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Beyond Mincer: Revisiting the Returns to Education in Thailand

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Abstract

This paper investigates the private and social return to higher education in Thailand. First, we analyze the individual return to higher education by using Socio-Economic Survey (SES) panel data and employing three treatment effects including propensity score matching (PSM), endogenous switching (ES) regression and endogenous binary treatment using probit two stage least square (Probit-2SLS) model. Then, we estimate the social return to higher education using Labor Force Survey (LFS). We identify the social return by estimating the effect of share of higher educated workers living in each province on individual wage and provincial wage gap using instrumental variable (IV) and pseudo panel approach at provincial level accounting for cohort effects. The results show that obtaining higher education increases wage by around 0.98 to 1.78 log points, and the increase in the provincial share of higher education raises individual's wage and reduce the wage inequality among different provinces. The findings suggest that investment in higher education will improve the income distribution as it contributes more to workers with less education and in lower wage occupations.

JEL Classification: I20; J24; J30

Keywords: Private returns to education; Social returns to education; Endogenous switching; Pseudo-panel approach, Thailand

1. Introduction

The return of higher education has been heavily investigated for decades due to the significant impact on the economic growth and human well-being (e.g. Schultz, 1960; Becker, 1964, 1994; Card, 2001; Horie and Iwasaki, 2023). It has been one of the most well-established empirical findings in economics that higher educated people obtain higher earnings in the labor market (e.g. Rosen, 1977; Card, 1999; Psacharopoulos, 1985; Kasnauskiene et al., 2024). Meanwhile, the economic value of higher education includes not only the private benefits but also social benefits (e.g. Psacharopoulos, 1981; Psacharopoulos and Patrinos, 2004; McMahon, 2009; Psacharopoulos, 2024). The benefits of higher education are not only towards educated individuals but also local economies (e.g. Acemoglu, 1996, 1998; Liu and Yang, 2019; Smith et al., 2025).

In recent decades, studies in developed countries have drawn more attention on the social return on education due to the significant implications for public policies. The spillover effect of education (also human capital externalities) is usually related to productivity, inequality, and economic growth (e.g. Shapiro, 2006; Winters, 2013; Breau et al., 2014; Liu, 2015). The consensus that the concentration of college graduates increases the wage of all workers in the area has been reached in the literature as the evidence of human capital externalities (e.g. Moretti, 2004b; Rosenthal and Strange, 2008; Liu, 2019). However, despite the significance of social return to education, the empirical evidence is very limited in the context of developing countries.

Thai labor market provides an interesting case study of return on higher education due to the recent development and policy implementation. Over the last three decades, Thailand has undergone a rapid economic growth, accompanying with increase of education and decrease of socio-economic inequality (Paweenawat and Liao, 2024). Public spending on education in Thailand ranks first out of all other spending, which is among the top list worldwide (Jenmana, 2015). Higher education has played a significant role in the development of Thailand, which contains a diversity of

institutions. Among them, Rajabhat universities have helped the spread of higher education throughout Thailand. In 1995, the teachers' training colleges were upgraded to Rajabhat Institutes as the comprehensive higher education to promote local development (Royal Thai Government Gazette, 1995) and then in 2004, these Institutes were transformed into Rajabhat University (Paweenawat and Liao, 2023).

As the limited and inconclusive empirical evidence of return on higher education, the objective of this paper is to estimate private and social return of higher education in Thailand. The primary challenge of estimating return to education is that education is an endogenous variable. For the private return, unobserved individual heterogeneity, such as ability, may correlate with wage and education attainments that bias the results. For the social return, the bias may rise from individual and provincial specific unobserved characteristics (Moretti, 2004b).

We start with estimating the individual return to higher education by using Socio-Economic Survey (SES) panel data from 2005 to 2017 and employing three treatment effects including propensity score matching (PSM), endogenous switching (ES) regression and endogenous binary treatment using probit two stage least square (Probit-2SLS) model. While the first method, PSM model, accounts for the observed selection bias, the second method, ES model, accounts not only for endogenous selection bias but also structural differences between two groups, providing more unbiased and consistent results (Seng, 2017). Moreover, ES model uses full information maximum likelihood (ML), based on a fully specified parametric model. As there is a trade-off between robustness and efficiency for ML estimators, our third method, the Probit-2SLS model, uses only conditional moment restriction and adopt distribution-free method to solve treatment endogeneity (Wooldridge, 2010; Cerulli, 2014). As the SES panel data has not been updated in recent years, we also use LFS data from 2001 to 2024 as robustness check for the private return.

Second, we investigate the social return to higher education in Thailand from 2001 to 2024 using Labor Force Survey (LFS). We identify the social return by estimating the effect of share of higher educated workers living in each province on individual wage using instrumental variable (IV) approach and pseudo panel approach at provincial level accounting for cohort effects. We account for the unobserved heterogeneity by exploiting provincial variations of Rajabhat universities in Thailand that results higher share of individual who lives in the provinces with Rajabhat universities obtains higher education.

Our study adds to the literature in several ways. First, by using novel techniques and considering both individual and aggregate level of the return in the context of developing countries, we provide an insightful analysis of return to education. Second, although previous studies in Thailand have broadly discussed the importance of education, they barely considered the effects of the concentration of human capital and fail to deal with challenges of endogeneity that tends to bias the estimates. Third, distinct from existing studies that mainly focused on individual return to education, we draw attention on the social return to higher education and use updated LFS with a large sample and detailed information.

The results of individual return to higher education under different approaches using SES data show a robust positive value, where obtaining higher education increases wage by around 0.98 to 1.78 log points and there is a downward bias of the returns in PSM. For the social return to higher education using LFS, we find that 1 percent increase in the share of higher education in the province raises the wage by 4 to 5 percent under IV approach. The social return is larger for rural residents than urban residents. The aggregated estimates under pseudo panel approach show a higher social return and a similar return on average years of schooling. Under different methodologies, the return of education can vary.

The remainder of the paper is organized as follows: The next section provides the theoretical overview and related studies. Section 3 introduces the data and section 4 describes the background information of Thailand. Section 5 discusses methodology and results for private return on higher education and section 6 discusses methodology and results for the social return on higher education. Section 7 concludes.

2. Literature review

Estimation of return on education has been one of the most popular topics in the literature since Mincer's seminal theoretical and empirical work (Mincer, 1974), as the correct return on education is essential to public policy-making (see Psacharopoulos and Patrinos, 2018 for decennial review of global literatures in return on education). There are two types of returns are frequently estimated, private return and social return (Psacharopoulos, 2024). Generally, previous studies suggest that spending on human capital is a good investment, where private return on higher education has increased in low-income and middle-income countries and social return has remained high (Psacharopoulos and Patrinos, 2004a).

Recent studies continue to document substantial private returns to education across diverse developing country contexts. Fasih et al. (2021) examine the private returns associated with university education in Indonesia, Pakistan, and South Africa, finding that economic crises such as COVID-19 tend to widen gaps in private returns. Ayyash, et al. (2020) employ Bayesian linear regression to estimate private returns to schooling in Palestine, reporting that females have higher returns than their male counterparts. Andrabi et al. (2020) use an experimental design in Pakistan to demonstrate that private returns to schooling vary depending on market structure, with greater private returns when only one school receives grants compared to when all schools receive grants.

