Section 2. The institutional background of the 1999 HE expansion and China's manufacturing industry is introduced in Section 3. Section 4 discusses the identification strategy for estimating the marginal treatment effects. Section 5 presents the data. The empirical results are discussed in detail in Section 6. Finally, Section 7 concludes.

2 Literature Review

Owing to China's rapid economic growth, there is a need to understand the elements driving this expansion, particularly with regards to a role assigned to HE.[5] Compared to the extensive international literature,[6] very few studies have leveraged Chinese data in uncovering causal returns to college education using quasi-experimental methods.

Using data from population surveys in 2000 and 2005, Wu and Zhao (2010) conduct empirical research on the expansion of HE. Estimation is based on a Difference-in-Differences (DiD) model to evaluate the impact of HE expansion on labour market outcomes for graduates in terms of labour participation, unemployment, and hourly wages. They further compare the ones who completed college and high school with a Difference-in-Difference-in-Differences (DDD) model. Further studies investigated the factors influencing the employability of college graduates (Ou and Zhao, 2022) and access to educational opportunities (Ou and Hou, 2019) by constructing DiD models based on the exogenous shock of the HE expansion.

Alternatively, from the perspective of Local Average Treatment Effect (LATE), Dai et al. (2022) find that each additional year of university education induced by the HE expansion increased monthly wage income by 21%, compared to an OLS estimate of only 8%, using

[5]A series of studies, using meta-analysis, on the returns to college education in China, indicate that HE had a positive impact on graduate earnings, which were higher than those with lower education (Churchill and Mishra, 2018; Ma and Iwasaki, 2021).

[6]For a comprehensive review, see e.g. Harmon et al. (2003); Psacharopoulos and Patrinos (2018); Patrinos and Psacharopoulos (2020); Gunderson and Oreopolous (2020); McKenzie et al. (2025).

the fuzzy Regression Discontinuity Design (RDD). According to Huang et al. (2022), the HE expansion raised earnings by 17% for men and 12% for women by applying HE expansion as an IV in their 2SLS estimation. These results can be interpreted as the LATE of education on earnings for urban students who enrolled solely due to the HE expansion.

The canonical exploration of heterogeneity in returns to college education concerns its observable characteristics. It explores heterogeneity by splitting the sample into groups, such as the rural-urban or male-female group. Applying Inverse Probability Weighted Regression Adjustment (IPWRA) as an identification strategy, Kang et al. (2021) demonstrate that HE expansion in China has reduced returns for more recent graduates in both ordinary universities and vocational colleges. In contrast, graduates from key universities who study subjects other than STEM (science, technology, engineering, and math/medicine) or LEM (law, economics, and management) are exceptions to the reductions in returns. However, the findings can be interpreted as causal under the assumption of selection on observables only. Heckman et al. (2010) conclude that the return to college education is random. The premise of their study is that individuals have different financial and psychic cost in college education.[7] For example, attending college for those from high-income families has a far lower psychic cost than for those from low-income families, as the cost of college education for the latter group is likely to be a substantial financial burden psychologically, even when student loans are available. If the psychic cost of attendance and the returns to college education are not independent, then the essential heterogeneity in the returns to education will emerge.

Only a few studies focus on the essential heterogeneity by estimating Marginal Treatment Effects (MTE) of the returns to college education in China (Heckman and Li, 2004; Wang et al., 2014; Liu and Zheng, 2019). Yet they don't directly consider those with weaker backgrounds in terms of socioeconomic status, such as SME employees in the manufacturing industry. Che and Zhang (2018) identify the impact of HE expansion on privately-owned manufacturing firms in China. They find that firms in more skilled-labour-intensive industries exhibited a relatively more significant increase in total factor productivity. Furthermore, previous studies do not examine differences in selection on gains by gender. Using data from Taiwan, Tsai and Xie (2011) find that the average earnings gap between college and high school graduates is substantially larger for women than for men. Their analysis reveals a pattern of positive selection on gains for women, whereas men exhibit reverse selection on gains.

[7]The adverse conditions under which people lead their lives can bring psychological changes such as increased risk aversion, leading to economically irrational behaviour, such as reduced investments in education and health, which offer long-term benefits despite certain risks (Banerjee et al., 2006; Haushofer and Fehr, 2014).

However, the estimated treatment effects for men are small and not statistically significant.

3 Institutional Background

3.1 The 1999 higher education expansion in China

Following major economic reforms and opening-up policies initiated in 1978, China transformed from a centrally planned economy to a more market-oriented system. This policy change, under the leadership of Deng Xiaoping, was about encouraging foreign investment, privatizing many of the state-owned enterprises, and promoting private entrepreneurship. These combined efforts soon shoved the economy on a much higher growth trajectory, speeded up the process of industrialization and urbanization, but at the same time created significant social problems, especially in employment.

As can be seen from Figure 2, the end of Cultural Revolution (1966-1976) in 1976 marked the beginning of a new era. During the Cultural Revolution, political ideology supplanted professional competence as the main objectives of education. In December 1977, the gaokao (National College Entrance Exam) was reinstated, marking the beginning of the age of educational reforms. The Compulsory Education Law, mandating 9 years of compulsory education, was put into place in 1986. Following on the success of the reform of compulsory education, the government realised in the 1990s that the heavily regulated HE system, with rigid institution-specific enrolment quotas set by the Ministry of Education (MoE), needs to be substantially expanded to ensure sufficient supply of a skilled workforce demanded by the country's rapid economic development and technological advances.

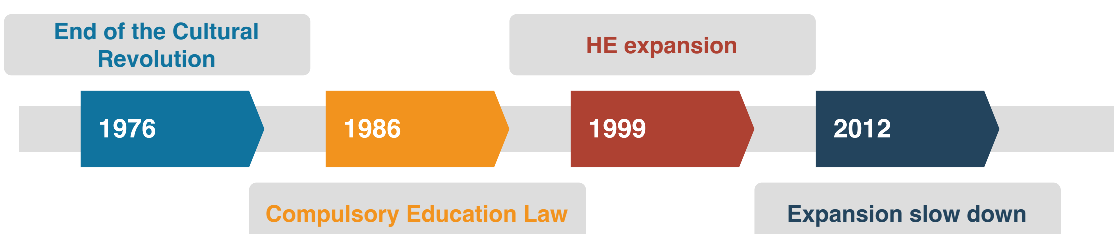

Figure 2. Timeline of relevant events.

In the meantime, the reform of state-owned enterprises during the late 1990s brought massive unemployment with millions of laid-off workers.[8] This situation was further exacerbated

[8]The background of the China state-owned enterprises (SOE), which triggered the massive layoffs in the late 1990s, is reviewed by Gu (1999) and Solinger (2002). Tian et al. (2022) evaluate the effect of SOE reform on labour market outcomes. Moreover, a byproduct of the SOE reform is that parental job loss has a significantly negative impact on children's health (Liu and Zhao, 2014).

by the 1997 Asian financial crisis, which pressured the Chinese economy, thereby reducing growth and increasing unemployment. The country's government was under much pressure to find ways for boosting domestic demand and sustaining economic stability. Hence, enlarging HE came in as a strategic policy response to the above economic pressures,[9] not only to invest in education for future development, but also to stimulate domestic consumption and relieve employment pressure on the labour market by absorbing high school graduates into college at a time when the nation was confronting the recession resulting from the Asian financial crisis (Wan, 2006; Wu and Zhang, 2010; Wu and Zhao, 2010).

On June 16, 1999, three weeks before the National College Entrance Examination (*gaokao*), the former State Development Planning Commission and the MoE jointly announced an increase of 0.33 million extra places for the September admissions to HE institutions. Together with the 0.23 million increases in the admission quota announced in January, this represented a more than 40% increase in annual enrolment compared to 1998.[10] The decision to increase college enrollment was sudden, colossal, and largely unanticipated. It was arguably exogenous in nature (Wang, 2014), as high school graduates and their families had little time to recalibrate their decisions before the National College Entrance Examination on July 7 and 8, 1999. There was minimal public consultation, and the country's HE institutions were given a few months to gear up for a massive influx of students (Wan, 2006; Wu and Zhao, 2010; Li et al., 2017). Figure 3 shows the trends in the number of college students, entrants, and graduates from 1989 to 2019. Prior to 1999, the scale of HE remained relatively stable. From 1999 onwards, the scale of HE expanded tremendously, and this trend only slowed down in 2012.[11]

The HE expansion was implemented alongside broader policies aimed at addressing acute economic challenges and positioning education as a key driver of future competitiveness. This initiative increased both the average years of schooling and the proportion of the population with postsecondary degrees. Growth in HE participation, particularly among rural children,

[9] In November 1998, Min Tang, the former Chief Economist at the China Representative Office of the Asian Development Bank, submitted a proposal to the central government recommending a doubling of university admissions. He presented five reasons: 1) the relatively low number of university students compared to similar countries; 2) the potential labour market conflicts arising from laid-off workers; 3) the necessity to stimulate domestic demand and economic growth; 4) the universities' capacity to accommodate more students; and 5) the significance of HE for national rejuvenation.

[10] Further details can be found in the memoir available on the Chinese central government official website (in Chinese): https://www.gov.cn/jrzg/2009-09/06/content_1410276.htm

[11] The period of rapid HE expansion only slowed down in 2012, when the Chinese Ministry of Education (MoE) announced that the emphasis should be switched to quality improvement. For the full original announcement (in Chinese) by the Ministry of Education of China on maintaining the HE scale, see: http://www.moe.gov.cn/srcsite/A08/s7056/201203/t20120316_146673.html

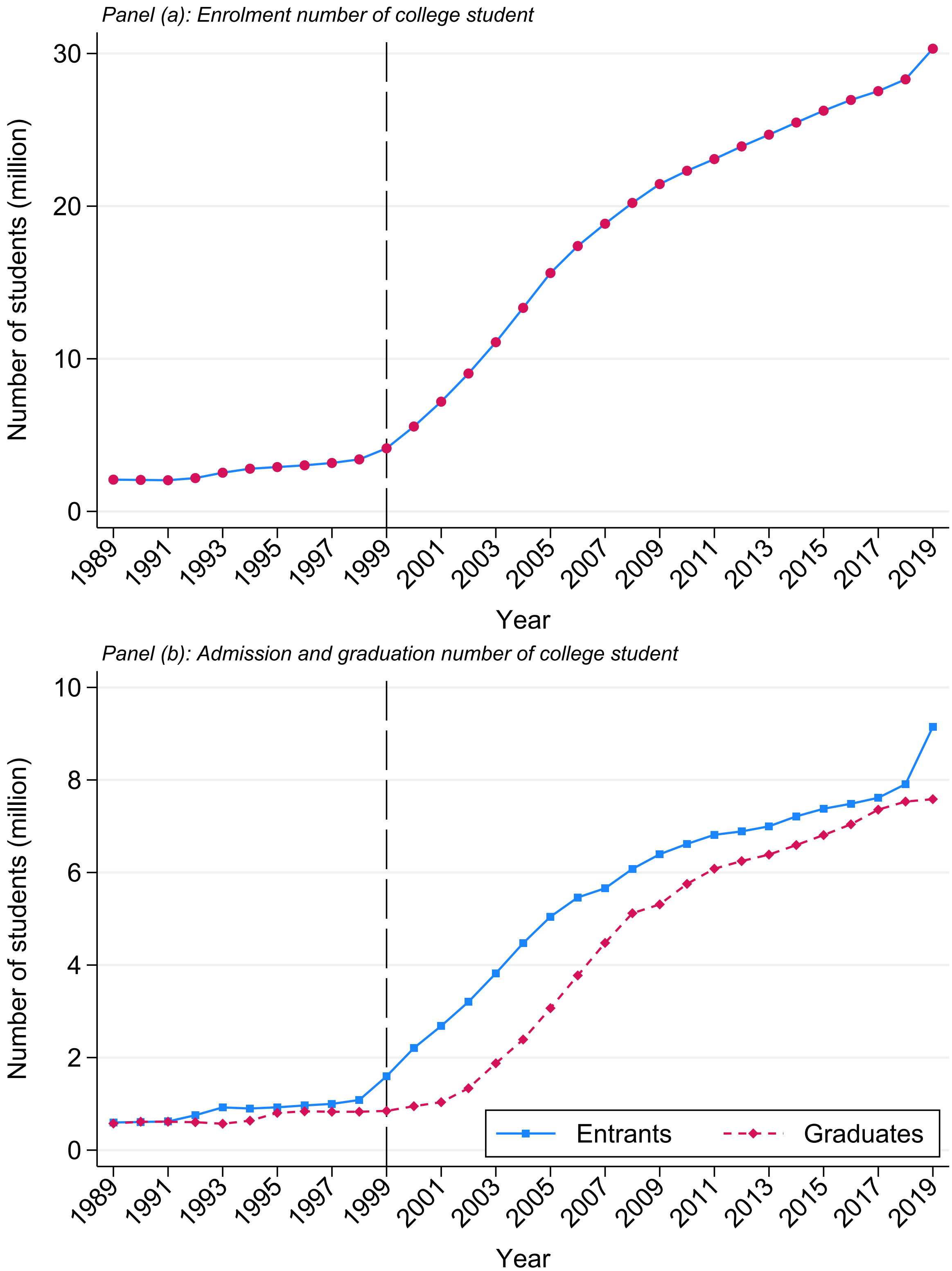

Figure 3. Trends of college student number in China.
Source: National Bureau of Statistics (China).

was primarily driven by improved access to senior high school education (Lu and Zhang, 2019). The expansion also produced positive labour market outcomes, including reduced short-term unemployment rates among males and college graduates (Ou and Zhao, 2022), higher monthly earnings (Dai et al., 2022), and improved firm productivity (Che and Zhang, 2018). These effects were especially pronounced for firms led by entrepreneurs with college degrees (Feng et al., 2022).

However, expanding HE further highlighted and perhaps worsened existing disparities, such as the urban-rural educational gap underpinned by the *hukou* system (Huang et al., 2022). Increased access to and graduation from four-year universities was primarily driven by individuals with higher social status, including males, those with better educated fathers, Han ethnic students, and urban students (Ou and Hou, 2019). Admittedly, equal opportunities have not followed the expansion of HE in China, and socioeconomic barriers are still very much present.

3.2 Manufacturing industry

With the reform of state-owned enterprises (SOE) in the late 1990s and China's accession to the World Trade Organization (WTO), the national economy experienced significant stimulation (Zhu, 2012). The expanded access to international markets and the growth in exports served as key drivers (Khandelwal et al., 2013; Yu, 2015). Consequently, China's manufacturing industry witnessed remarkable productivity growth throughout the 1990s and 2000s (Brandt et al., 2012, 2017). As a secondary industry, manufacturing is generally characterized by lower skill requirements compared to the tertiary industry. However, in the context of China, manufacturing industry as the cornerstone employment sector absorbs a substantial proportion of the educated labour force. As illustrated in Figure 4, the proportion of college degree holders employed in the manufacturing industry among males was higher than that of all industries until 2010, when the pattern was reversed. Similarly, college-educated workers were over-represented in manufacturing among females until 2009, although the gap was smaller.