As education is not randomly assigned to the population, a reliable approach to identify the causal effect usually requires exogenous sources of variation in education. In the

recent study by Heckman et al. (2018), two general approaches of estimating return on education are summarized, including structural models and treatment effect models with instrumental variables. It suggests that treatment effect models rely on fewer assumptions and are more transparent source of identification than structural models (also see Imbens and Angrist, 1994; Angrist and Pischke, 2009; Eisenhauer et al., 2015).

The social return includes private return and the external benefits, where similarly to Acemoglu and Angrist (2000), Moretti (2004b), we define the external benefits as the effect of an increase in share of higher educated workers in a province on wage excluding the effect of private return to education. Theoretical economic model predicts that share of educated workers increases the total wage due to imperfect substitution and human capital spillover (e.g. Katz and Murphy, 1992; Acemoglu and Angrist, 2001). Only when the increase of wage of educated workers responds to supply increase and outweighs the negative substitution effect, the spillover effect will show.

In developed countries, studies suggested that social return may exceed private return and several explanations have been offered. First, the presence of higher educated worker can raise the productivity of other workers through interactions and information sharing (Lucas, 1988; Bronzini and Piselli, 2009; Borjas and Doran, 2015; Breschi and Lenzi, 2016). However, there are also arguments of negative spillover effect relating to education as productivity ability, in which results in social return less than private return (Moretti, 2004a). Second, the spillover effect may differ the return to skills across cities driven by the skill-biased technology change (Acemoglu, 1998; Glaeser et al., 2009; Perez-Silva and Partridge, 2020; Paweenwat and Liao, 2024). Third, education may have positive economic and non-economic spillover effect in addition to earnings. For example, cities with higher share of educated people may have better policy makers to make better decisions (Friedman, 1962). Promoting the higher education is likely to improve states' budget outlooks in the long run (Smith et al., 2025).

The difficulty in estimating social return arises from the unobservable factors that correlate with both wage and share of higher education across the regions. Individual fixed effect with augmented Mincerian model and IV are the most used methods in previous studies to account for individual and community-level heterogeneity. The previous results on social return show that increase in average education or share of college graduates increase the wage of other individuals (Acemoglu and Angrist, 1999; Moretti, 2004b; de Blasio, 2007; Liu, 2007).

Despite its significance, the empirical studies on social return to education in developing countries are very limited. As an exception, the recent study by Joshi et al. (2019) has estimated the social return to education in Indonesia and found a statistically significant positive social return, around 2.44 percent. It argued that instrumental variables defined at high level of aggregation are not appropriate for the context of Indonesia due to its high level of heterogeneity in education across localities. Indeed, very few studies in developing countries have employed IV to solve the endogeneity of education (Patrinos and Psacharopoulos, 2020). The exogenous variations of education have been used including institutional changes in educational system, such as reform in compulsory schooling or change in duration of schooling and accessibility of education, such as school construction projects (Patrinos and Sakellariou, 2006; Duflo, 2001; Chen et al., 2020).

Thailand provides us a valuable setting to test the effect of public policy on education. Previous studies in Thailand have focused on the private return on education (e.g. Amornthum and Chalamwong, 2001; Hawley, 2004; Wannakraijoj, 2013), while the social return is hardly touched. Tangtipongkul (2015) using a Mincerian model investigates both private and social return to schooling, where schooling has significant positive effect on both returns. However, the study did not consider any endogenous issues that may bias the results. Korwatanasakul (2023) employs a regression discontinuity design using Thailand's 1978 compulsory schooling law as a natural experiment to estimate causal returns to schooling, which finds that IV estimates of

around 8% while OLS overestimates such returns. Sirisrisakulchai and Leurcharusmee (2025) apply a multinomial treatment effects model incorporating a correction for sample selection to assess returns to higher education by field of study in Thailand for 2019 and 2021, and suggest significant variation across fields.

We start with private return using three treatment methods and then move on to social return using IV approach and pseudo panel approach. The appropriate instrument for private return should not correlate to individual wage through channels other than education, while for social return it should correlate to share of workers with higher education in the province but should uncorrelate to unobserved factors to generate consistent estimates. Card (1993) firstly proposed the presence of nearby college as a proxy for college attendance, and has been widely applied in the literatures (e.g. Kling, 2001; Moretti, 2004a; Carneiro et al., 2011; Carneiro et al., 2013; Nybom, 2017). According to Russell et al. (2024), the presence of college in the county has positive causal effect on the local education attainment and using the presence of local college as IV can ensure the robustness of the results.

Students face higher cost without college in their residence area, which will reduce the investment in higher education, especially for students from relatively poorer families. The presence of Rajabhat University in a province is expected to lower the cost of education and therefore correlates with the level of education achieved by individuals (Warunsiri and McNown, 2010; Paweenawat and Liao, 2023). In this paper, we exploit the exogeneity of provincial variations of Rajabhat universities as IV to identify the casual effect of education on wages.

3. Data

We used two nationally representative datasets for the empirical analysis. Both of the datasets are conducted by National Statistical Office (NSO) of Thailand and have covered every province in Thailand. First, six waves of SES panel data conducted in

2005, 2006, 2007, 2010, 2012, and 2017 including information on educational levels and monthly earnings, are used to analyze the individual return on higher education. Higher education includes vocational diplomas, bachelor's degrees, master's degrees, and doctoral degrees (UNESCO, 2011). This panel data is generated by tracking households and split-off individuals from sample households in basic SES data¹. The second data is the cross-section LFS from 2001 to 2024 containing large observations and more detailed information on workers such as years of schooling, working hours, industrial sectors and occupations, which is used to estimate the social return on higher education. We employ only the third quarter in the analysis to avoid the effect of seasonal labor migration (Sussangkarn and Chalamwong, 1996).

We restrict the sample in both data to working-age individual age between 25 to 45 years old and exclude those who are retired or students. Table 1 presents the summary statistics of SES data. We obtain 17,236 observations, where 6,639 of them have higher education and 10,597 have no higher education. SES does not report the working hours. The monthly wage is drawn directly from the survey. Table 2 presents the summary statistics of LFS data from 2001 to 2024, where we have 610,192 observations. The hourly wage is generated by dividing weekly wage by the sum of working hours each week². The higher education is defined as with university level or higher level of education. There are 14.4 percent of the sample obtained higher education and the average year of schooling is 10.6.

4. Background

The Rajabhat universities are Thailand's historical teachers' colleges designed to provide higher education in provinces, which compose one of the university system in Thailand³. In order to promote the education level and cultivate local intelligence,

¹ See Chawanote and Barrett (2013), Kilenthong and Rueanthip (2018) for more description of the data.

² Wages are deflated by the Thailand Consumer Index (Bureau of Trade and Economic Indices, Ministry of Commerce, Thailand).

³ The Higher Education Institutions comprises 26 autonomous universities, 11 public universities, 38 Rajabhat universities, 9 Rajamangala Universities of Technology, and 72 private higher education institutions (Office of the

Rajabhat Institutes and the Rajamangala Institutes of Technology were formally transformed into full university status following (The Rajabhat University Act, 2004). In 1995, there were around 300,000 students enroll in Rajabhat university. The number has risen to over 570,000 in 2012 (Welch, 2011; OHEC, 2012). We limited the provinces of having Rajabhat universities established before 1974, resulting in 32 provinces with Rajabhat universities. The instrument is constructed from the location of Rajabhat universities, which is assumed to be randomly assigned.

Using the LFS 2001 to 2024, figure 1 shows the average share of higher education by provinces with and without Rajabhat universities. During the time, the share of higher education has increased in both categories. Provinces with Rajabhat universities have an average 2.3 percentage points higher share of higher education than provinces without. To assess the difference of regional education attainments, we assign the provinces to five regions, including Bangkok, Central, North, Northeast, and South. Figure 2 shows the share of higher education by five regions. Bangkok has the highest concentration of educated workers, where the gap between Bangkok and other four regions is over 10 percent on average during the time. Moreover, the gap has become larger in recent years. Figure 3 shows the average years of schooling in the five regions. Similarly, Bangkok has higher year of schooling than the other four regions, which has increased from 9.6 to 11.6 years, while North and Northeast are the lowest (6.6 to 9.3 years; 7 to 9.1 years). Figure 4 presents the average log hourly wage by provinces with and without Rajabhat universities. Provinces with Rajabhat universities have higher wage than those do not have throughout the time.

5. Private return on education-Individual level (SES 2005-2017)

5.1 Methodology

To identify the causal effect of higher education on wage, the estimation needs to control for both observed and unobserved characteristics. In this paper, we employ PSM, ESR and endogenous binary treatment using Probit-2SLS approaches to deal with the endogenous bias.

We start with a conventional Mincer-type model (Mincer 1974):

$$\log w_i = \alpha_0 + \alpha_1 HE_i + \alpha_2 X_i + \varepsilon_i \quad (1)$$

where w_i is the monthly wage of individual i at time t . HE_i is a dummy variable indicating whether individual i obtains the higher education or not (binary choice indicator that $HE=1$ if individual select into treatment and $HE=0$ if not). X_i is vector of controlling variables, including age, age square, number of children, marital status, residence area, work status (including private or public sector), gender, job types⁴, provincial labor force participation rate, year dummies, five regional dummies.

First, PSM approach matches the treated individuals with similar untreated ones. Average treatment effect on treated (ATT) is as follows

$$ATT = E[Y(1) - Y(0)|T = 1] \quad (2)$$

where $Y(1)$ is the treated individuals and $Y(0)$ is untreated individuals. T is the treatment indicator, obtaining higher education or not.

⁴ There are eight job types, including famer/fisherman, production (manufacturing), production (industry), merchandise/own-business, government employee, company/business employee, general worker/laborer, and others.

Given a set of covariates, propensity score is the probability of assignment to the treatment group as

$$p(X) = P(T = 1|X) \quad (3)$$

Under PSM, it only considers the bias from observables and assumes that no systematic differences in unobserved individual characteristics between two groups

$$ATT = E[Y(1)|T = 1, p(X)] - E[Y(0)|T = 0, p(X)] \quad (4)$$

While PSM solves the bias arising from observables, it can not correct bias from misspecification and endogeneity from unobservables (Imbens and Wooldridge 2009; Wooldridge 2010). Therefore, additional two approaches are applied to deal with the issues.

Next, we employ the maximum-likelihood estimation of endogenous switching regression (ESR) model to account for the bias arisen from both observed and unobserved individual characteristics (Shiferaw et al. 2014; Ma and Abdulai 2016; Wossen et al. 2017). The outcome equations conditioning on treatment are defined as

$$\text{Regime1: } \ln W_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \quad \text{if } I_i = 1 \quad (5)$$

$$\text{Regime2: } \ln W_{2i} = X_{2i}\beta_2 + \varepsilon_{2i} \quad \text{if } I_i = 0 \quad (6)$$

$$I_i^* = \delta(\ln W_{1i} - \ln W_{2i}) + Z_i\theta + \epsilon_i \quad (7)$$

where I_i^* is a latent variable that determines the education level in which individual i obtained; W_{ji} is the wage of individual i in education level j ($=1$ or 2); Z_i is a vector of controlling variables that are related to wage. The error terms in equation (7), equation (5) and (6) are assumed to follow a trivariate normal distribution with a zero mean vector and the following covariance matrix::

$$\Omega = \begin{bmatrix} \sigma_{\epsilon}^2 & \sigma_{1\epsilon} & \sigma_{2\epsilon} \\ \sigma_{1\epsilon} & \sigma_1^2 & . \\ \sigma_{2\epsilon} & . & \sigma_2^2 \end{bmatrix} \quad (8)$$

where σ_{ϵ}^2 is the variance of error term in eq.(7), $\sigma_{\epsilon}^2 = \text{var}(\epsilon_i)$, which is assumed to equal to 1 (Maddalla 1983); $\sigma_1^2 = \text{var}(\epsilon_1)$, $\sigma_2^2 = \text{var}(\epsilon_2)$; $\sigma_{1\epsilon}$ is the covariance of ϵ_i and ϵ_1 ; $\sigma_{2\epsilon}$ is the covariance of ϵ_i and ϵ_2 . The covariance of ϵ_1 and ϵ_2 is not defined, as $\ln W_{1i}$ and $\ln W_{2i}$ cannot be observed at the same time.

The selection bias occurs when the correlation of ϵ_i and ϵ_1 , or ϵ_i and ϵ_2 is not equal to 0. To test the endogeneity, ESR model includes the inverse mills ratio (λ) and $\sigma_{1\epsilon}$, $\sigma_{2\epsilon}$ as auxiliary regressors in equation (5) and (6). If $\sigma_{1\epsilon} = \sigma_{2\epsilon} = 0$, it is exogenous switching, otherwise endogenous switching. The conditional expectations are

$$E[\ln W_{1i} | I_i = 1] = X_{1i}\beta_1 + \lambda_{1i}\sigma_{1\epsilon} \quad (9)$$

$$E[\ln W_{2i} | I_i = 0] = X_{2i}\beta_2 + \lambda_{2i}\sigma_{2\epsilon} \quad (10)$$

$$E[\ln W_{2i} | I_i = 1] = X_{1i}\beta_2 + \lambda_{1i}\sigma_{2\epsilon} \quad (11)$$

$$E[\ln W_{1i} | I_i = 0] = X_{2i}\beta_1 + \lambda_{2i}\sigma_{1\epsilon} \quad (12)$$

The ATT is the difference between (9) and (11)

$$ATT = E[\ln W_{1i} | I_i = 1] - E[\ln W_{2i} | I_i = 1] \quad (13)$$

$$= X_{1i}(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\epsilon} - \sigma_{2\epsilon}) \quad (14)$$

In equation (14), ATT is accounted for selection bias, where $\sigma_{1\epsilon} - \sigma_{2\epsilon}$ is not equal to 0. For example, if the individual self-select to higher education due to higher intelligence or ability, $\sigma_{1\epsilon} - \sigma_{2\epsilon}$ will be positive. Those may have a higher wage than the randomly assigned ones. Identification of ESR model needs to include at least one additional variable in Z_i as an instrument in equation (7). The instrument is directly related to choice into education attainment but not the wage. We use the provincial

variations of Rajabhat universities as instrument for higher education.