According to Figure 5, the wage gap between the manufacturing industry and other industries still persists, although it was not significant until the late 2010s. Despite the average earnings in the manufacturing industry being relatively low, this sector constitutes a substantial portion of China's labour market.[12] The labour force in manufacturing is characterized as having below-average earnings, unfavourable working conditions compared to those in the service sector, and often low socioeconomic status, particularly evident in our sample from the China Employer-Employee Survey (CEES), which mainly includes non-listed firms, with only 1% of firms being publicly traded (Cheng et al., 2019). The survey is broadly representative of the overall situation in China's manufacturing industries, based on a stratified random sampling of both firms and employees. Moreover, our sample specifically represents individuals employed by SMEs in the manufacturing industry, accounting for unobservable factors which might be overlooked in other surveys.

[12] According to the China Stock Market and Accounting Research (CSMAR) database, there are over 5,100 companies listed on the Shanghai or Shenzhen Stock Exchange that can be categorized according to the China Securities Regulatory Commission (CSRC) 2012 framework. Of these, more than 3,000 are classified as manufacturing industry firms. For detailed information on classified firms, please refer to the CSMAR database: https://global.csmar.com/

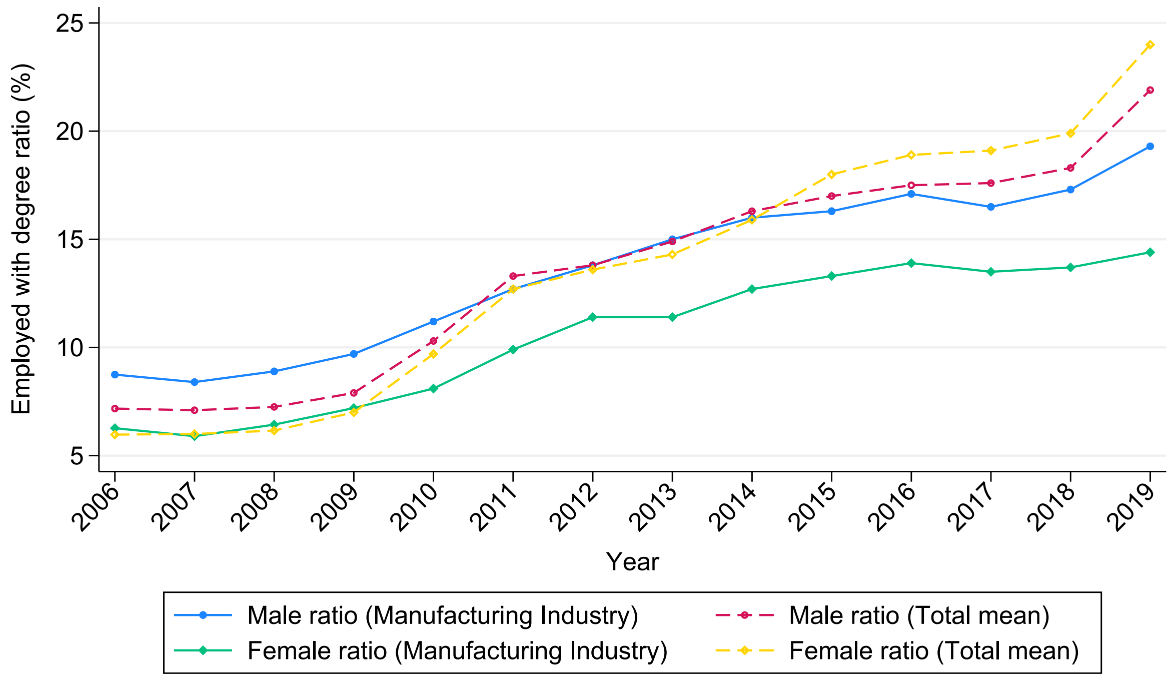

Figure 4. Ratio of college degree holders employed in manufacturing industry and overall, by gender.

Source: National Bureau of Statistics (China).

Notes: The solid dots/lines denote ratio of college degree holder employed in manufacturing industry and dashed dots/lines denote the mean ratio of aggregated 19 industries.

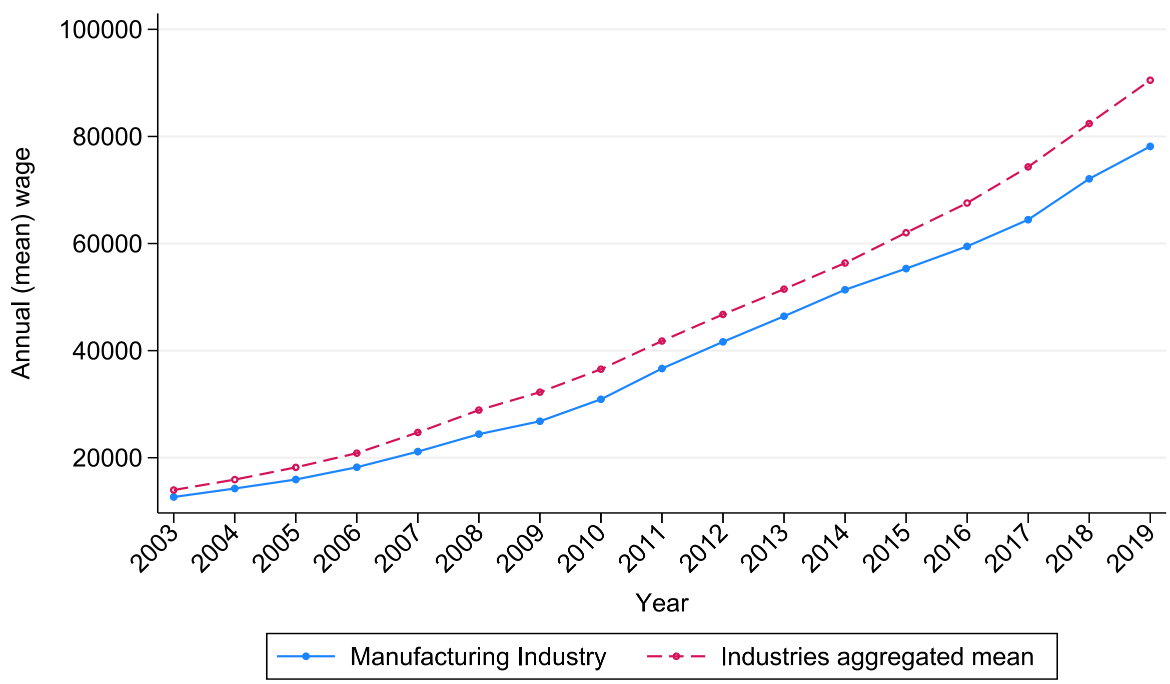

Figure 5. Annual (mean) wage trend in China.

Source: National Bureau of Statistics (China).

4 Identification Strategy

This study examines the education returns to employees in China's manufacturing industry, focusing on the extent and patterns of heterogeneous treatment effects. The analysis employs the Marginal Treatment Effect (MTE) framework (Heckman and Vytlacil, 1999, 2005, 2007) to explore the impact of both observable and unobservable characteristics.

Estimating the returns to education presents significant challenges, including potential sorting, self-selection, and endogeneity linked to the decision to attend college. These issues can introduce bias, complicating the identification of causal effects. To address these concerns, the MTE framework is adopted as it accounts for endogeneity and selection bias effectively. Additionally, it provides insights into unobservable factors, such as an individual's intention to pursue college education.

4.1 Generalized Roy model

The MTE estimation is based on the generalized Roy model,[13] which is a basic choice-theoretic framework utilized in the realm of policy analysis. We start with the potential outcome model, where Y^1 and Y^0 denote the potential outcome with and without treatment. Y is the observed outcome[14] either equals Y^1 in case an individual received treatment (have a college degree) or Y^0 in the absence of treatment. Hence, we have the returns to education $Y_1 - Y_0 = \beta = E[X\beta_1 - X\beta_0 + U_1 - U_0]$, the Average Treatment Effect (ATE) $\bar{\beta}(x) = E(\beta \mid X = x) = X\beta_1 - X\beta_0$ conditional on $X = x$, and the Average Treatment effect on the Treated (ATT) $E(\beta \mid X = x, D = 1) = \bar{\beta}(x) + E(U_1 - U_0 \mid X = x, D = 1)$ conditional on $X = x$.[15] College attendance is voluntary, rendering the treatment dummy D endogenous. This endogeneity is explicitly modeled by a latent index model, that is a choice equation to represent an individual's decision to attend college, we specify as follows:

$$Y^0 = X\beta_0 + U_0 \tag{1}$$

$$Y^1 = X\beta_1 + U_1 \tag{2}$$

$$D^* = Z\delta - V, \quad \text{where} \quad D = \mathbb{1}[D^* \geq 0] = \mathbb{1}[Z\delta \geq V] \tag{3}$$

[13] Heckman and Vytlacil (2007) provide a comprehensive discussion on the origins of this model, along with its broad applications in economics.

[14] Obviously, for each respondent it is possible to observe only one of the potential outcomes, never both; Y is the factual outcome observed by researcher, and we can have $Y = DY^1 + (1 - D)Y^0$.

[15] It is worth noting that X does not need to be statistically independent of U_0 and U_1, and we condition on X throughout our study. For a detailed description on calculating treatment effects, see Heckman and Vytlacil (2007).

where X includes the observed control variables, U_0 and U_1 are unobserved factors that affect the potential outcomes. D^* is the latent intention to attend college, which depends on observed variable Z and the unobservable V. Z encompasses all variables in X plus the instrumental variables (IV) that are assumed to affect the decision to attend college but not the returns to education (i.e. the exclusion restriction). V is assumed to be a continuous random variable, characterized by a monotonically increasing distribution function, denoted as F_V. Furthermore, since V enters equation (3) with a negative sign, it represents the (psychic) cost associated with attending college, where a higher value corresponds to increased cost. U_0, U_1, and V are potentially correlated, which results in the endogeneity of the treatment (decision to attend college) and in heterogenous outcome (returns to education). $\mathbb{1}(\cdot)$ is the indicator function, which assumes a value of one if the condition within the brackets is true, and zero otherwise. The individual chooses to attend college whenever $D^* \geq 0$. Equations (1) – (3) consist of the generalized Roy model, where the observables are (Y, D, X, Z) and the unobservables (U_0, U_1, V).

We rewrite the choice equation (3) by applying some distribution function:

$$P(Z) = Pr(D = 1 \mid Z) = F_V(Z\delta), \quad D = \mathbb{1}[D^* \geq 0] = \mathbb{1}[P(Z) \geq U_D] \tag{4}$$

where $P(Z)$ (quantiles of Z) is the probability of an individual to decide to attend college ($D = 1$) conditional on Z. $P(Z)$ is sometimes called the propensity score, as noted by Heckman et al. (2006). Define $U_D = F_V(V)$, U_D is the quantiles of V, which is uniformly distributed in the unit interval ($U_D \sim [0, 1]$). $F_V(\cdot)$ is the cumulative distribution function (CDF) of V that transform the linear index $Z\delta$ into a probability.

With the above model setup, the marginal treatment effects can be derived as the conditional difference in returns between attending college and not-attending college:

$$\begin{aligned} MTE(x, u_D) &= \mathbb{E}(Y_1 - Y_0 \mid X = x, U_D = u_D) \\ &= \underbrace{x(\beta_1 - \beta_0)}_{\text{heterogeneity in observables}} + \underbrace{\mathbb{E}(U_1 - U_0 \mid U_D = u_D)}_{k(u)\text{: heterogeneity in unobservables}} \end{aligned} \tag{5}$$

The MTE represents the returns to education for individuals possessing specific observed characteristics $X = x$, situated within the $U_D = u_D$ quantile of the V distribution. This is a marginal individual, characterized by indifference towards the decision of either attending or not-attending college, with a propensity score $P(Z)$ equals to U_D.

4.2 Estimation of the MTE

We estimate the Marginal Treatment Effect (MTE) through a semiparametric approach[16] employing the Local Instrumental Variables (LIV) method proposed by Heckman and Vytlacil(1999; 2001; 2005), wherein the MTE is identified by differentiating the conditional expectation of Y with respect to p. The propensity score $P(Z)$ functions as the LIV, and the MTE can be calculated over the support of the distribution of $P(Z)$. Following Carneiro et al. (2011), we first have the observed earnings as follows:

$$\begin{aligned} Y &= DY_1 + (1-D)Y_0 \\ &= X\beta_0 + \big[X\beta_1 - X\beta_0 + U_1 - U_0\big]D + U_0 \\ &= X\beta_0 + \big[X\beta_1 - X\beta_0\big]D + \big\{U_0 + D(U_1 - U_0)\big\} \end{aligned} \tag{6}$$

Then we can have the expectation of Y conditional on $X = x$ and $P(Z) = p$ by:

$$\begin{aligned} \mathbb{E}(Y \mid X = x, P(Z) = p) = \mathbb{E}(Y_0 \mid X = x, P(Z) = p) \\ + \mathbb{E}(Y_1 - Y_0 \mid X = x, D = 1, P(Z) = p)p \end{aligned} \tag{7}$$

We impose the exclusion restriction of p on Y based on the choice equation (3), and insert in the potential outcome equation with the counterfactuals in equation (2) and (3) (Heckman and Vytlacil, 2007). The above expression can be written as:

$$\begin{aligned} \mathbb{E}(Y \mid X = x, P(Z) = p) &= \mathbb{E}(Y_0 + D(Y_1 - Y_0) \mid X = x, P(Z) = p) \\ &= x\beta_0 + px(\beta_1 - \beta_0) + p\underbrace{\mathbb{E}(U_1 - U_0 \mid U_D \leq p)}_{K(p)} \end{aligned} \tag{8}$$

where the final term $K(p)$ represents a nonlinear function of the propensity score $P(Z) = p$ that captures heterogeneity along the unobservable resistance to treatment U_D.