Another method to deal with endogenous binary treatment use Probit-2SLS (Heckman et al. 2006; Wooldridge 2010; Cerulli 2012). Unlike ES model using full information maximum-likelihood estimation, Probit-2SLS model applies conditional moment restriction and distribution-free method. The identification strategy is by imposing IV that affects only the selection process but not the outcome. The application of the model relies on the work of Cerulli (2014). Under the hypothesis of selection-on-unobservable by using IV and a generalized Heckman-style selection model, provide consistent estimates of ATE, ATT and ATNT. The estimation starts with following models

$$\ln W_1 = \mu_1 + X\beta_1 + \varepsilon_1, E(\varepsilon_1) = 0, E(\varepsilon_1|X) = 0 \quad (15)$$

$$\ln W_2 = \mu_2 + X\beta_2 + \varepsilon_2, E(\varepsilon_2) = 0, E(\varepsilon_2|X) = 0 \quad (16)$$

$$\ln W = \ln W_1 + \sigma(\ln W_1 - \ln W_2) \quad (17)$$

where $\ln W$ is the observed outcome; σ is the binary treatment variable.

There are four steps under probit-2SLS. First, by applying a Probit of σ on X and Z , where Z is the instrument, directly correlating with the treatment σ and uncorrelating with outcome, we get the predicted probability of σ , p_σ . Second, run OLS of σ on p_σ to get the fitted value σ_{fv} . Third, use OLS to estimate $\ln W$ on σ_{fv} and $\sigma_{fv}(X - E(X))$. Lastly, the estimated parameters are incorporated into the corresponding sample formulas to derive the causal effects, obtaining ATT via bootstrap.

5.2 Results

Table 3 presents the treatment effect of higher education using PSM, ESR and Probit-2SLS. Obtaining higher education increases wage by 0.59 log points under PSM. Once we account for both observable and unobservable sources of bias, the effect of higher

education increases to 0.98 log points under ESR and 1.78 log points under Probit-2SLS. In panel (A), using ESR, the conditional expected wage for those with higher education $E(\ln W_1|I=1)$ is 9.498 log points per month, while the conditional expected wage for those who would have if they did not obtain higher education $E(\ln W_2|I=1)$ is 8.515 log points. Therefore, on average, higher education increases workers' wage by approximately 0.983 log points per month.

In panel (B), using Probit-2SLS, the ATT is higher than those from ESR. Figure 5 shows the distribution of ATE, ATET (ATT), and ATENT, where the values are all positive. ATET (ATT) is more concentrate at lower value than ATE and ATENT. Higher value of ATENT predicts that workers without higher education would have higher wages if they had been more educated.

ESR suggests that obtaining higher education has a around 12 percent increase in wage while Probit-2SLS reports a around 24 percent increase, which correspond to 3 percent to 6 percent annual rate of return of 4-year college education. Using the marginal treatment effects, Belskaya et al. (2017) has suggested that average return of one year of college education in Russia is around 7.3 percent, while Carneiro et al. (2011) has found a 6.7 percent in US. Clark (2024) provides a meta-study on the return to education and suggests that the average gain from additional year of education is 8.5 percent.

Table 4 reports the estimates of OLS and 2SLS in Probit-2SLS model. The results are consistent with previous findings of positive return on education. Compared OLS to 2SLS, the effect of higher education using OLS estimation shows a downward bias (0.59 to 1.87) (e.g. Trostel et al., 2002; Patrinos and Psacharopoulos, 2020). This estimate exceeds the OLS estimate, consistent with the literature on returns to education, where IV estimates are often larger than OLS due to measurement error in schooling and heterogeneous treatment effects (Card, 2001; Patrinos and Psacharopoulos, 2026). We regard the IV estimate as more credible for causal inference, as it addresses

endogeneity and measurement error.

There are two major possible sources of bias. First is the measurement error, which may aggravate the bias due to the on-going changes in education system in Thailand. Second, the selection bias arises when unobservables, such as the ability, affect people's decision to higher education. As the SES panel data has not been updated in recent years, we also use LFS data from 2001 to 2024 to investigate the recent trends of private return. The results show that obtaining higher education has a around 33.3 percent increase in wage using OLS, while 43.3 percent using pseudo panel approach⁵.

6. Social return--Provincial level (LFS 2001-2024)

6.1 Methodology

Beyond the private return on higher education, there are external social benefits that may also contribute to wage. Next, we estimate to the spillover effect from higher education by comparing wages of workers in different provinces with different shares of higher education in the labor market.

Starting with Morreti's model (Moretti, 2004b), an augmented Mincer-type equation with aggregate human capital in the province:

$$\log w_{ipt} = \alpha_0 + \alpha_1 HE_share_{pt} + \alpha_2 X_{it} + \alpha_3 P_{pt} + \varepsilon_{ipt} \quad (18)$$

where $\log w_{ipt}$ is the log real hourly wage of worker i in the province p at time t ; HE_share_{pt} is the average share of workers with higher education in the province p at time t ; X_{it} is a vector of individual characteristics, including years of schooling, age, age square, number of children, marital status, residential area, work status, gender,

⁵ The results are presented in Appendix Table 2A. The construction of pseudo panel is shown in section 6.1.

industries, occupations, and year effects.⁶ P_{pt} is the provincial labor force participation rate. To separate the external return from the private return, we instrument HE_share_{pt} with provincial Rajabhat university presence and estimate Equation (18) using a pseudo-panel approach, which allows province fixed effects to absorb time-invariant unobservables while retaining variation in HE_share_{pt} across cohorts.

We are interested in the coefficient of share of higher education, α_1 , which is the effect after controlling for private return on years of schooling. The identification of α_1 is complicated by unobservables in wage determination at both individual level and provincial level. As the presence of Rajabhat universities in the province increases the share of higher education there, we use the provincial variations of Rajabhat universities as instrument for higher education. The key assumption is that workers in the province with Rajabhat universities do not differ systematically from workers with same education in the province without Rajabhat universities. The province-based instrument cannot be employed in the specification, incorporating provincial fixed effects, as it will be absorbed by the fixed effect (Moretti 2004b).

According to Deaton (1985), by classifying the sample into cohort groups basing on time invariant characteristic can correct unobserved heterogeneity. Next, we aggregate the data by birth year, provinces and time to construct a pseudo panel. We use 7 birth cohorts from 1956 to 1999 with 5-year interval, interacting with 77 provinces, and 24 survey years. After withdrawing the missing values, we obtain 6,952 observations in the pseudo panel and the average observations in each cohort are 265. We use weighted least square (WLS) to account for heteroscedasticity across observations within each cohort (Pencavel, 1998).

$$\overline{\log w_{ct}} = \beta_0 + \beta_1 \overline{HE_{ct}} + \beta_2 \overline{X_{ct}} + \alpha_c + \overline{\varepsilon_{ct}} \quad (19)$$

⁶ There are nine industrial dummies, including agriculture, mining, manufacturing, utilities, construction, commercial, transportation and communication, services and others; and nine occupational dummies, including managers & legislators, professionals, technicians, clerks, service workers, agriculture, craft worker, plant & machine, unskilled.

where $\overline{\log w_{ct}}$ is the log hourly wage in cohort c at time t ; $\overline{HE_{ct}}$ is the share of higher education in cohort a at time t ; α_c is the fixed effect for workers in cohort c at time t .

Lastly, we estimate the effect of share of higher education in the province on provincial wage gap using OLS and IV

$$Gap_{pt} = \alpha_0 + \alpha_1 HE_share_{pt} + \alpha_2 X_{pt} + \varepsilon_{pt} \quad (20)$$

where Gap_{pt} is the difference in mean of log wage between those with higher education and those without in the province at time t .

6.2 Results

Table 5 presents the estimates of equation (18). The coefficient of share of higher education using OLS suggests that 1 percent increase in the share of higher education in the province will increase the wage by 0.76 percentage points, while IV provides a larger effect, where 1 percent increase in the share of higher education in the province will increase the wage by 4.5 percentage points. The private return on education, the effect of year of schooling is similar for the two methods, approximately 5 percent.