Finally, the MTE can be obtained by taking the derivative of equation (8) with respect

[16] The semi-parametric estimation is widely used for flexibility and weaker assumption. The parametric estimation comes with distributional assumption on $K(p)$: the maximum likelihood estimation (**MLE**) assumes the unobservables (U_0, U_1, V) are jointly normally distributed with mean 0 and an unknown variance-covariance matrix of three unobservables, and are independent of (X, Z), for further technical details see Lokshin and Sajaia (2004) and Andresen (2018); the assumption of joint normality can be partially relaxed with flexible approximation of $K(p)$ based on an L_th order **polynomial** of the propensity score with mean zero, see for example Basu et al. (2007), Brave and Walstrum (2014) and Andresen (2018) for further technical details.

to $P(Z) = p$ and evaluating it at $U_D = u_D$:

$$
\begin{aligned}
MTE(x, u_D) &= \frac{\partial \mathbb{E}(Y \mid x, p)}{\partial p} \\
&= x(\beta_1 - \beta_0) + \frac{\partial K(p)}{\partial p} \\
&= x(\beta_1 - \beta_0) + \underbrace{\mathbb{E}(U_1 - U_0 \mid U_D = u_D)}_{k(u)}
\end{aligned} \tag{9}
$$

The significant advantage of estimating MTE is that it can generate the conventional treatment parameters like the Average Treatment Effect (ATE), the Average Treatment on Treated (ATT), the Average Treatment on Untreated (ATUT) and the Local Average Treatment Effect (LATE) by taking different weighted averages of the MTE curve (Heckman and Vytlacil, 2005, 2007). This can be written as:

$$
\Delta_j(x) = \int_0^1 MTE(x, u_D) h_j(x, u_D)\, du_D \tag{10}
$$

where $\Delta_j(x)$ is the treatment parameter, and the treatment effects can be expressed as follows:

$$
\begin{aligned}
ATE(x) &= \int_0^1 MTE(x, u_D) h_{ATE}(x, u_D)\, du_D \\
ATT(x) &= \int_0^1 MTE(x, u_D) h_{ATT}(x, u_D)\, du_D \\
ATUT(x) &= \int_0^1 MTE(x, u_D) h_{ATUT}(x, u_D)\, du_D \\
LATE(x) &= \int_0^1 MTE(x, u_D) h_{LATE}(x, u_D)\, du_D
\end{aligned} \tag{11}
$$

the weights for ATE, ATT, ATUT and LATE are as follows:

$$
\begin{aligned}
h_{ATE}(x, u_D) &= 1 \\
h_{ATT}(x, u_D) &= \frac{\int_{u_D}^1 f(p \mid X = x)\, dp}{E(P \mid X = x)} \\
h_{ATUT}(x, u_D) &= \frac{\int_0^{u_D} f(p \mid X = x)\, dp}{E(1 - P \mid X = x)} \\
h_{LATE}(x, u_D) &= \frac{\int_{u_D}^1 (p - E(P \mid X = x)) f(p \mid X = x)\, dp}{Var(P \mid X = x)}
\end{aligned} \tag{12}
$$

where $f(p \mid X = x)$ is propensity score density. For further details on other treatment parameters and weights, see Carneiro et al. (2011) and Andresen (2018).

5 Data description

This study employs firm-individual level data from the China Employer-Employee Survey (CEES), conducted in three waves across five provinces using a two-stage probability proportional to size (PPS) sampling method.[17] The data used are pooled cross-sectional, with no repeated individuals across survey waves. Although the same provinces are included in each wave, such as Guangdong province, the specific firms sampled may vary. We have attempted to construct a longitudinal dataset from the CEES, but the resulting sample size, especially taking account of the third wave conducted in 2018, was substantially reduced. Therefore, we pool data from all three waves to increase both sample size and informational richness. The sample includes male and female small and medium-sized enterprises (SME)[18] manufacturing employees born in or after September 1970 and aged 25 or older, excluding individuals aged above 48 in 2018 due to early retirement trends and educational disruptions caused by the Cultural Revolution (1966–1976). Individuals with education below the lower secondary level are excluded from the analysis, as they constitute a small proportion of the sample and are classified as never-takers.

Table 1 summarizes the variables used in the empirical analysis Y, D, X and Z (along with papers that have previously adopted similar instruments). Detailed descriptions of variable measurements are provided in the appendix.

The outcome variable (Y) is the log of net hourly income, adjusted using the CPI deflator specific to the surveyed provinces. Observations below the 1st percentile and extreme outliers are trimmed to reduce measurement error. The treatment variable (D) is binary, set to 1 for respondents with vocational college degrees or higher.

The instrumental variables (Z) are derived from both external and internal perspectives. External IVs include the 1999 HE (HE) expansion, which influenced college enrolment decisions, and the provincial unemployment rate at age 18, representing the opportunity cost of attending college. Internal IVs consist of the father's and mother's years of education, which affect college attendance through preferences and financial constraints.

[17] The CEES data has been collected in 2015 (limited to Guangdong province), 2016 (encompassing both Guangdong and Hubei provinces), and 2018 (including Guangdong, Hubei, Jiangsu, Sichuan, and Jilin provinces). For detail information regarding the CEES data, refer to https://cep.hkust.edu.hk/news/data-archive-china-employer-employee-survey-cees, where both the manual and questionnaire (available exclusively in Chinese) are accessible.

[18] The definition of small and medium-sized enterprises (SMEs) in this study follows the classification established by the National Bureau of Statistics. In the manufacturing sector, firms are categorized as SMEs if they employ fewer than 1000 workers or generate annual revenue below 400 million Chinese yuan. For further details, refer to the official source (in Chinese) at the provided link: https://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902763.html

Table 1. Variable definitions for empirical analysis.

Variable	Definition
Y	Log of net hourly income (deflated by provincial CPI)
$D = 1$	If the respondent is a college degree holder; zero otherwise
X	Age, age squared, reside in rural area at age 16, local people, rural hukou, labour demand index of surveyed city, work in SOE, work in firm accredited as High-tech enterprise, firm located in economic development zone, work in capital intensive firm, firm age, log of firm's employee number
Z	China HE expansion (Liu and Zheng, 2019; Huang et al., 2022), provincial unemployment rate at age 18 (Arkes, 2010; Carneiro et al., 2011; Kyui, 2016), parental years of education (Taber, 2001; Lemke and Rischall, 2003; Stella, 2013; Gong, 2019)

Notes: The references in parentheses are studies that previously used these instruments. Detailed information of variable measurement is in the Appendix A.

Instrumental variables must influence earnings only indirectly by affecting the probability of attending college. This condition is known as the exclusion restriction. For the HE expansion instrument, the exclusion restriction assumes that, conditional on cohort, province, and other relevant covariates, the expansion impacts earnings or job outcomes in the manufacturing sector solely through its effect on college attainment. It does not exert a direct influence on labour market outcomes. For provincial unemployment at age 18, the exclusion restriction posits that variation in unemployment rates at that age affects labour market outcomes only by influencing the decision to pursue college education. It assumes no lasting impact from early labour market conditions. This assumption is supported by the inclusion of province and cohort fixed effects and by focusing on the manufacturing sector, where employees are less exposed to long-term effects of early unemployment due to job mobility and industry-specific dynamics. For parental education, the exclusion restriction assumes that parental years of schooling do not directly affect their children's adult labour market outcomes once the children's own education is accounted for. This assumption is plausible given that labour market outcomes are observed many years after college entry. Additionally, the analysis focuses on adult workers in the manufacturing industry, where the influence of parental networks or social capital is likely weaker compared to professional fields.[19] Although these exclusion restrictions may not be optimal, no clearly superior alternative is available for addressing this question. It is expected that the resulting estimates are less biased than those obtained through ordinary least squares (OLS).

Control variables (X) are selected to address potential confounders and enhance model accuracy by accounting for demographic, geographic, and economic factors. To reflect disparities in educational access and regional development, variables such as *hukou* status and residence type are included. A Bartik-style index is constructed to capture demand-side labour market dynamics shaped by the HE expansion. Employer-specific factors, such as firm type and size, are also incorporated to account for firm-level heterogeneity, providing a comprehensive analysis of the factors influencing outcomes.

Table 2 provides descriptive statistics by gender as preliminary evidence.[20] College-educated respondents are *more* likely to have parents with advanced education. They are also *less* likely to have lived in a rural area at age 16 or hold a rural *hukou*. Individuals with a college degree generally earn higher incomes, with income differentials of 0.257 log points for males and 0.288 for females. However, comparing incomes alone does not confirm the causal effect of college education on returns. Thus, further empirical analysis is needed.

[19] Gong (2019) finds that among migrant workers who pursue education and relocate for employment, parental education influences their educational attainment but does not affect their wages. In contrast, for local residents who remain in the same city throughout childhood and adulthood, parental education directly impacts wages. This is attributed to family networks and occupational inheritance, especially within state-owned enterprises (SOEs). In our context, we argue that parental years of education can still serve as a valid instrumental variable. This is justified by the focus on employees in the manufacturing industry, which is generally less preferred, and by our restriction to SMEs. We also test the robustness of our results by excluding SOE employees. The findings remain consistent. Further analysis is provided in Appendix A, where we examine a subgroup defined by local status. Local individuals are those born in the current city, possessing local hukou, and who have never moved away. The subgroup results mirror the baseline findings, though the effects are more pronounced for local male employees and female migrant employees. Due to limitations in sample size, it is not feasible to apply the local status subgrouping across all parts of the analysis.

[20] The gender wage gap, while interesting, is out of scope of this paper. Using the CEES, Deng et al. (2025) document a 16.3% monthly earnings premium for male workers in Chinese manufacturing, driven by within-firm variations. Moreover, the adoption of industrial robots narrows the gender earnings gap within the firm.

Table 2. Descriptive statistics.

	Male		Female		
	w/o college degree	with college degree	w/o college degree	with college degree	Total
Dependent variable					
Log of net hourly income	2.867 (0.459)	3.124 (0.491)	2.630 (0.396)	2.918 (0.442)	2.847 (0.476)
Treatment variable					
College degree					0.340 (0.474)
Instruments					
Post-1980.09 birth	0.514 (0.500)	0.714 (0.452)	0.552 (0.497)	0.830 (0.397)	0.608 (0.488)
Expansion intensity	0.194 (0.029)	0.198 (0.026)	0.193 (0.029)	0.196 (0.026)	0.195 (0.028)
Provincial unemployment rate at age 18	3.203 (0.858)	3.469 (0.821)	3.190 (0.839)	3.464 (0.804)	3.289 (0.847)
Father's years of education	7.511 (3.462)	9.527 (3.453)	7.726 (3.362)	9.821 (3.221)	8.312 (3.530)
Mother's years of education	5.966 (3.528)	8.029 (3.771)	6.092 (3.649)	8.588 (3.540)	6.795 (3.773)
Control variables					
Age	36.653 (6.503)	34.080 (5.932)	36.206 (6.320)	32.628 (5.660)	35.409 (6.394)
Age 16 in rural area residence	0.571 (0.495)	0.350 (0.477)	0.542 (0.498)	0.283 (0.451)	0.476 (0.499)
Local people	0.472 (0.499)	0.447 (0.497)	0.529 (0.499)	0.549 (0.498)	0.498 (0.500)
Rural Hukou	0.507 (0.500)	0.267 (0.442)	0.516 (0.500)	0.298 (0.457)	0.433 (0.496)
Labour demand index of surveyed city	−0.018 (0.193)	−0.019 (0.219)	−0.034 (0.192)	−0.028 (0.231)	−0.025 (0.204)
Work in a State-owned firm	0.090 (0.286)	0.089 (0.285)	0.098 (0.297)	0.080 (0.271)	0.091 (0.287)
Work in firm accredited as High-tech enterprise	0.769 (0.422)	0.598 (0.490)	0.803 (0.398)	0.615 (0.487)	0.724 (0.447)
Firm located in economic development zone	0.508 (0.500)	0.575 (0.495)	0.496 (0.500)	0.551 (0.498)	0.523 (0.499)
Whether firm is capital intensive	0.469 (0.499)	0.584 (0.493)	0.418 (0.493)	0.570 (0.495)	0.490 (0.500)
Firm age	12.388 (8.020)	14.907 (10.733)	12.506 (7.743)	14.916 (10.507)	13.285 (8.991)
Log of firm's employee number	5.045 (1.247)	5.328 (1.183)	5.217 (1.173)	5.352 (1.131)	5.200 (1.200)
Education background					
Years of education	10.754 (1.479)	15.539 (0.837)	10.486 (1.500)	15.501 (0.814)	12.291 (2.663)
Higher degree		0.027 (0.161)		0.030 (0.171)	0.010 (0.097)
Observations	3652	1991	3440	1669	10752

Notes: Standard deviations in parentheses.

6 Empirical results

This section begins by presenting the estimation results for returns to education using Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) methods, serving as benchmarks for analysis. We then estimate the Marginal Treatment Effect (MTE) to deepen the investigation. Next, we perform robustness checks, examining alternative model specifications, the potential effects of China's WTO accession, and the wage premium associated with employment in State-Owned Enterprises (SOEs). Finally, we explore the mechanisms[21] through which college education impacts labour market outcomes, focusing on variations by labour structure, birth cohort, degree type, and field of study. Additionally, we consider non-monetary returns to education.

6.1 Results of OLS and 2SLS

While our primary interest lies in analysing the returns to college education for marginal individuals, we start with conventional 2SLS and OLS estimation as benchmarks. All model specifications include a comprehensive set of fixed effects. These account for birth cohort, province of residence at age 16, city of residence in the survey year, the two-digit industry classification of the employing firm, and the survey year.

We present the 2SLS estimates by gender in Table 3.[22] The first-stage results, shown in columns (1) and (3), analyse the likelihood of college enrolment based on observable factors. They indicate that the HE expansion has no significant impact on male employees' college attainment but significantly increases the probability of attainment for female employees, boosting enrolment by 23.7%. In the second-stage of 2SLS, presented in columns (2) and (4), college education significantly increases the returns for both genders. For males, the increase is 45.20%, while for females, it is 88.33%.[23] When converted to annual return rates, these values correspond to 12.91% for males and 25.24% for females.[24]

[21] For the sake of brevity, our discussion concentrates on the treatment parameters relevant to these potential mechanisms.

[22] We present alternative results using monthly income and working hours as outcome variables. The findings for monthly income are consistent with those reported in Table 3, which use hourly income as the outcome. In line with Cheng et al. (2020), college education is associated with a significant reduction in working hours for both male and female employees.

[23] Effect size is interpreted by applying the exponential transformation to the coefficient in the log-linear model: $(Exp(coefficient) - 1) \times 100$.

[24] To compute the annual rate of return, the overall rate of return is divided by 3.5 years, accounting for both first-degree (4-year) and vocational college degree (3-year) holders. We assume the effects accumulate linearly each year for computing the annual rate of return.

Table 3. 2SLS results by gender.