Consistent with previous studies, the estimates for social return are usually higher using IV than OLS (e.g. Fan et al., 2015; Liu, 2007; Filiztekin, 2011). Similarly, Joshi et al. (2019) found the social return in Indonesia is around 2.44 percent and the return is higher in urban area than rural area. Liu (2007) suggested that the social return varies between 11 to 13 percent using IV in China, while Filiztekin (2011) found the private return is around 5 percent and social return is around 3 to 4 percent in Turkey.

Column 3 and 4 reports the sub-sample results of men and women. The estimates show that men have a slightly higher social return than women (4.6 percent for men and 4.4

percent for women). The return on years of schooling is higher for women than men (4.9 percent for women and 4.7 percent for men). The results are consistent with previous findings that women have higher returns on education than male in Thailand (Warunsiri and McNown, 2010).

In addition, the social return of cities does not need to be the same with the social return of a country, in which has an important policy implication for the government. Comparing the sub-sample results of urban and rural residents in column 5 and 6, the social return is higher in rural area than urban area (4.9 percent and 4.3 percent). Conversely, the return on years of schooling is higher in urban than rural area (5 percent and 4.2 percent). Higher educated workers concentrate in urban areas due to more opportunities to exploit their skills and higher return to their education than in rural area. Our results suggest that investment on education is likely to increase the productivity of the rural workers more than urban workers, whereas the private return on education is higher in urban area than in rural area.

In addition to residence area and gender, we re-estimate the IV model accounting for cohort effects, educational levels, income quantiles, younger and older generations, and age groups. Table 6 presents the results of the coefficient of share of higher education under each estimation. Adding controls for birth cohorts does not have much change from the basic estimation in table 5 (4.52 percent to 4.54 percent). Compared the social return of higher education to different educational groups, those with university level education have a negative social return on wage, while those without have a positive social return on wage. For the bottom 25 percent income quantile group, the social return is higher than the top 25 percent (5.3 percent to 0.3 percent). The results suggest that individuals with less education and lower income benefit more from the social return to higher education.

Younger generation has lower social return than older generation (2.9 percent to 8 percent), while younger workers also has lower social return than older ones (3.7

percent to 5.5 percent). The results echo the recent phenomenon of overeducation accompanying with a wage penalty for younger workers in Thailand, which is a result of the continued expansion of higher education and governments' policies on education (Paweenawat and Vechbanyongratana, 2015).

Using the IV approach, we control for the unobserved heterogeneity in return across the provinces, where the results suggest that it is likely to have high heterogeneity causing bias. Additionally, as suggested by Moffitt (1993) that grouping can be an instrumental variable procedure, we account for the time and provincial-specific cohort effects with pseudo panel approach. The fixed effect in pseudo panel approach imposes the restriction that unobserved heterogeneity is equal across cohorts. Table 7 reports the estimates of equation (19) using the pseudo panel approach. The estimated social return to higher education on aggregated wage with cohort fixed effects is around 43.3 percent after controlling for the aggregated covariates. The positive effect is consistent with previous finding. The aggregated estimate of private return is lower comparing to the results under individual level (3.8 percent to 4.9 percent).

To increase the robustness of positive social return on education, lastly, the estimates in table 8 show the results for equation (20)⁷. Compared OLS and IV estimates, the positive coefficient of share of higher education under OLS estimation is biased without considering the endogenous issues. The negative coefficient of share of higher education using IV estimation suggests that the increase of share of higher education in the province reduces the wage gap between those with higher education and those without. In other words, there is positive social return on higher education in term of wage inequality.

⁷ We conduct the placebo test using the time before and after the upgrade of Rajabhat universities.

7. Conclusion

This paper estimates both private and social return to higher education in Thailand. In the first part, the private return is estimated by using three treatment effect models with SES panel data from 2005 to 2017. We account for the selection bias and unobserved individual heterogeneity and find significantly positive return that having higher education increases the wage ranging from 0.98 to 1.78 log points. It is important to note that these estimates refer to the wage premium associated with holding a higher-education qualification, rather than the annual rate of return to investment in education. In the second part, we present estimates of social return to higher education using IV approach and pseudo panel approach to control for possible unobservables at both individual level and provincial level. We use LFS from 2001 to 2024 and find a robust positive social return, which is around 4 to 5 percent using IV approach.

There are several important takeaways from our study. First, the estimated return on higher education shows a downward bias without considering the endogeneity of unobservables. Under different approaches, the magnitudes of positive return vary. Second, the positive social return suggests that investment in higher education in Thailand will improve the income distribution as it contributes more to workers with less education and in lower wage occupations. Besides, the social return is more pronounced to rural residents than urban residents. Third, the social return accounts for the unequal increase in wage and decrease in wage inequality among different provinces. Lastly, it is important to notice that we do not distinguish the imperfect substitution between workers with higher education and those without and the education spillover that provide the positive social return. The results can be thought as lower bound estimates of education spillover on wage. A limitation of our approach is that it assumes the return to higher education remains constant over the working life; future work could extend this by estimating experience-wage profiles or allowing the return to vary with age and years since graduation.