	Male		Female	
	(1)	(2)	(3)	(4)
	First-stage	Second-stage	First-stage	Second-stage
College degree		0.373***		0.633***
		(0.084)		(0.087)
Post-expansion cohort × Expansion intensity	0.106		0.237**	
	(0.150)		(0.103)	
Provincial unemployment rate at age 18	0.041***		0.037**	
	(0.013)		(0.016)	
Father's years of education	0.015***		0.013***	
	(0.002)		(0.002)	
Mother's years of education	0.010***		0.010***	
	(0.002)		(0.002)	
Controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓
Observations	5641	5641	5109	5109
Clusters	400	400	368	368
First-stage F-stat.		48.607		36.213

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

Table 4 reports the OLS estimates of returns to college education as a baseline for comparison with the 2SLS results. The findings are broadly consistent, although 2SLS estimates are higher than those from OLS. This discrepancy aligns with prior studies (Li et al., 2017; Liu and Zheng, 2019; Dai et al., 2022; Huang et al., 2022), which also report higher 2SLS estimates. The difference may arise from endogeneity in OLS, causing downward bias. Additionally, the 2SLS estimates represent the Local Average Treatment Effect (LATE), reflecting returns for marginal individuals who pursued college education primarily due to the HE expansion.

Table 4. OLS and 2SLS results by gender.

	Male		Female	
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
College degree	0.236***	0.373***	0.241***	0.633***
	(0.017)	(0.084)	(0.018)	(0.087)
Controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓
Observations	5641	5641	5109	5109
Clusters	400	400	368	368
First-stage F-stat.		48.607		36.213

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

We will follow up on the source of the downward bias in the OLS estimates by employing the decomposition approach developed by Ishimaru (2024). Under the econometric structure presented in Ishimaru (2024), the difference between the IV-OLS coefficients usually consists of three components that can be estimated: the difference in weights on covariates, the difference in weights on treatment levels, and the difference in identified marginal effects due to endogeneity bias. These inconsistencies can be derived in the returns to education domain as follows: (i) through heterogeneous returns across observed personal backgrounds with varying responses to the instrument; (ii) through nonlinear returns at different education levels, with different sensitivities to the instrument; and (iii) source of endogeneity bias that arises from omitted unobserved variables.

The results from the decomposition are presented in Table 5, which indicates that OLS estimates exhibit a downward bias about the IV estimates. This mainly emanates from the differences in the marginal effects. These findings imply that a substantive amount of endogeneity or omitted variable bias is present in the OLS estimates. On the other hand, the IV-OLS coefficient gap decomposition technique cannot allow further decomposition of the difference in the marginal effects into the components of the endogeneity bias and unobservable-driven weight differences to exist under unobserved heterogeneity in treatment effects. In other words, only the endogeneity bias of unobservable heterogeneity has not been attributed to the difference in the marginal effect, as described in Ishimaru (2024).

Table 5. Decomposition of the IV–OLS gap in returns to college education.

Models	Coefficients			Decomposition		
	OLS	IV	IV-OLS gap	Covariate weight difference	Treatment level weight difference	Marginal effect difference
Male	0.236	0.373	0.137	–0.012	0.000	0.149
	(0.017)	(0.083)	(0.083)	(0.021)	(0.000)	(0.081)
Female	0.241	0.633	0.392	0.031	0.000	0.361
	(0.018)	(0.085)	(0.086)	(0.022)	(0.000)	(0.085)

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level.

6.2 MTE estimates

We employ probit regressions to estimate the propensity scores in the first-stage and Figure 6 plots the histogram of common support.[25] For both the male and female models, the estimated propensity scores nearly encompass the unit interval.[26] The estimation of the Marginal Treatment Effect (MTE) depends on the full support of predicted propensity scores, which represent the probabilities of college degree attainment for individuals with and without a degree.

We estimate the MTE semiparametrically using a second-degree local polynomial regression with an Epanechnikov kernel function.[27] Moreover, we apply bandwidths for these

[25]The common support is defined as the intersection of the support of $P(Z)$ given $D = 1$ and the support of $P(Z)$ given $D = 0$.

[26]The identification within the semiparametric estimation, fundamentally hinges on the common support assumption (Brave and Walstrum, 2014). This may be considered as a limitation of the MTE approach that it is restricted to identification solely within the support of the propensity score $P(Z)$ (Kamhöfer et al., 2019). Nevertheless, it may be argued that the MTE over the support of $P(Z)$ is considerably informative, given that the computed common support encompasses a wide range of the unit interval. Many scholars think it contains better information than LATE. Carneiro et al. (2011) point out "better MTE than LATE" in addressing policy questions, in response to "better LATE than nothing" (Imbens, 2010). The MTE identifies the margins that different instruments identify.

[27]A comprehensive examination of the properties of local polynomial estimators is elaborated by Fan and Gijbels (1996). Employing higher-order polynomials may diminish bias but augment variance due to the inclusion of additional parameters. Fan and Gijbels (1996) advocate that the order π of the polynomial should be set to $\pi = \tau + 1$, where τ represents the order of the derivative of the target function. They recommend employing a local linear estimator for approximating the function and a local quadratic estimator for estimating a first-order derivative. Consequently, we estimate the derivative $\frac{\partial K(p)}{\partial p}$ using a local quadratic estimator.

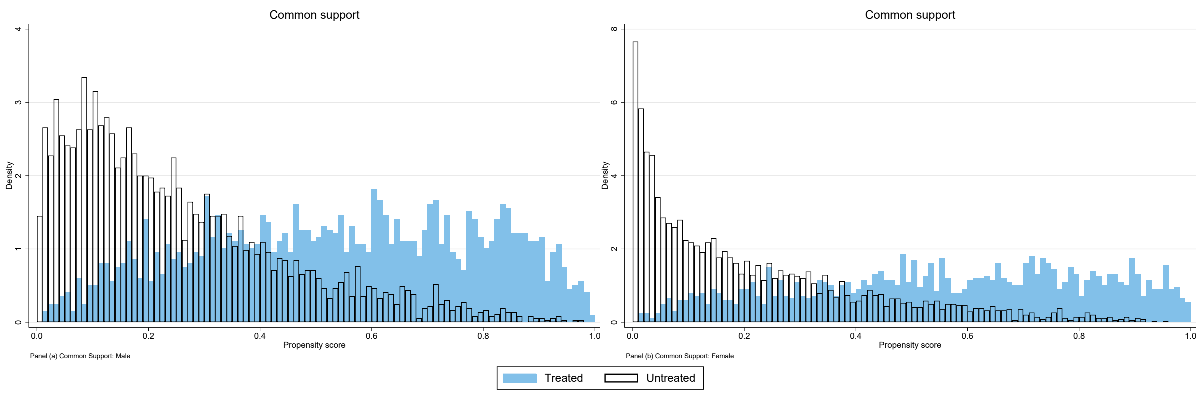

Figure 6. Common support for baseline model by gender.

Notes: This figure plots the number of treated and untreated employee by gender. It graphically represents each percentile of the propensity score, revealing that the common support nearly spans the entire unit interval.

regressions, determined by the asymptotically optimal constant bandwidth.[28] The specific bandwidth values are: 0.200 for male, and 0.149 for female.

Figure 7 illustrates the relationship between the MTE and unobservable resistance to treatment, denoted as U_D, within the unit interval. The horizontal axis represents U_D, which reflects individuals' unobserved resistance to pursuing college education. Those with high U_D incur substantial unobserved costs, making them less likely to be treated. From the MTE curves, we reject the null that the treatment effects are homogeneous across observed characteristics, as evidenced by the results of the no observable heterogeneity tests (p-values = 0.000; 0.000). Conversely, we cannot reject the tests for no unobservable heterogeneity for male employee group, which hypothesize that MTEs vary with unobserved treatment costs (p-values = 0.501; 0.029).

[28] Bandwidths are utilized to minimize the residual square criterion, as discussed by Fan and Gijbels (1996). The optimal bandwidth for local linear regressions is determined using Stata's *lpoly* rule of thumb. Reference for the computational methodologies can be made to De Groote and Declercq (2021).

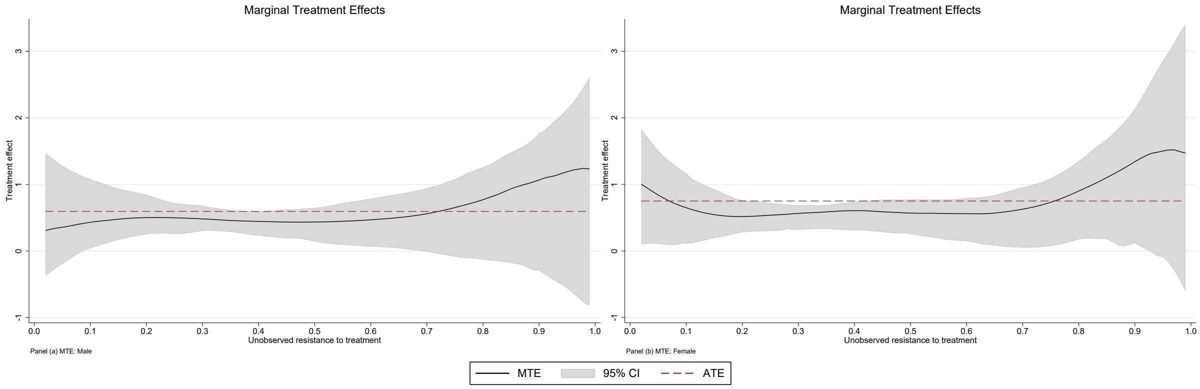

Figure 7. Estimated marginal returns to college education by gender.
Notes: The MTEs are calculated by gender using a second-degree local polynomial regression with an Epanechnikov kernel function. Standard errors are computed with a bootstrap procedure (250 replications) and clustered at birth year - residence province at age 16 level. The p-values for no observable heterogeneity (0.000; 0.000). The p-values for no unobservable heterogeneity (0.501; 0.029).

Individuals with high values of U_D tend to realize the greatest returns from college education. This outcome is particularly pronounced among female employees. High values of U_D indicate that these individuals are exceedingly unlikely to enroll in college, corresponding to the transformed choice equation (4) in section 4.1. For female employees, the returns to college education are notably higher, with a coefficient of 1.474 observed at the 99th quantile of U_D. This corresponds to an annual return rate of 0.421, as described earlier. Overall, the returns to college education remain positive across all quantiles of U_D. However, individuals with medium resistance exhibit below-average effect sizes. The MTE curves reveal a near U-shaped pattern, particularly pronounced in the female model. This U-shaped MTE aligns with the presence of unobserved barriers to college attendance in China, such as psychic costs or hidden financial constraints and son preference in parental investment (Wang et al., 2014).

Similar to the finding of Kamhöfer et al. (2019) in Germany, we also observe no negative effects, in contrast to those identified by Carneiro et al. (2011) in United States. In the studies by Carneiro et al. (2011) and Kamhöfer et al. (2019), individuals exhibiting higher returns are those who self-select into college education (lower values of U_D, higher returns). The principal distinction in our MTE curve is the presence of reverse selection on gains[29]

[29] The concept of 'reverse selection on gains' is introduced and explained by Cornelissen et al. (2016). When the MTE curve exhibits an upward shape, it signifies a pattern of reverse selection on gains. Specifically, returns to a college degree is more substantial for the employees with higher resistance to obtaining college degree (high u_D). In our study, the ATUT, which indicates the extent to which obtaining college degree would boost the returns for employees who currently have no degree, exceeds the ATE and ATT. The pattern of reverse selection on gains is documented in literature; see Cornelissen et al. (2018), Liu and Zheng (2019), De Groote and Declercq (2021), and Spanos (2021).

among China's manufacturing industry employees in SMEs: these individuals who did not attend HE would have realized higher returns had they self-selected into college education.[30]

This finding highlights a distinct divergence in the self-selection into HE between developed and developing countries. In nations like Germany and the United States, those best prepared for college tend to achieve the highest returns from college education. In contrast, in China, the highest returns to college education are found among the least prepared individuals, had they attended. This discrepancy highlights the significant role of external barriers, such as credit constraints and travel restrictions under the *hukou* system, which limit access to college education in China. These factors differ from internal barriers, like a lack of interest in pursuing college, commonly observed in developed countries. Additionally, the wide socioeconomic disparities and the urban-rural divide exacerbate these challenges in the Chinese context.

Table 6 presents the conventional treatment parameters estimated using the MTE for both male and female models. These include the Average Treatment Effect (ATE), the Average Treatment Effect on the Treated (ATT), the Average Treatment Effect on the Untreated (ATUT), and the Local Average Treatment Effect (LATE). The effect sizes for the entire cohort (ATE), individuals with a college degree (ATT), and those without a college degree (ATUT) in Table 6 represent the cumulative returns to college education.

Table 6. Results of estimated treatment parameters.

	(1) Male	(2) Female
ATE	0.595***	0.751***
	(0.165)	(0.163)
ATT	0.394**	0.553***
	(0.169)	(0.148)
ATUT	0.702***	0.846***
	(0.269)	(0.241)
LATE	0.373***	0.618***
	(0.106)	(0.116)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

Table 6 summarizes the MTE into single values, offering a clear representation of average

[30] While our primary emphasis is on the returns to college education among employees in China's manufacturing sector, Liu and Zheng (2019) report similar findings using data from the Chinese General Social Survey (CGSS). To some extent, these findings could be generalized across China.

effect sizes. The observed differences among treatment parameters emphasize the importance of effect heterogeneity. In the female model, the ATUT significantly exceeds the ATT. The LATE represents an average effect weighted by the conditional density of the instruments, gives more weight to individuals who pursue college education only at high U_D values, reflecting substantial inherent barriers or reluctance. Compared to the OLS estimates in the previous section, the LATE parameters derived from the MTE are noticeably larger. This result aligns with a context of heterogeneous effects, often attributed to the group of compliers (marginal students whose treatment status changes only in response to the instrument) who tend to exhibit higher individual treatment effects than the average population Card (2001).

The treatment parameters estimated by MTE is shown in Table 6, with Figure 8 illustrating the weights assigned to returns across each quantile of U_D along the MTE curve. It is worth noting that the LATE in Table 6 shows a slight deviation from the corresponding 2SLS estimates presented in the previous section. This difference arises because the LATE is calculated using the weights depicted in Figure 8.

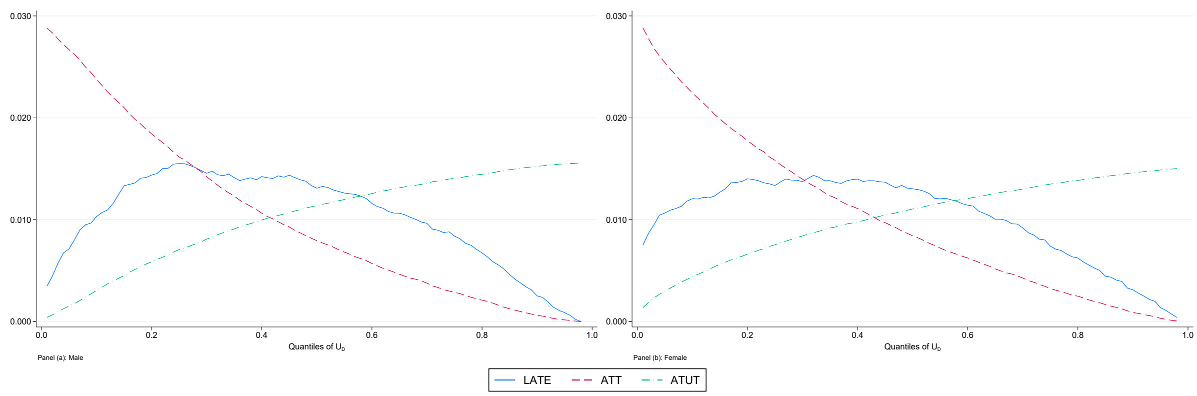

Figure 8. Weights for treatment parameters conditional on propensity scores.

6.3 Robustness checks

To examine the robustness of our results, we run a series of checks using different measurements for HE expansion, alternative specifications of MTE estimation, and addressing the potential impact of World Trade Organization (WTO) accession and working in State-Owned Enterprises (SOE). All robustness test results are presented in the Appendix B and consistent with our main findings.

(1) Alternative model specifications

We assess the robustness of our 2SLS estimates by exploring two alternative measures of HE expansion: firstly, adjusting the cut-off year for HE expansion and secondly, calculating

HE intensity using two different methods. Additionally, we adopt alternative specifications on MTE estimation, where we switch the link function to logit instead of probit and employ parametric polynomial estimation. Our findings remain unchanged across all alternative specifications.

(2) China's WTO accession shock

Most of the college graduates in 2001 might be enrolled during the HE expansion, which coincides with China's accession to the WTO. Although we include a Bartik-style index to control the changes from demand side, we conduct further analysis to address this concern. Similar to Che and Zhang (2018), we exclude the firms that have export trade. After sample exclusion, our results remain substantially unchanged.

(3) Premium of working in SOE

SOEs in China might offer higher wages to college graduates and encourage training (Cheng, 2022), creating a direct policy effect on wages independent of education's impact on productivity. This might violate the exclusion restriction. To mitigate this concern, we exclude the employees of SOE. The results of SOE excluded sample hardly changed.

6.4 Mechanisms

6.4.1 Effects on firms' different labour structure

The employer-employee linked data enables a deeper investigation into firm-level dynamics. Specifically, we analyse how different aspects of a firm's labour structure respond to education. This analysis focuses on three dimensions: workplace characteristics, occupational roles, and shifts in labour demand. Evidence from Portugal illustrates the relevance of these factors. Using linked employer-employee data, Portugal et al. (2024) find that approximately 30% of the return to schooling is explained by workplace characteristics, underscoring the role of firm composition in determining labour market returns. They also show that occupational roles account for 12% of the return to education, which is distinct from workplace-related effects. Similarly, Martins and Jin (2010), drawing on the same data source, report that returns to education differ across firms. These differences appear to reflect firm composition and potentially workforce characteristics, including hiring practices and employee turnover.

As regards the workplace dimension, we estimate labour returns for employees working in firms where the share of female employees exceeds the median within their respective two-digit industry. Results presented in Table 7 indicate a reverse selection on gains pattern. Individuals who are least likely to complete college tend to benefit the most from it, as shown by higher average treatment effects on the untreated (ATUT) for both male and female employees. This may suggest that female-majority workplaces provide more supportive environments or fewer gender-based constraints, allowing late entrants to HE to fully realize its returns.

Turning to the job role dimension, we estimate labour returns for employees working as managers or first-line workers.[31] Among female managers, the results indicate a reverse selection on gains pattern. Male managers, however, exhibit no statistically significant effect. This implies that women with lower predicted probabilities of attending college still benefit substantially when they assume leadership positions. These findings support the idea that college education can serve as a pathway for upward mobility among women. In contrast, male managers show no statistically significant returns, which may reflect a ceiling effect or limited variation in educational returns at higher occupational tiers among men. Among first-line workers, the pattern differs by gender. Male workers show positive selection on gains, meaning those more likely to attend college benefit more. This may be due to a stronger match between college-acquired skills and the demands of technical or supervisory roles in male-dominated sectors. Female first-line workers, on the other hand, exhibit no significant returns. This could reflect structural barriers that prevent women in lower-tier roles from converting education into earnings or a misalignment between job content and the skills developed through college.

Regarding labour demand changes, we examine the effect of working in firms with high recruitment intensity. A firm is classified as recruitment-intensive if its hiring rate exceeds the median within its two-digit industry. Recruitment intensity is measured by the ratio of new hires to the existing number of employees. The examination of labour demand dynamics in recruitment-intensive firms further supports the presence of gendered heterogeneity in returns. Female employees in these firms experience large and statistically significant treatment effects, along with reverse selection on gains. This suggests that women with a lower likelihood of pursuing HE benefit most in firms undergoing expansion and skill upgrading. These effects are particularly important in the context of SMEs in the manufacturing industry, where firms are often actively growing their workforce and seeking new skill sets. In comparison, returns for male employees in these settings are positive but smaller in magnitude and not statistically significant at conventional levels.

[31]The CEES data includes various job roles such as Manager, Technician or Designer, First-line Worker, Sales, and Other employment categories. However, the sample sizes for the Technician or Designer and Sales and Other groups are relatively small. This limitation causes the MTE estimation to fail in convergence and produce errors. Therefore, the analysis is restricted to the roles of Manager and First-line Worker.

Table 7. Treatment parameters of different labour structure.

	Parameters			
	ATE	ATT	ATUT	LATE
Workplace – female percentage above 2-digit industry median				
Male	0.639**	0.221	0.850*	0.259
	(0.286)	(0.272)	(0.460)	(0.196)
Female	0.614**	0.566***	0.633*	0.603***
	(0.254)	(0.180)	(0.365)	(0.142)
Job role - Manager				
Male	0.175	0.073	0.269	0.176
	(0.201)	(0.333)	(0.335)	(0.193)
Female	0.632***	0.510**	0.738**	0.577***
	(0.185)	(0.218)	(0.336)	(0.189)
Job role – First line worker				
Male	-0.071	0.417*	-0.170	0.149
	(0.255)	(0.252)	(0.295)	(0.211)
Female	0.342	0.216	0.360	0.370
	(0.225)	(0.295)	(0.259)	(0.225)
Changes in labour demand – Recruit intensive firm				
Male	0.462*	0.384	0.500	0.286
	(0.275)	(0.266)	(0.402)	(0.242)
Female	0.751***	0.745***	0.754**	0.708***
	(0.230)	(0.162)	(0.333)	(0.140)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

6.4.2 Effects on different birth cohorts

Returns to education may vary across different cohorts, especially considering the marginal effect of HE expansion could be decreasing. Walker and Zhu (2008) analyse the HE expansion in the UK by comparing the returns to education across different cohorts. Their findings indicate no change in returns for men but a significant increase in returns for women. Li et al. (2017) find that the HE expansion in China increased college premiums for older cohorts and decreased college premiums for younger cohorts.

We split individuals with college degree (i.e., treated group) into three distinct cohorts.[32] The early birth cohort includes those born in 1983 or earlier, who graduated around the time of China's WTO accession. The middle birth cohort comprises individuals born between 1984

[32] As additional evidence, we decompose the HE expansion IV by individual birth years rather than using broader cohort categories in the first-stage estimation. This method provides a more detailed view of how individuals' likelihood of treatment aligns with their actual exposure to the HE expansion. Figure C1 shows a clear increase in the estimated treatment effects for cohorts born immediately after the HE expansion cut-off. This rise is especially marked among female workers, indicating that the expansion had a greater influence on their educational attainment. These results align with the estimated treatment parameters, which suggest that younger cohorts, particularly women in the middle and late birth groups, gain more from expanded access to HE. This pattern may reflect both the structural expansion of HE opportunities and shifting social attitudes toward women's participation in HE and skilled employment.

and 1987, with graduation coinciding with the global financial crisis. Lastly, the late birth cohort consists of those born after 1987, who graduated around 2010. We estimate our baseline model with re-defined treated group, and Table 8 reports the results.

The ATT for the middle birth cohort is higher than that of the early birth cohorts for both male and female employees, the ATT for early male birth cohort is the highest and showing the selection into gain pattern. The results are mostly consistent with our main findings that college degree has more pronounced impacts on returns for female employees, as evidenced by the larger treatment parameters for females compared to males in the middle and late birth cohort.

With respect to selection patterns, the early cohort, especially males, shows evidence of positive selection on gains. The ATT exceeds the ATUT indicating that those who chose to attend college were also those who gained the most from it. Beginning with the middle cohort, the pattern changes. ATT falls below ATUT, particularly among females, indicating reverse selection on gains. This suggests that in later cohorts, individuals who attended college were not necessarily those who derived the greatest benefit. One possible explanation is a shift in the characteristics of marginal students following the expansion of HE. Despite this reverse selection on gains pattern, the middle-cohort females show a notably high ATT. This may reflect an increase in overall average returns, possibly driven by growing labour market demand for educated women or improvements in the efficiency of educational and occupational matching over time.

Table 8. Treatment parameters of different birth cohorts.

	Parameters			
	ATE	ATT	ATUT	LATE
Early birth cohort				
Male	0.309	0.848***	0.107	0.548**
	(0.403)	(0.286)	(0.563)	(0.220)
Female	0.524	0.643***	0.495	0.688**
	(0.504)	(0.209)	(0.633)	(0.306)
Middle birth cohort				
Male	0.643**	0.516**	0.700*	0.372**
	(0.265)	(0.228)	(0.389)	(0.157)
Female	1.086***	0.810***	1.186***	0.789***
	(0.285)	(0.184)	(0.385)	(0.128)
Late birth cohort				
Male	0.529***	0.537***	0.526*	0.307**
	(0.196)	(0.206)	(0.305)	(0.136)
Female	0.701***	0.622***	0.736***	0.707***
	(0.197)	(0.186)	(0.280)	(0.197)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

6.4.3 Effects on different degree and subject types

Balestra and Backes-Gellner (2017) analyse potential heterogeneity in returns from different educational paths in Switzerland, finding that academic education generally offers higher average returns. Kang et al. (2021) observe that HE expansion in China has lowered returns for graduates of ordinary universities and vocational colleges. However, exceptions are noted among graduates of key universities in non-STEM (science, technology, engineering, and math/medicine) and non-LEM (law, economics, and management) fields, where returns are not significantly reduced.

We restrict the treated group into 4 different groups: academic degree holders, vocational degree holders, STEM majors, and non-STEM majors. Treatment parameters for these subgroups, broken down by gender, are detailed in Table 9.

Analysis by degree type reveals clear heterogeneity in selection patterns and effect sizes across gender and educational track. Among female graduates from the academic track, we observe reverse selection on gains. This suggests that women who pursue academic degrees are not necessarily those who benefit most in terms of labour market outcomes. Such a pattern aligns with the possibility that non-economic factors, such as social norms or institutional incentives, influence women's educational choices.

In contrast, female vocational graduates display positive selection on gains. Those who choose vocational education also appear to derive the greatest benefits from it, indicating a stronger alignment between their abilities and the training provided. This pattern is supported by the trend shown in Figure C2, which demonstrates a steady rise in the share of female vocational degree holders. Their proportion consistently surpasses that of female academic degree holders over time. The combination of increasing participation and positive selection into vocational education among women points to a gradual improvement in the efficiency of educational matching, particularly within vocational pathways.

Turning to field of study, both male and female STEM graduates exhibit reverse selection on gains. However, non-STEM male graduates show evidence of positive selection on gains. Despite the reverse selection on gains, female STEM graduates experience the largest average treatment effects (ATE). This indicates that STEM degrees yield high labour market returns for women, even though those who pursue them may not be the most likely to benefit. One explanation may be the growing demand for technically skilled women in STEM fields or selection processes that lead to under-representation of more capable women in these majors, despite their strong performance when they do participate.

Taken together, the results underscore that the returns to college education vary by gender, degree type, and field of study. The case of female vocational graduates is particularly notable. It combines high returns with positive selection, suggesting that vocational pathways may serve as an effective channel for gender-focused human capital policies.

Table 9. Treatment parameters of different degree and subject types.

	Parameters			
	ATE	ATT	ATUT	LATE
Academic track				
Male	0.578*	0.766***	0.531	0.548***
	(0.323)	(0.174)	(0.408)	(0.118)
Female	0.420	-1.036***	0.725**	-0.866***
	(0.268)	(0.164)	(0.319)	(0.141)
Vocational track				
Male	0.621	0.448	0.678	0.379
	(4.545)	(0.335)	(6.080)	(0.720)
Female	0.656	0.692***	0.643	0.587*
	(2.918)	(0.252)	(3.856)	(0.320)
Major in STEM				
Male	1.104***	0.604**	1.246***	0.462***
	(0.338)	(0.246)	(0.434)	(0.173)
Female	1.248***	0.431**	1.349***	0.513***
	(0.374)	(0.219)	(0.427)	(0.144)
Major in non-STEM				
Male	0.323	0.552***	0.262	0.384
	(1.003)	(0.205)	(1.262)	(0.302)
Female	0.745***	0.634***	0.786***	0.647***
	(0.224)	(0.152)	(0.309)	(0.114)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

6.4.4 Non-monetary returns

We further investigate the potential mechanisms through which college education impact on labour market outcomes. As suggested by Kamhöfer et al. (2019), there are three potential channels through which education impacts long-term health and cognitive abilities: a direct influence from education; elevated health capital and cognitive reserve accumulated during college mitigating the age-associated decline in health and abilities, as articulated in the "cognitive reserve hypothesis" (Meng and D'Arcy, 2012); jobs that are less detrimental to health and more cognitively demanding (Stern, 2012).

However, the cross-section nature of the CEES data prevent us from observing changes in one channel that are independent of other channels, nor from analysing how these effects causally relate to enhanced skills or improved health, as demonstrated by Heckman et al. (2013). The subsequent analysis concentrates on the potential channels of job activities and health behaviours. The specification of the models remains unchanged from our baseline model but substitutes the outcome variables with indicators of the mechanisms of interest. For the sake of brevity, our discussion concentrates on the treatment parameters relevant to these potential mechanisms.