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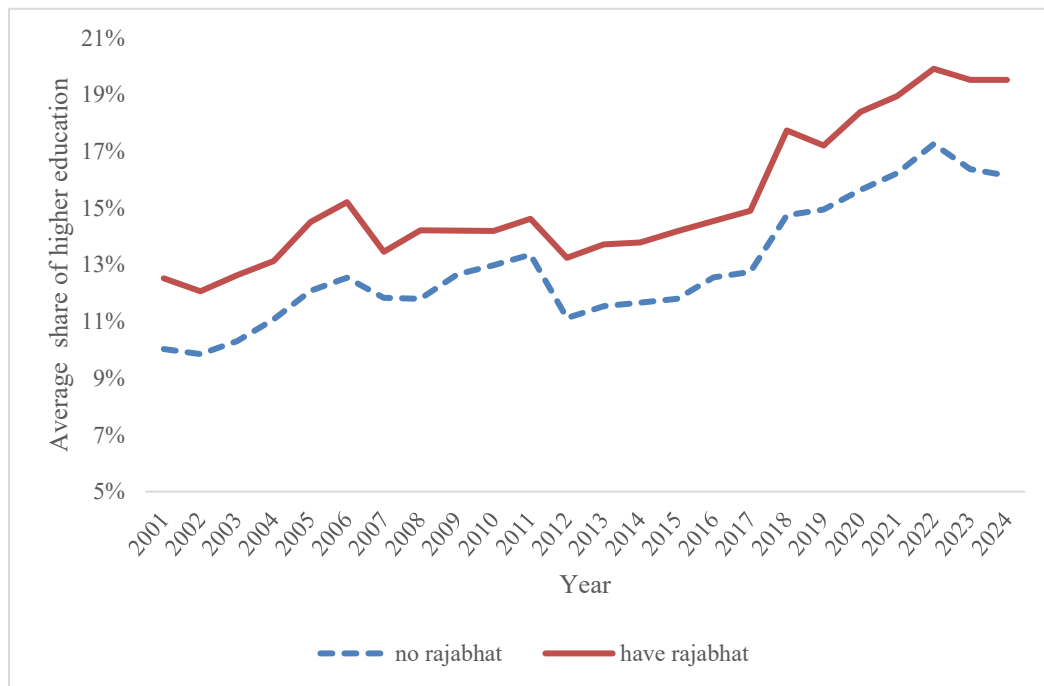
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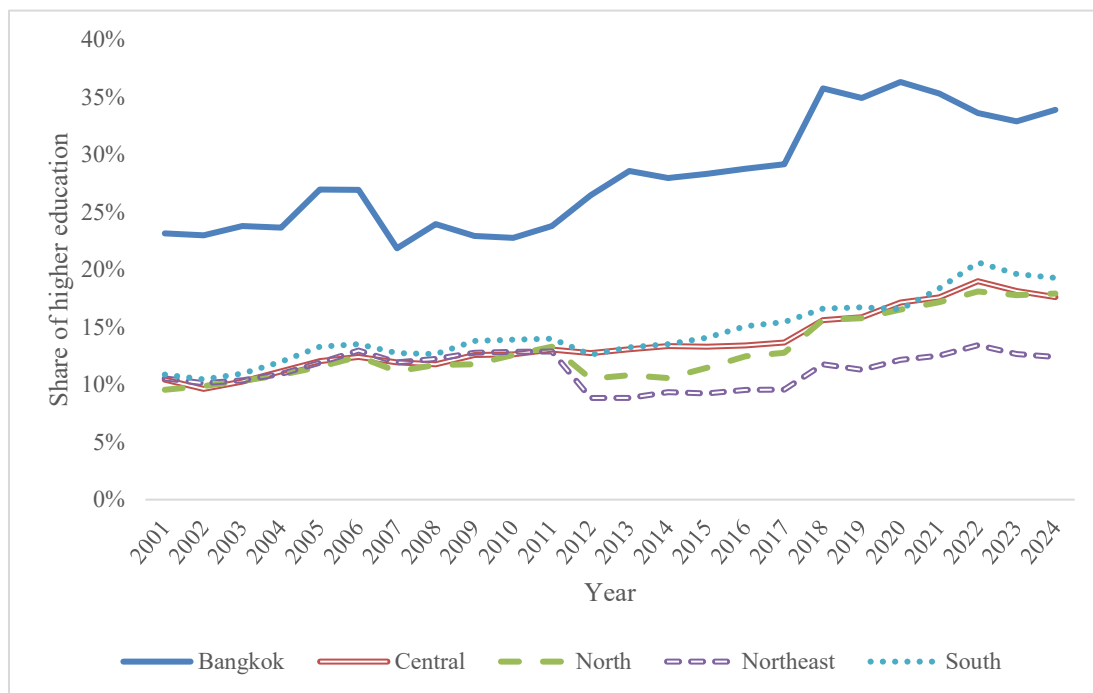
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Figure 1. Average share of higher education by having Rajabat or not (LFS 2001-2024)



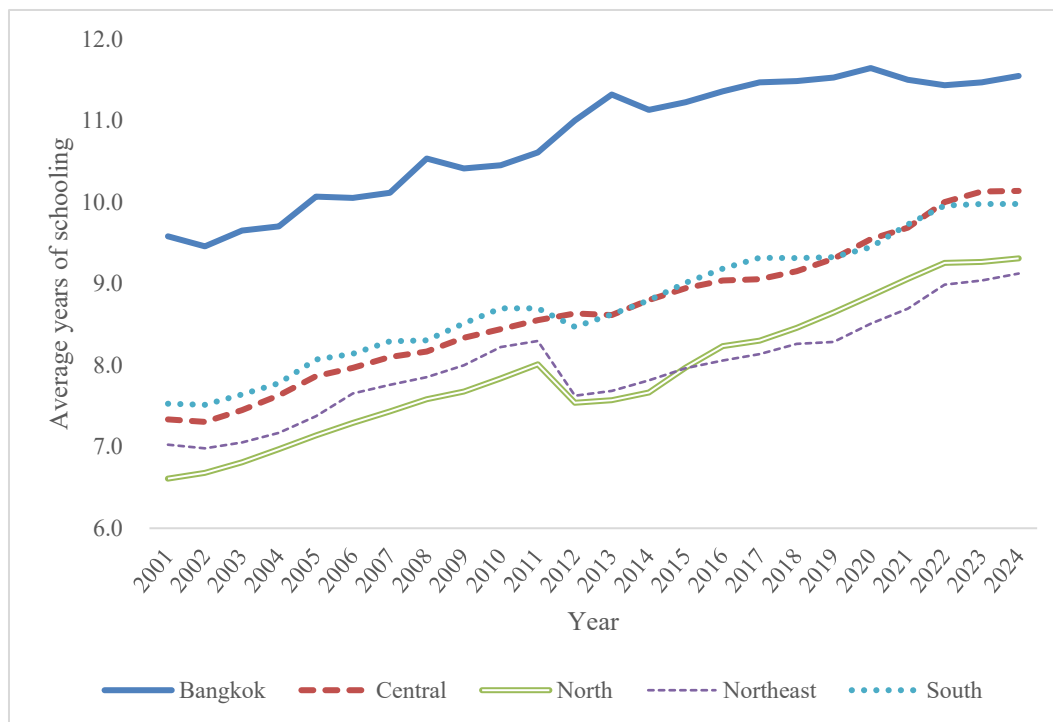
Source: Authors' calculation.

Figure 2. Share of higher education by regions (LFS 2001-2024)



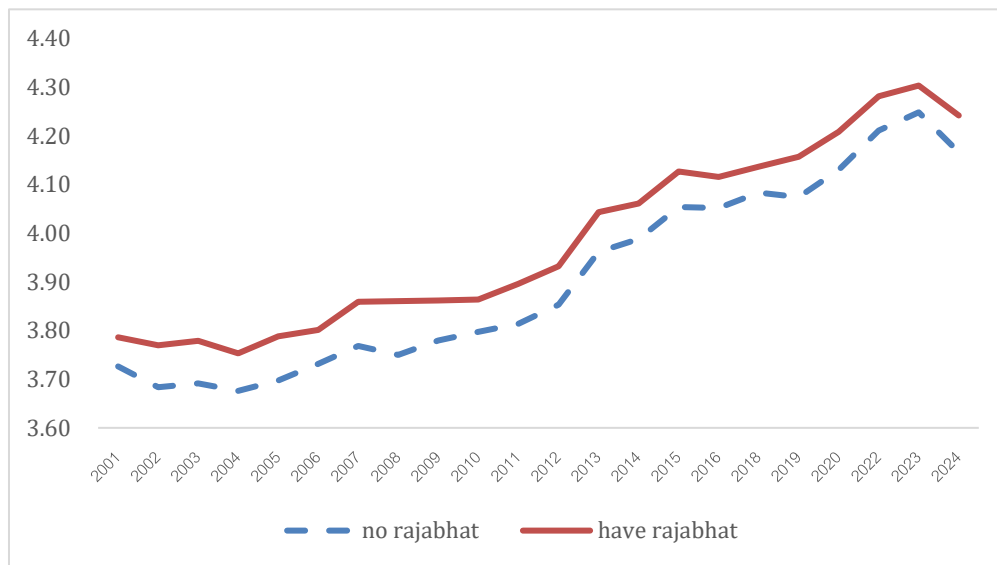
Source: Authors' calculation.