(1) Cognitive skills

Individuals possessing a college degree may intellectually stimulate their minds when they engage in more cognitively demanding activities, such as sophisticated jobs, an effect known as the *use-it-or-lose-it* hypothesis (Rohwedder and Willis, 2010). We use information on employees' job activities to explore whether a more cognitively challenging occupation could serve as a potential mechanism, as proposed by Fisher et al. (2014). We examine three outcome variables for cognitive abilities, each a binary variable assigned a value of 1 when the job requires the use of advanced mathematics (e.g., calculus), document reading (exceeding one page), or foreign language (mainly English).

The results reported in Table 10 indicate a significant and substantial effect of college education on the likelihood of engaging in document reading tasks, particularly among female employees with a college degree. This aligns with expectations, as analytical and professional occupations often require extensive processing of written information.

Regarding advanced mathematics, the findings reveal evidence of positive selection on gains. The ATT exceeds the ATUT, especially among male employees. This suggests that individuals more likely to obtain a college degree are also more likely to enter math-intensive roles, potentially due to a pre-existing comparative advantage or personal preferences.

By contrast, college education does not appear to influence foreign language use for either gender. This differs from the other two cognitive indicators. A possible explanation is that language-intensive roles, particularly those involving English, are structurally concentrated in specific industries, urban areas, or multinational firms. In such contexts, college education may be necessary but insufficient for access. Other factors, including academic major, geographic location, and firm characteristics, may play a more decisive role. Furthermore, limited use of English across the observed labour markets could weaken any aggregate-level effect.

In sum, the findings suggest that cognitively demanding occupations, particularly those involving reading and quantitative skills, contribute to the long-term economic returns to HE. Nonetheless, the development of cognitive skills in college may also affect occupational sorting. These results should be interpreted as suggestive rather than conclusive evidence of a causal mechanism.

(2) Health

Regarding the health mechanisms, we investigate through two distinct avenues: job-related effects and health behavior effects. The CEES data capture levels of physically demanding activities in respondents' jobs, such as standing, carrying loads, operating machines, driving vehicles, and performing handicrafts or repairs. We define a binary indicator, coded as 1 when the respondent reports engagement in any of the aforementioned activities for more than half the workday, and 0 otherwise. The estimated effects presented in Table 10 suggest that possessing a college degree significantly decreases the likelihood of obtaining positions that entail more physically demanding activities for female employees.

In addition to occupational physical activities, health behaviour may be viewed as a crucial dimension influenced by education (Cutler and Lleras-Muney, 2010). We utilize a dichotomous variable for obesity, assigned a value of 1 when the body mass index (BMI) exceeds 28, and 0 otherwise.[33] However, the treatment parameters in Table 10 demonstrate that no significant effects for male and female employees.

Health is a multifaceted measure, the potential mechanisms available are naturally unable to fully account for the health returns attributable to college education. Notwithstanding, the findings lend support on the mediating effects of college education via health behaviour.

[33] The calculation of BMI is given by $\frac{Weight \quad \text{(in kg)}}{Height^2 \quad \text{(in m)}}$). Given that our sample comprises Chinese individuals, the appropriate BMI threshold is set at 28, as recommended by the WHO expert consultation (2004). This is corroborated by Li et al. (2023), who assert that Asian populations should adopt lower BMI cutoffs for obesity, rather than the standard threshold of 30.

Table 10. Treatment parameters of different degree and subject types.

	Sample mean	Parameters			
		ATE	ATT	ATUT	LATE
Usage of advanced math (e.g., calculus)					
Male	0.172	0.240	0.394***	0.158	0.235***
		(0.169)	(0.141)	(0.272)	(0.086)
Female	0.073	0.005	0.152*	-0.065	0.064
		(0.128)	(0.089)	(0.192)	(0.070)
Need to read documents (more than one page)					
Male	0.665	0.712***	0.793***	0.670***	0.635***
		(0.158)	(0.196)	(0.259)	(0.108)
Female	0.602	0.476	1.097***	0.179	0.711**
		(0.303)	(0.531)	(0.287)	(0.332)
Foreign language (English)					
Male	0.581	-0.094	0.006	-0.145	-0.057
		(0.146)	(0.121)	(0.236)	(0.085)
Female	0.603	-0.161	0.105	-0.288	-0.021
		(0.121)	(0.101)	(0.185)	(0.076)
Physically demanding activities (over half day)					
Male	0.510	-0.165	0.117	-0.315	0.062
		(0.158)	(0.174)	(0.254)	(0.107)
Female	0.527	-0.279*	-0.332*	-0.256	-0.261**
		(0.168)	(0.179)	(0.263)	(0.110)
Obesity (BMI≥28)					
Male	0.060	0.085	0.131	0.061	0.066
		(0.111)	(0.097)	(0.180)	(0.062)
Female	0.020	0.038	0.018	0.048	0.001
		(0.047)	(0.064)	(0.071)	(0.035)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

7 Conclusion

We estimate the returns to college education employing the Marginal Treatment Effect (MTE) framework. Our analysis is specifically applied to employees across China's manufacturing sector which is dominated by small and medium-sized enterprises (SMEs), utilizing unique firm-individual level data from the China Employer-Employee Survey (CEES). Employing instruments based on Higher Education (HE) expansion to exploit exogenous variation in college attendance opportunities, we further examine the marginal returns to college education.

The main findings of our study are summarized as follows: The HE expansion does not significantly affect male manufacturing industry employees' college enrolment, but it does notably increase female enrolment by 23.7%. The study reports evidence of significant returns to college education in terms of wages. Furthermore, the MTE estimation shows heterogeneity: individuals who did not attend college would have experienced higher returns compared to college graduates, suggesting a *reverse selection on gains* into HE according to potential benefits. This implies that the benefit of college education is not only significant on average but also particularly large for the marginal student who narrowly missed out on college education, possibly due to credit constraints and disadvantaged family background.

The analysis of firm-level labour structures shows that returns to college education differ substantially across workplace settings, occupational roles, and labour demand conditions. The marginal effects for treated individuals decline across successive birth cohorts, as HE participation rate increases. Moreover, the selection pattern varies by degree type: male academic degree holders and female vocational degree holders exhibit positive selection on gains, while female academic degree holders show reverse selection on gains. Additionally, STEM degree holders of both genders experience larger average treatment effects compared to non-STEM degree holders, likely due to the better fit of their technical skills in the manufacturing industry.

We further explore the potential mechanisms through which college education influences labour market outcomes. The evidence indicates that observed cognitive abilities and health behaviours are crucial mediators: individuals with a college degree are more likely to secure employment in positions requiring advanced mathematics, foreign languages, and reading comprehension skills; additionally, a college education reduces female employees' the likelihood of engagement in occupations that demand physically demanding tasks for more than half of the working day.

In summary, college education in China serves as an ascending pathway for individuals from less advantaged backgrounds in the manufacturing sector. Consequently, the HE expansion increases the likelihood of college enrolment, benefiting the marginal student who would otherwise not attend college without this expansion and enhances their returns, thereby reducing inequality to some extent. Furthermore, college-educated employees in the manufacturing industry are more likely to secure positions requiring advanced skills and involving less physically demanding tasks.

Limitations of this paper are worth highlighting. First, restricted by the survey design, we are unable to empirically generalize the findings to other industries. Second, due to the absence of *hukou* information at youth, the analysis cannot be stratified by *hukou* status. These are left for future work.

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Appendix to "Returns to college education of Chinese manufacturing employees: Who benefits more?"

Appendix A More on data and baseline results

A.1 Description of the data

The CEES adopted a two-stage probability proportional to size (PPS) random sampling approach. Initially, around 20 county-level districts are randomly selected within each province. From each district, 50 firms are chosen as the sample group. In the next step, between 6 and 10 employees are sampled from each firm. This employee sample included approximately 30% senior and middle managers, with the remaining 70% consisting of regular employees.

The sample in our study comprises both male and female employees within the manufacturing industry, born in September 1970 or later, and are aged 25 or above in surveyed year. We restricted the birth cohort for several reasons. The first restriction to the oldest birth cohort, September 1970, aims to exclude individuals aged 48 or above in 2018. Primarily, due to China's liberal state retirement age and the prevalent incidence of early retirement, particularly among blue-collar female workers, the excluded group is likely to experience selective attrition. Secondly, the Cultural Revolution, which occurred from 1966 to 1976, would have significantly disrupted the education of cohorts born before 1970. Thirdly, the introduction of the 9-year compulsory education law in 1986 likely resulted in higher rates of completion of lower secondary education among post-1970 cohorts. Given the increase in college premium for workers aged 25 or above following the expansion of higher education (Li et al., 2017), we imposed the second limitation on the youngest birth cohort to be aged 25 or above. Finally, individuals with education below the lower secondary level are excluded from the analysis. They represent a small proportion of the overall sample, accounting for less than 5%. Moreover, they are classified as never-takers. Figure A1 shows the educational distribution in the sample.

We report the measurement of variables used in the empirical analysis below.

(1) Outcome variable

The (log) net hourly income of respondent is the main outcome of interest in this study. For this outcome variable, it is deflated using the Consumer Price Index (CPI) deflator, which corresponds to the surveyed provinces. To mitigate measurement error in earnings, we trim observations below the 1^{st} percentile and eliminate outliers with abnormally low values. The full distribution of wages is shown as Figure A2.

(2) Treatment variable

The treatment variable is binary, assigned a value of 1 if the respondent holds a college degree. The treated group includes individuals with a vocational college degree or higher. Figure A3 shows the trend of college degree holders in the sample. The proportion increases significantly for those born after 1980, aligning with China's higher education expansion. This rise is more pronounced among females.

(3) Instrumental variables

The MTE estimation requires valid instruments that are relevant for college enrolment decisions, satisfy the exclusion restriction (no direct effect on outcome), and are independent of unobserved characteristics affecting both treatment and outcome. In this study, instrumental variables (IVs) are employed from both external and internal perspectives.

The first two IVs based on an external perspective are the 1999 Higher Education (HE) expansion in 1999, an exogenous shock that influenced intentions to pursue college education (Liu and Zheng, 2019; Huang et al., 2022), and the provincial unemployment rate at age 18 (Arkes, 2010; Carneiro et al., 2011; Kyui, 2016).

The HE expansion primarily benefits marginal students (compliers) who could enroll only after its implementation. The IV is constructed by interacting a dummy variable for experiencing the HE expansion with the intensity of expansion in the respondent's province at age 16, analogous to a Difference-in-Differences (DiD) estimator. Census data shows most 18-year-olds remain in upper secondary school, with higher proportions still in senior high at 19 (Wu and Zhao, 2010). Thus, individuals born in or after September 1980 are defined as experiencing the HE expansion. The expansion's intensity is measured by the ratio of college student number and senior high school student in the year 1998, one year before the HE expansion (Wang et al., 2022):

$$ExpIntensity_p^I = \frac{U_{p,1998}}{H_{p,1998}}$$

where $U_{p,1998}$ is the stock of HEI student number and $H_{p,1998}$ is the stock of senior high school student in province p in the pre-expansion base year 1998.

The provincial unemployment rate serves as a proxy for the opportunity cost of attending college. We use the unemployment rate at age 18, one year before individuals take the college entrance examination (*gaokao*) in our specification. Due to limited data on *gaokao* locations, we assume individuals reside in the same province as recorded at age 16. A consistency check shows that 89.26% of respondents reside in the same province during the survey year as they did at age 16.

The final two IVs, based on an internal perspective, are the father's and mother's years of education. Parental education influences respondents' education through preferences for college or borrowing constraints (Taber, 2001). While these exclusion restrictions may be imperfect, they are expected to introduce less bias than ordinary least squares (OLS).

Some studies have used the spouse's education as an instrument (Trostel et al., 2002; Chen and Hamori, 2009; Liu and Zheng, 2019). Spouse's education correlates with academic achievement but is generally unlinked to wage rates due to the assortative nature of marriage, where couples often share similar educational backgrounds and interests (Pencavel, 1998). However, it is these shared interests and preferences that render spouse's education endogenous. Additionally, spouses typically make joint decisions about family income, meaning spouse's education can directly affect labour supply.

(4) Control variables

We employ general demographic variables as controls, like age and age squared. Considering China's extensive geographic diversity and varying stages of economic development, it is imperative to account for the inequality in educational resources. We take into account three dichotomous variables: whether the respondent resided in a rural area at the age of 16, if the respondent is a local inhabitant (born with the *hukou* in the current city and has continued residing there since birth), and whether the respondent possesses a rural *hukou*.

Considering the shock to the supply-side of the labour market induced by the HE expansion, we construct a Bartik-style index to take the demand-side effect into account. This index is formulated in accordance with the industry structure of 2014, in alignment with methodologies outlined in the literature (Acemoglu et al., 2016; Diamond, 2016; Ou and Zhao, 2022) and is computed as follows:

$$LD_{c,t} = \sum_{I=1}^{19} \frac{l_{I,c,2014}}{L_{c,2014}} \times (\ln l_{I,c,t} - \ln l_{I,c,2014}), \quad t \in \{2015, 2016, 2018\}$$

where $l_{I,c}$ is the number of employed (total labour employed in industry I in city c in 2014). L_c is the total labour employed in city c in 2014.

The firm-individual level data enables the inclusion of more employer-side characteristics in the model. Variables include firm type, such as employment in a State-Owned Enterprise (SOE), High-Tech Enterprise status, and location in an economic development zone. On the firm scale, we account for firm age, size (measured by the number of employees), and capital intensity. A firm is classified as capital-intensive if its total capital per employee exceeds the median for its 2-digit industry group.

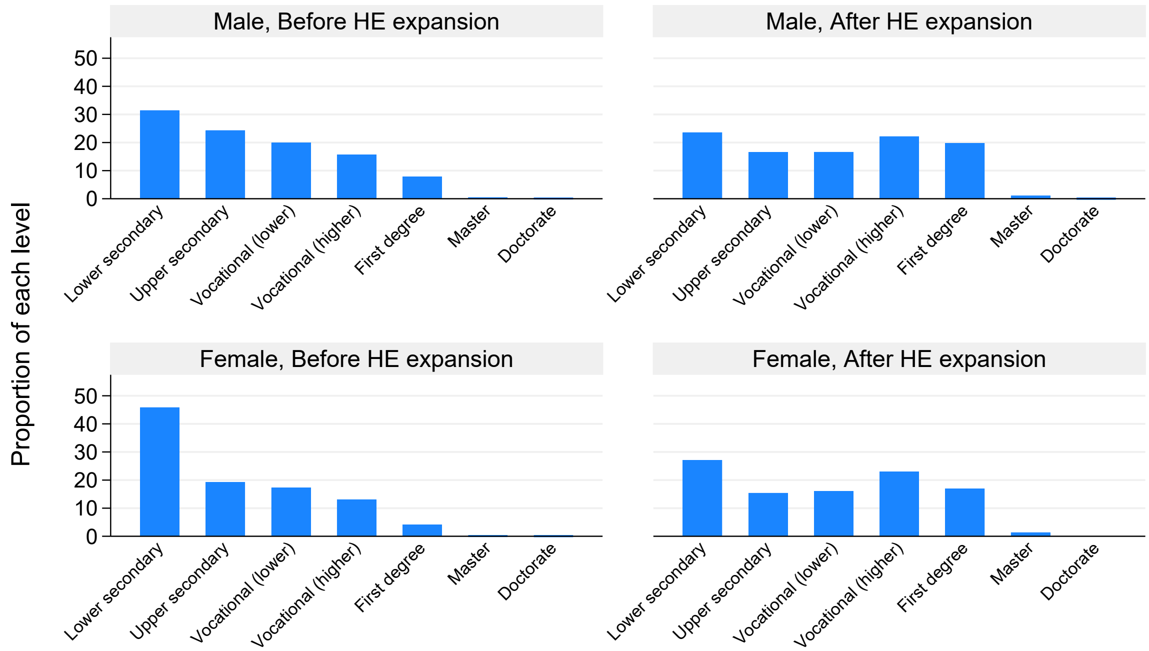

Figure A1. Education levels by gender and HE expansion period.

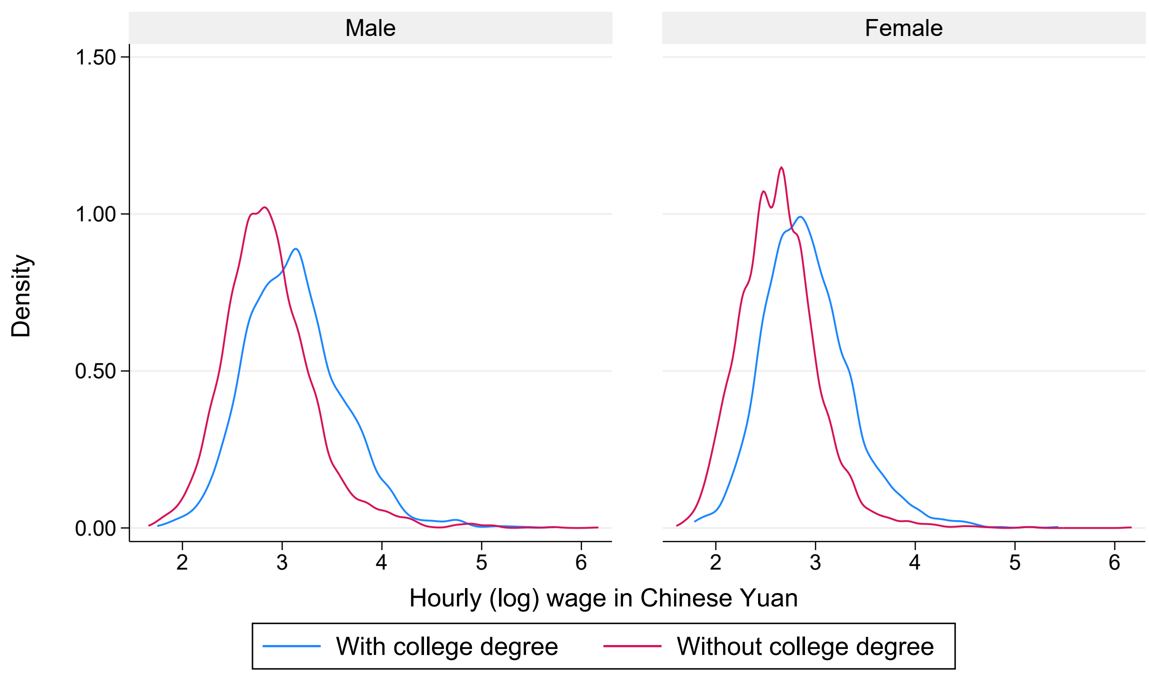

Figure A2. Distribution of dependent variable by college degree.

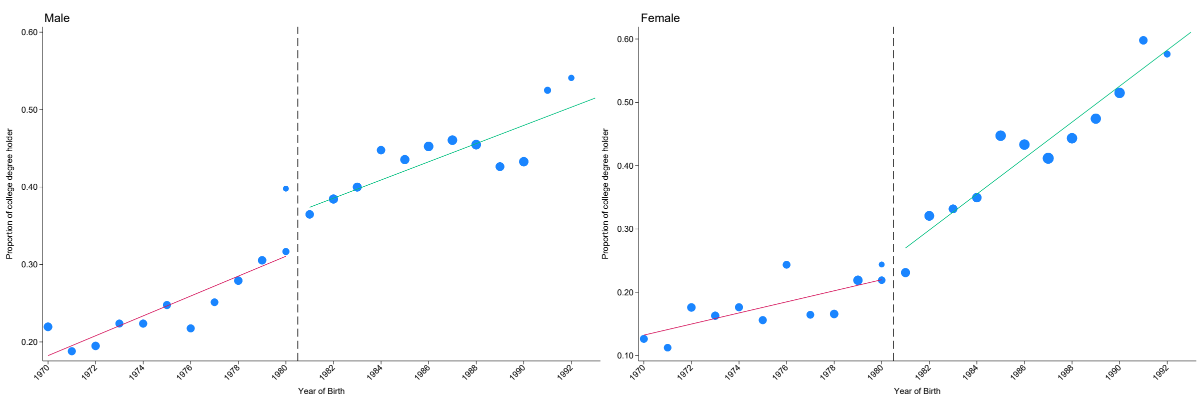

Figure A3. Proportion of respondents with college degree, by year of birth.

Notes: Samples aged from 25 to 48. Marker size proportional to number of observations.

A.2 Supplementary information of baseline results

Table A1. 2SLS results of monthly income and monthly working hours.

	Male		Female	
	(1) Monthly income	(2) Monthly working hours	(3) Monthly income	(4) Monthly working hours
College degree	0.262***	-0.110**	0.448***	-0.185***
	(0.071)	(0.049)	(0.072)	(0.046)
Controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓
Observations	5641	5641	5109	5109
Clusters	400	400	368	368
First-stage F-stat.	48.607	48.607	36.213	36.213

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

Table A2. Results of estimated treatment parameters for alternative outcomes.

	Parameters			
	ATE	ATT	ATUT	LATE
Monthly income				
Male	0.415***	0.471***	0.387*	0.284***
	(0.151)	(0.139)	(0.232)	(0.101)
Female	0.616***	0.297	0.769***	0.439*
	(0.159)	(0.191)	(0.225)	(0.228)
Monthly working hours				
Male	-0.180*	0.077	-0.316**	-0.089
	(0.093)	(0.106)	(0.151)	(0.058)
Female	-0.130	-0.257*	-0.069	-0.177***
	(0.105)	(0.154)	(0.125)	(0.054)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

Table A3. 2SLS results of local and migrant employees.

	Male		Female	
	(1)	(2)	(3)	(4)
	Local employees	Migrant employees	Local employees	Migrant employees
College degree	0.330***	0.425***	0.460***	0.724***
	(0.098)	(0.137)	(0.094)	(0.130)
Controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓
Observations	2610	3028	2731	2371
Clusters	119	400	119	366
First-stage F-stat.	28.606	17.604	22.850	17.370

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

Table A4. Results of estimated treatment parameters for local and migrant employees.

	Parameters			
	ATE	ATT	ATUT	LATE
Local employees				
Male	0.671***	0.323	0.847***	0.334**
	(0.214)	(0.204)	(0.322)	(0.137)
Female	0.389**	0.433***	0.367	0.423***
	(0.176)	(0.155)	(0.267)	(0.125)
Migrant employees				
Male	0.610***	0.697**	0.560	0.471**
	(0.233)	(0.278)	(0.381)	(0.199)
Female	1.109***	0.348	1.468***	0.729
	(0.334)	(0.298)	(0.429)	(0.643)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

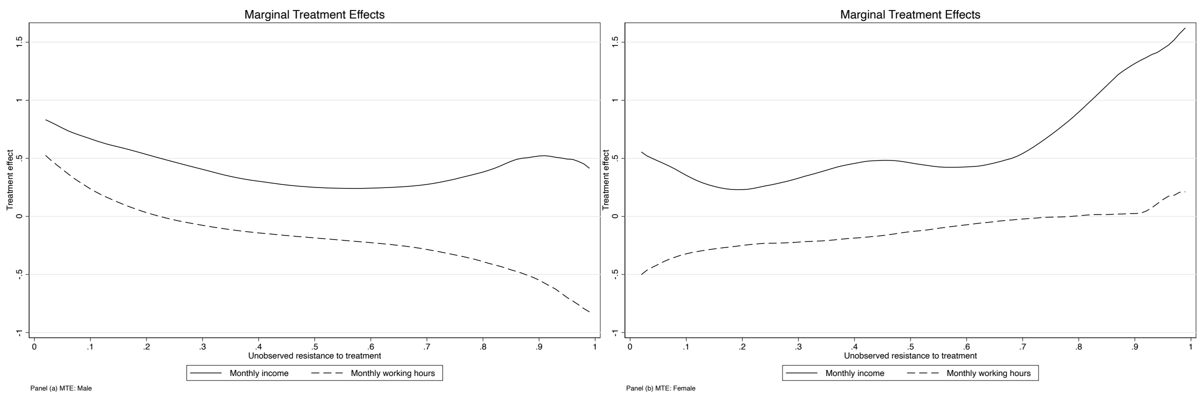

Figure A4. MTE estimation with switching the outcomes by gender.

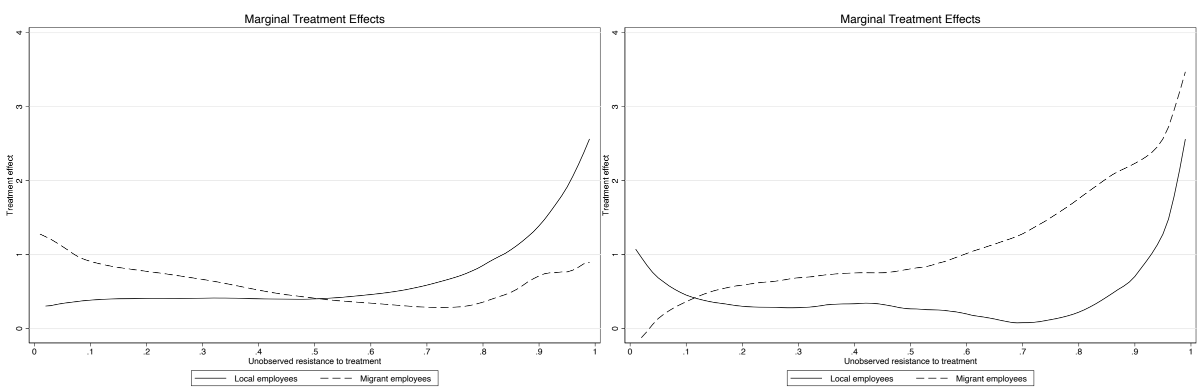

Figure A5. Estimated marginal returns to college education by gender and migrant status.

Appendix B More on robustness checks

B.1 Checks on alternative model specifications

B.1.1 Alternative measurement of Higher Education expansion

The alternative measurements of HE expansion is characterized by ambiguity from two distinct perspectives. Firstly, our dataset does not precisely ascertain the specific year in which participants commenced their college education; instead, we infer this from their year of birth. As elucidated in section 5, we designate September 1980 as the birth cutoff for experiencing HE expansion. In an alternative analysis, we adjust this birth cutoff to September 1979 (corresponding to respondents aged 20 in 1999) and September 1981 (corresponding to respondents aged 18 in 1999). The findings, delineated in Table B1, are in alignment with our main results. Secondly, the measurement of HE expansion is not fixed, we adopt another expansion's intensity, which is measured by the average annual growth in university slots in province p (1998–2001), divided by the number of senior high school graduates in 1999 (Ou and Hou, 2019; Ou and Zhao, 2022):

$$ExpIntensity_p^{II} = \frac{AdmNum_{p,avg(1998-2001)}}{GradNum_{p,1999}}$$

where $AdmNum_{p,avg(1998-2001)}$ is the increase in annual average Higher Education Institution (HEI) admissions from 1998 to 2001 in province p, $GradNum_1 999$ is the number of high school graduates in that province in 1999.

And the alternative measurement following Wang et al. (2022):

$$ExpIntensity_p^{III} = \sum_{t=1999}^{2012} \left(\frac{U_{p,t^+}}{P_{p,t^+}} - \frac{U_{p,1998}}{P_{p,1998}} \right)$$

where $U_{p,t}$ is the stock of HEI student number and $P_{p,t}$ is the population size in province p in the year t.

The indicators of HE expansion intensity in are as follows: the *static* corresponds to $ExpIntensity_p^I$, *static average* corresponds to the $ExpIntensity_p^{II}$, and *dynamic* corresponds to the $ExpIntensity_p^{III}$. As evidenced in Table B2, our results demonstrate robustness, even when altering the HE expansion intensity indicators.

Table B1. Robustness checks with altering HE expansion cut-off year.

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sep. 1980	Sep. 1981	Sep. 1979	Sep. 1980	Sep. 1981	Sep. 1979
College degree	0.373***	0.360***	0.357***	0.633***	0.623***	0.637***
	(0.084)	(0.082)	(0.082)	(0.087)	(0.087)	(0.087)
Controls	✓	✓	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓	✓	✓
Observations	5641	5641	5641	5109	5109	5109
Clusters	400	400	400	368	368	368
First-stage F-stat.	48.607	49.411	51.124	36.213	35.509	37.218

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

Table B2. Robustness checks with different HE intensity measures.

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
	Static	Static Average	Dynamic	Static	Static Average	Dynamic
College degree	0.373***	0.372***	0.372***	0.633***	0.638***	0.641***
	(0.084)	(0.085)	(0.085)	(0.087)	(0.088)	(0.088)
Controls	✓	✓	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓	✓	✓
Observations	5641	5641	5641	5109	5109	5109
Clusters	400	400	400	368	368	368
First-stage F-stat.	48.607	48.104	48.140	36.213	36.264	37.042

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

B.1.2 Alternative specifications of MTE estimation

To verify the robustness of the MTE estimation, we validate it through two approaches. Initially, we alter the link function in the first stage from a probit to a logit model. As depicted in Figure B1, the trend of MTE curves remains stable despite the change in the link function. Secondly, we conduct functional form checks using parametric polynomial estimation and contrast these with semiparametric estimation (Cornelissen et al., 2018). We implement second- and fourth-order polynomial estimations, as illustrated in Figure B2, which demonstrate that the MTE curves exhibit similar trends, thereby confirming the robustness of our results.