Figure 3. Average years of schooling by regions (LFS 2001-2024)



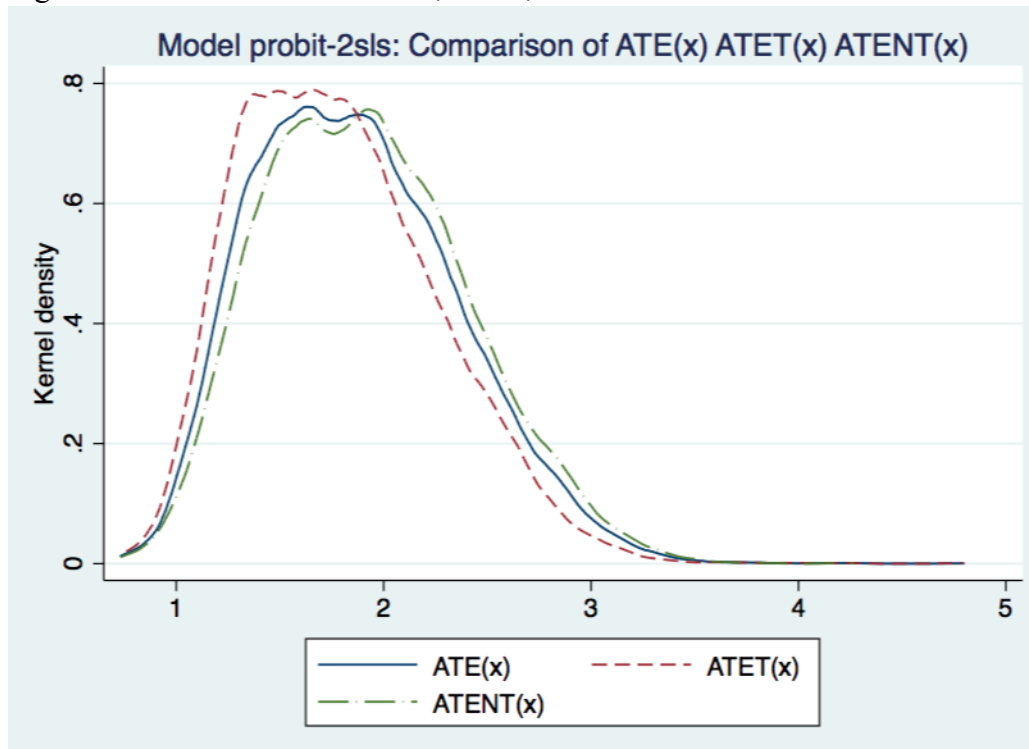
Source: Authors' calculation.

Figure 4. Log hourly wage by having Rajabat or not (LFS 2001-2024)



Source: Authors' calculation.

Figure 5. The distribution of ATE, ATET, and ATENT under Probit-2SLS



Source: Authors' calculation.

Table 1. Summary statistics by treatment group, SES 2005-2017

	All (N=17,236)		Higher education (N=6,639)		No higher education (N=10,597)	
	Mean	SD	Mean	SD	Mean	SD
Log monthly wage	8.980	0.851	9.517	0.712	8.643	0.752
Age	34.887	5.968	33.959	6.042	35.468	5.848
Number of children	1.284	1.503	1.041	1.463	1.429	1.508
Marital status (=1 if married)	0.684	0.465	0.564	0.496	0.759	0.428
Residence area (=1 if urban)	0.479	0.500	0.644	0.479	0.375	0.484
Sector (=1 if public sector)	0.316	0.465	0.417	0.493	0.256	0.436
Gender (=1 if male)	0.516	0.500	0.437	0.496	0.566	0.496
Provincial LFPR	0.912	0.040	0.912	0.038	0.913	0.042

Source: Authors' calculation.

Table 2. Summary statistics, LFS (2001-2024)

	Mean	SD
Log hourly wage	3.853	0.730
Year of schooling	10.628	4.727
Age	34.874	6.005
Number of children	1.072	1.102
Marital status (=1 if married)	0.618	0.486
Residence area (=1 if urban)	0.638	0.481
Sector (=1 if public sector)	0.291	0.454
Gender (=1 if male)	0.517	0.500
Share of higher education (%)	14.406	5.897
Provincial LFPR	0.864	0.029
Number of provinces	77	
Individuals (Obs.)	610,192	

Source: Authors' calculation.

Table 3. Effect of obtaining higher education on wage outcome, SES 2005-2017

	PSM	ESR	IV
ATT	0.590*** (0.021)	0.983*** (0.016)	1.784*** (0.238)
Obs.	17,236	17,236	17,236

(A) ESR

	Obs.	Mean	Std. Dev.
E(lnW ₁ I=1)	8,607	9.498	0.300
E(lnW ₂ I=1)	20,638	8.515	0.330

(B) Probit-2SLS

	Observed Coef.	Bootstrap Std. Err.	z	P>z
ATT	1.784	0.238	7.490	0.000
ATNT	1.920	0.269	7.140	0.000

Note: (1) Mean standardized bias before matching is 19.9, which reduces to 3.2 after matching. (2) LR test of independence, $p > \chi^2 = 0.00$. (3) Bootstrap standard errors are from 100 bootstrap replications. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' estimates.

Table 4. Estimation results of OLS and Probit-2SLS, SES 2005-2017

	OLS	2SLS(IVtreat)
Dependent variable: log monthly wage		
Higher education (HE)	0.586*** (0.011)	1.868*** (0.192)
Age	0.0482*** (0.010)	-0.027 (0.065)
Age square	-0.000485*** (0.000)	0.00112 (0.001)
Number of children	-0.0160** (0.007)	0.217*** (0.061)
Marital status (=1 if married)	0.0221** (0.011)	-0.0279 (0.091)
Residence area (=1 if urban)	0.0968*** (0.012)	-0.413*** (0.096)
Sector (=1 if public sector)	0.236*** (0.022)	-0.0713 (0.070)
Gender (=1 if male)	0.198*** (0.010)	-0.0745** (0.029)
Control for provincial LFPR	Yes	Yes
Control for job types	Yes	Yes
Control for regional dummies	Yes	Yes
Control for year effects	Yes	Yes
Observations	17,236	17,236

Note: The first stage of Probit-2SLS (Probit regression of higher education on the instrument), reports the coefficient of instrument is 0.097*** (0.022). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

Table 5. The effect of share of higher education on wage, LFS 2001-2024

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV (Men)	IV (Women)	IV (Urban)	IV (Rural)
Share of higher education	0.00760*** (0.000)	0.0454*** (0.004)	0.0464*** (0.005)	0.0438*** (0.005)	0.0430*** (0.005)	0.0490*** (0.005)
Years of schooling	0.0513*** (0.000)	0.0487*** (0.000)	0.0470*** (0.000)	0.0490*** (0.001)	0.0504*** (0.000)	0.0420*** (0.000)
Number of children	-0.0121*** (0.001)	- 0.00463*** (0.002)	-0.000624 (0.002)	-0.0103*** (0.002)	-0.00314 (0.002)	- 0.00855*** (0.002)
Marital status (=1 if married)	0.0509*** (0.001)	0.0557*** (0.001)	0.0832*** (0.002)	0.0296*** (0.002)	0.0579*** (0.002)	0.0505*** (0.003)
Residence area (=1 if urban)	0.0455*** (0.001)	0.0518*** (0.002)	0.0553*** (0.002)	0.0457*** (0.002)		
Sector (=1 if public sector)	0.278*** (0.002)	0.301*** (0.003)	0.279*** (0.004)	0.327*** (0.005)	0.324*** (0.004)	0.260*** (0.005)
Gender (=1 if male)	0.127*** (0.001)	0.126*** (0.001)			0.124*** (0.002)	0.130*** (0.002)
Control for age and age square	Yes	Yes	Yes	Yes	Yes	Yes
Control for industrial groups	Yes	Yes	Yes	Yes	Yes	Yes
Control for occupational groups	Yes	Yes	Yes	Yes	Yes	Yes
Control for provincial LFPR	Yes	Yes	Yes	Yes	Yes	Yes
Control for year effects	Yes	Yes	Yes	Yes	Yes	Yes
IV-First stage		0.446*** (0.006)	0.455*** (0.009)	0.436*** (0.009)	0.415*** (0.009)	0.482*** (0.009)
Observations	610,192	610,192	315,332	294,860	389,319	220,873