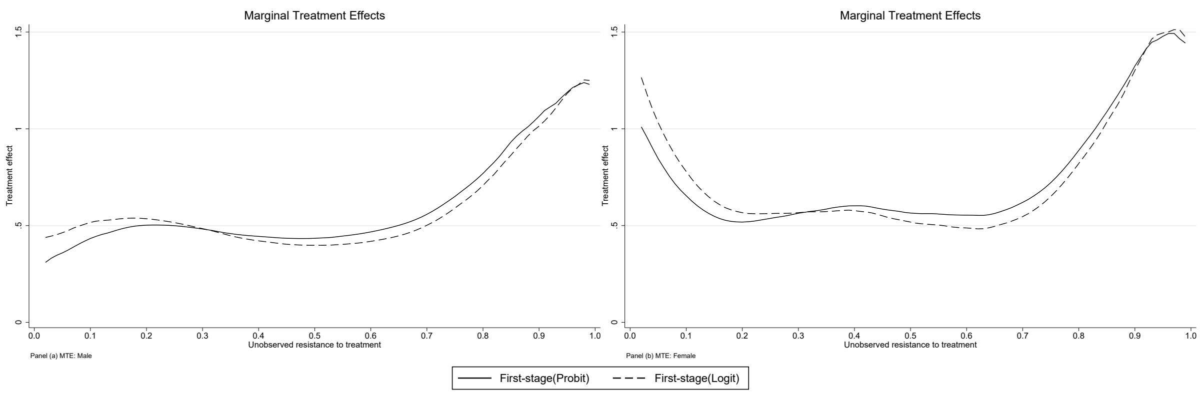

Figure B1. Switching the link function of propensity score.
Notes: The solid MTE curve employed probit as link function is the one in our baseline model.

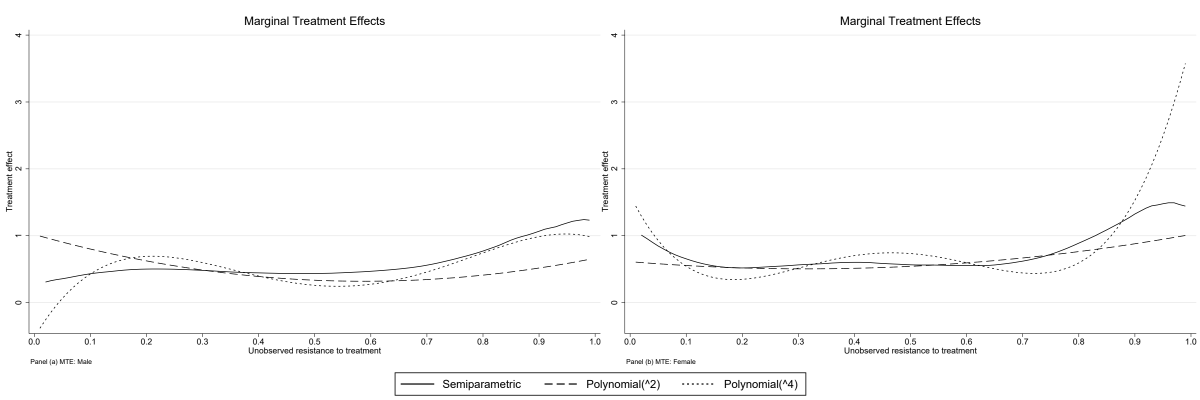

Figure B2. Functional form robustness checks.
Notes: The solid MTE curve employed semiparametric estimation is the one in our baseline model.

B.2 WTO accession

The surge in college graduates from 2001 coincides with China's accession to the WTO. The large-scale expansion of college graduates could trigger general equilibrium effects, affecting overall wage structures. The influx of graduates may have compressed wages for degree holders or displaced non-degree workers. While we include a Bartik-style index to control the changes from demand side in our baseline model, we conduct further analysis to address this concern.

Export-intensive Chinese firms have particularly benefited from WTO accession, as reduced trade barriers facilitated greater access to international markets. To ensure our findings are not driven by the potential general equilibrium effects, we estimate the baseline model excluding firms that have export trade, similar to Che and Zhang (2018). 45.64% of the sample remain after exclusion. Results of 2SLS estimation and treatment parameters of MTE estimation are reported in Table B3 and Table B5, respectively. The results consistent with our baseline model results. Figure B3 shows the MTE curves that estimated with exclusion of firms that have export trade, has a similar trend as Figure 7.

B.3 SOE premium

From the previous literature, it is evidenced that SOEs have higher labour and total factor productivity compared to private enterprises due to the enhanced human capital of their employees (Cheng et al., 2021). In China, SOEs may provide higher wages to college graduates and actively promote training initiatives (Cheng, 2022). This creates a direct policy influence on wages that operates independently of educational effects on productivity, potentially violating the exclusion restriction.

To address this issue, the baseline model is estimated without including employees of SOEs. Given that the sample primarily comprises SMEs, only 9.07% of the data, representing SOEs, is excluded. The 2SLS estimation results and treatment parameters from the MTE estimation are presented in Table B4 and Table B6, respectively. These findings are consistent with the baseline model results. Furthermore, Figure B4 illustrates MTE curves estimated after excluding SOEs, which closely follow the trend observed in Figure 7.

Table B3. 2SLS results excluding firms that have export trade.

	Male		Female	
	(1)	(2)	(3)	(4)
	First-stage	Second-stage	First-stage	Second-stage
College degree		0.225**		0.705***
		(0.108)		(0.159)
Post-expansion cohort × Expansion intensity	-0.001		0.212	
	(0.199)		(0.145)	
Provincial unemployment rate at age 18	0.048**		0.021	
	(0.020)		(0.025)	
Father's years of education	0.018***		0.013***	
	(0.003)		(0.003)	
Mother's years of education	0.010***		0.008***	
	(0.003)		(0.003)	
Controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓
Observations	2586	2586	2318	2318
Clusters	329	329	297	297
First-stage F-stat.		28.731		15.749

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

Table B4. 2SLS excluding SOEs.

	Male		Female	
	(1)	(2)	(3)	(4)
	First-stage	Second-stage	First-stage	Second-stage
College degree		0.406***		0.649***
		(0.089)		(0.087)
Post-expansion cohort × Expansion intensity	0.110		0.233	
	(0.178)		(0.137)	
Provincial unemployment rate at age 18	0.046***		0.035*	
	(0.014)		(0.018)	
Father's years of education	0.015***		0.015***	
	(0.002)		(0.002)	
Mother's years of education	0.010***		0.008***	
	(0.002)		(0.002)	
Controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Residence province at age 16 FE	✓	✓	✓	✓
City FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Surveyed year FE	✓	✓	✓	✓
Observations	5136	5136	4639	4639
Clusters	392	392	364	364
First-stage F-stat.		40.673		33.060

Notes: Standard errors in parentheses are clustered at Birth year - Residence province at age 16 level. * p <0.10, ** p <0.05, *** p <0.01. Singletons are automatically excluded to prevent the overstatement of statistical significance, which could lead to incorrect inferences.

Table B5. Estimated treatment parameters excluding firms that have export trade.

	(1) Male	(2) Female
ATE	0.200	1.170***
	(0.216)	(0.284)
ATT	0.468*	0.418
	(0.264)	(0.305)
ATUT	0.062	1.513***
	(0.352)	(0.382)
LATE	0.245*	0.769
	(0.144)	(0.879)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

Table B6. Estimated treatment parameters excluding SOEs.

	(1) Male	(2) Female
ATE	0.643***	0.775***
	(0.178)	(0.189)
ATT	0.466**	0.509**
	(0.198)	(0.219)
ATUT	0.737***	0.905***
	(0.279)	(0.260)
LATE	0.419***	0.625*
	(0.115)	(0.372)

Notes: Bootstrapped standard errors in parentheses are clustered at Birth year - Residence province at age 16 level (250 reps.). * p <0.10, ** p <0.05, *** p <0.01.

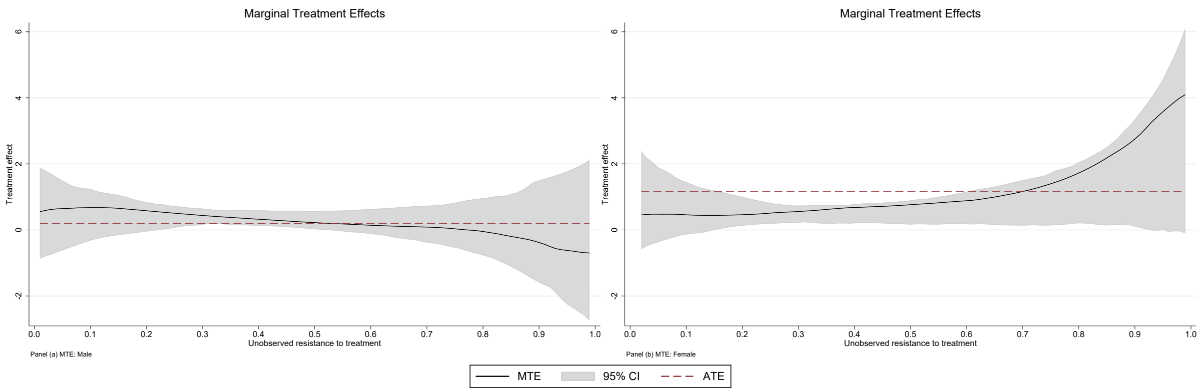

Figure B3. MTE estimated with excluding firms that have export trade.

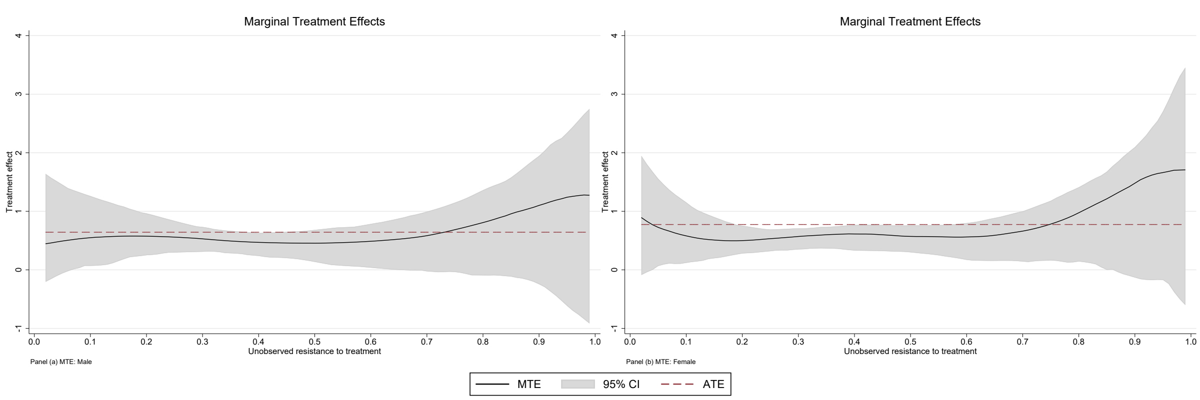

Figure B4. MTE estimated with excluding SOEs.

Appendix C More on mechanisms

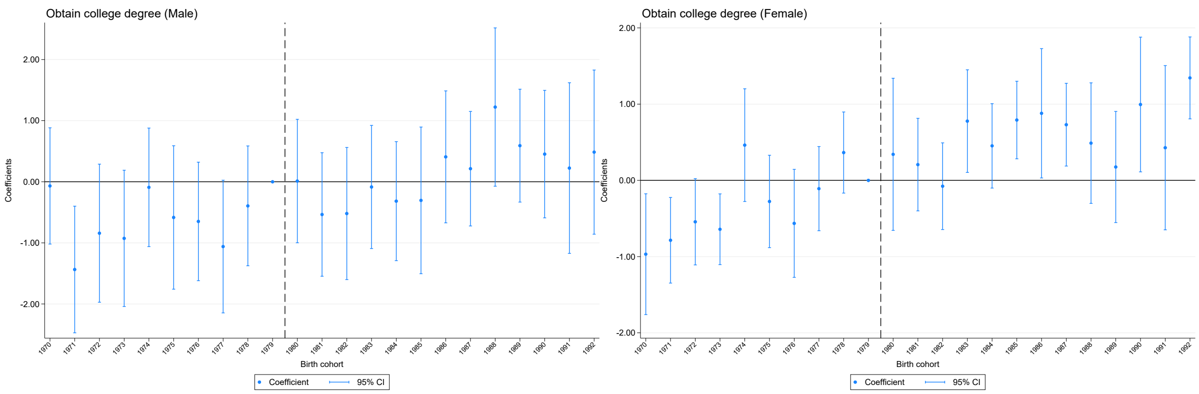

Figure C1. Event-study style graph for HE expansion IV in the first-stage.
Notes: This figure illustrates the estimation in the first stage. The higher education expansion IV is decomposed from the 1980 birth year dummy to each year dummy, analogous to a series of event-study dummies. Overall, the effects of obtaining a college degree are increasing after the 1980 cohort and more pronounced in the female group.

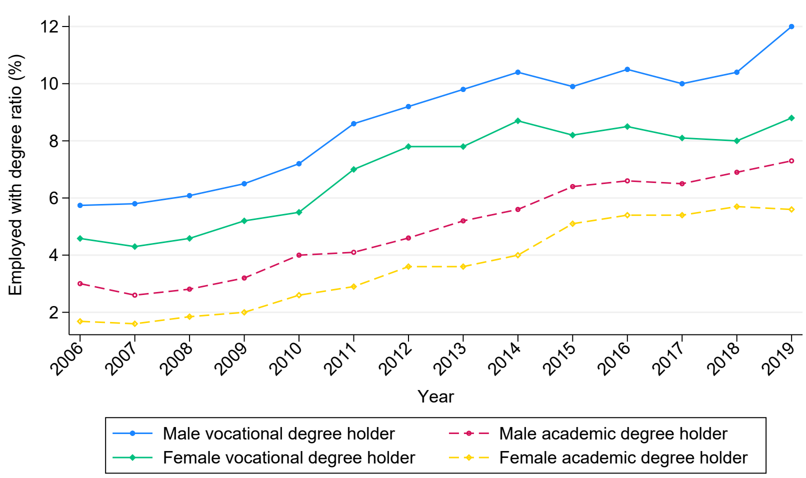

Figure C2. Trend of in college degree holders the manufacturing industry, by gender.
Notes: This figure shows the percentage of employees in China's manufacturing industry who hold either an academic or vocational degree, categorized by gender. Vocational degree holders are represented with solid lines, while academic degree holders are indicated with dashed lines. The data reveal a greater proportion of vocational degree holders compared to academic degree holders. Male employees consistently exhibit a higher share of degree attainment than female employees.