Note: IV-weak identification test Fstat>10. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

Table 6. Subgroup analysis with IV estimations, LFS 2001-2024

	Effect of share of higher education on wage	Observations
IV-Add control for cohort groups	0.0452*** (0.004)	610,192
IV-University level	-0.283*** (0.077)	152,952
IV-Non-university level	0.0616*** (0.004)	457,240
IV-Income quantile≤25%	0.0528*** (0.003)	158,058
IV-Income quantile≥75%	0.00369 (0.002)	149,867
IV-Born before 1975	0.0796*** (0.010)	279,724
IV-Born after 1975	0.0287*** (0.003)	330,468
IV-age≤35	0.0370*** (0.005)	326,395
IV-age>35	0.0549*** (0.006)	283,797

Note: Each row is a separate estimation of the subgroup. The entries are the coefficients of share of higher education. Controlling variables include years of schooling, number of children, marital status, residence area, sector, gender, age and age square, industrial and occupational groups, provincial LFPR and year effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' estimates.

Table 7. The effect of share of higher education on wage using pseudo panel approach, LFS 2001-2024

	Pseudo-panel
	WLS
Share of higher education	0.433*** (0.053)
Years of schooling	0.0384*** (0.003)
Number of children	-0.0897*** (0.020)
Marital status (=1 if married)	0.0525* (0.032)
Residence area (=1 if urban)	-0.0254 (0.020)
Sector (=1 if public sector)	0.0530** (0.027)
Gender (=1 if male)	0.330*** (0.041)
Observations	6,952

Note: The estimation controls for number of children, marital status, residence area, sector, gender, age and age square, industrial and occupational groups, provincial LFPR and year effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

Table 8. The effect of share of higher education on wage gap, LFS 2001-2024

	(1)	(2)
	OLS	IV
Share of higher education	0.00286*** (0.000)	-0.0218*** (0.000)
Years of schooling	-0.0319*** (0.000)	-0.00734*** (0.000)
Number of children	0.0236*** (0.000)	0.0662*** (0.001)
Marital status (=1 if married)	0.0119*** (0.000)	-0.0386*** (0.001)
Residence area (=1 if urban)	0.0704*** (0.001)	0.0276*** (0.001)
Sector (=1 if public sector)	0.0233*** (0.001)	-0.0804*** (0.002)
Control for provincial characteristics	Yes	Yes
Observations	610,192	610,192

Note: IV-weak identification test $F_{stat} > 10$. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' estimates.

Appendix

Table 1A. List of Rajabhat University

	University	Founded	Main campus	LFS province code
1	Bansomdej Chaopraya Rajabhat University	1896	Bangkok	10
2	Buri Ram Rajabhat University	1971	Buriram	31
3	Chaiyaphum Rajabhat University	1997	Chaiyaphum	36
4	Chandrakasem Rajabhat University	1940	Bangkok	10
5	Chiang Mai Rajabhat University	1924	Chiang Mai	50
6	Chiang Rai Rajabhat University	1973	Chiang Rai	50
7	Dhonburi Rajabhat University	1948	Bangkok	10
8	Kamphaeng Phet Rajabhat University	1973	Kamphaeng Phet	62
9	Kanchanaburi Rajabhat University	1973	Kanchanaburi	71
10	Lampang Rajabhat University	1971	Lampang	52
11	Loei Rajabhat University	1973	Loei	42
12	Maha Sarakham Rajabhat University	1925	Maha Sarakham	44
13	Muban Chom Bung Rajabhat University	1954	Ratchaburi	70
14	Nakhon Pathom Rajabhat University	1936	Nakhon Pathom	73
15	Nakhon Ratchasima Rajabhat University	1913	Nakhon Ratchasima	30
16	Nakhon Sawan Rajabhat University	1922	Nakhon Sawan	60
17	Nakhon Si Thammarat Rajabhat University	1957	Nakhon Si Thammarat	80
18	Phetchabun Rajabhat University	1973	Phetchabun	67
19	Phetchaburi Rajabhat University	1926	Phetchaburi	76
20	Phranakhon Rajabhat University	1892	Bangkok	10
21	Phranakhon Si Ayutthaya Rajabhat University	1985	Phra Nakhon Si Ayutthaya	14
22	Phuket Rajabhat University	1971	Phuket	83
23	Pibulsongkram Rajabhat University	1926	Phitsanulok	65
24	Rajanagarindra Rajabhat University	1940	Chachoengsao	24

25	Rambhai Barni Rajabhat University	1972	Chantaburi	22
26	Roi-Et Rajabhat University	2001	Roi Et	45
27	Sakon Nakhon Rajabhat University	1964	Sakon Nakhon	47
28	Sisaket Rajabhat University	1997	Sisaket	33
29	Songkhla Rajabhat University	1919	Songkhla	90
30	Suan Sunandha Rajabhat University	1937	Bangkok	10
31	Suratthani Rajabhat University	1973	Surat Thani	84
32	Surindra Rajabhat University	1973	Surin	32
33	Thepsatri Rajabhat University	1920	Lopburi	16
34	Ubon Ratchathani Rajabhat University	1947	Ubon Ratchathani	34
35	Udon Thani Rajabhat University	1923	Udon Thani	41
36	Uttaradit Rajabhat University	1936	Uttaradit	53
37	Valaya Alongkorn Rajabhat University	1932	Bangkok	10
38	Yala Rajabhat University	1934	Yala	95

Source: Bureau of International Cooperation Strategy, Office of the Higher Education Commission, Thailand (2019)

Table 2A. Estimation results of OLS, LFS 2001-2024

	(1) OLS
Higher education (HE)	0.334*** (0.002)
Age	0.0226*** (0.001)
Age square	-0.000136*** (0.000)
Number of children	-0.00244* (0.001)
Marital status (=1 if married)	0.0462*** (0.001)
Residence area (=1 if urban)	0.0518*** (0.001)
Sector (=1 if public sector)	0.332*** (0.002)
Gender (=1 if male)	0.152*** (0.001)
Observations	616,376

Note: The estimation controls for number of children, marital status, residence area, sector, gender, age and age square, industrial and occupational groups, provincial LFPR and year effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.

Table 3A. : Placebo Regressions - Share of higher education and wage

	(1)	(2)
	Before 2004	After 2004
Share of higher education	0.00473	0.767***
	(0.11)	(0.10)
Controls	Yes	Yes

Note: The estimation controls for number of children, marital status, residence area, sector, gender, age and age square, industrial and occupational groups, provincial LFPR and year effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' estimates.