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Thailand's Vocational Training and Upward Mobility: Impact Heterogeneity and Policy Implications

Patima Chongcharoentanawat[a] , Franziska Gassmann[a], Pierre Mohnen[a,b]

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Abstract:

This paper provides the first impact evaluation of vocational training in Thailand using various treatment effect methods with unique longitudinal survey data, covering seven years, to evaluate the impact of vocational training on economic and social mobility in the short, medium and long term. We find that vocational training fails to move participants upward both in terms of earning and employment. However, training participation is found to increase expenditures in the short and medium term but these positive impacts vanish when we strictly confine counterfactuals or allow for the endogeneity of the decision to attend the programme. We also examine the heterogeneity of effects with respect to individual and programme characteristics to answer the questions for whom the training works and which type of training works best. The results suggest that women, rural residents, youth (aged 15-24) and elderly (aged 60 and above), low-educated workers, and economically inactive people, benefit less from the programme. With regard to heterogeneity by type of training, we find that computer training courses, training offered by private institutions and a cooperation of government and private agencies, and training financed by employers are associated with better outcomes.

Key words: vocational training, socioeconomic upward mobility, human development, impact evaluation, Thailand

JEL Classification: J08, J24, O15

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1. Introduction

Upward mobility, a movement to a higher socioeconomic status, is a policy objective in its own right. It indicates the extent to which opportunity exists in society. In the presence of mobility, inequality is less problematic as individuals, through their own ability and effort, can rise into higher socioeconomic classes regardless of what class they were born into. However, recent studies have revealed the limited opportunities for people, especially those among the bottom of the ranking, to move upward. This phenomenon is not only against the moral principal but also leads to long-term economic inefficiency, the persistence of inequality and disruption of social harmony. Among several factors, the insufficient development of human capital has been described as a critical constraint to the prospect for upward mobility (Woolard & Klasen, 2005). This limitation, therefore, must be overcome to ensure that upward mobility remains achievable.

Vocational training[1], which aims to impart skills and enable participants to be more productive, has long been the common policy expected to augment human capital and move people upward. However, the empirical evidence regarding the effectiveness of vocational training has been inconclusive as there is a substantial variation in training impact depending on characteristics of programmes and participants (Borkum et al., 2015; Maitra & Mani, 2013). An insight into impact heterogeneity is thus crucial to improve the effectiveness of training programmes. Nevertheless, most of the studies to date have simply focused on the overall impact of a particular programme. The most important questions, *for whom the training works best and which type of training are the most effective,* have rarely been answered. Therefore, the existing body of literature is not informative for policy design. Moreover, the econometric evaluation of training programmes has been mostly derived from advanced economies. The evidence from developing countries remains limited. On top of that, the small existing literature from developing countries hardly captures changes that take place in the informal sector. Hence, the results do not represent the real impact of training programmes in developing economies.

The objective of this research is to fill these knowledge gaps by using a large-scale vocational training programme in Thailand as a case study. Although vocational training has been provided to Thai workers for decades, studies on vocational training in Thailand have been simply institutional assessments or programme monitoring report. No rigorous impact evaluation has been conducted. In this study, the impact of training on economic and social mobility is examined by both exogenous and endogenous treatment effect approaches. With regard to economic mobility, in addition to the

[1] Vocational training in this study refers to training to prepare a person to work in a job that requires a particular set of skills. It is held outside of the regular schooling system and excludes apprenticeships and staff trainings by firms.

impact on earnings which is quite common in previous training evaluations, we also consider the impact on household expenditures which may better reflect changes in individual's living standards. Moreover, we break new ground by not only looking at absolute but also relative changes, which are measured by the change of position in the earnings and expenditure distribution. This approach is justified by the fact that people tend to assess their living conditions by comparing themselves to others and develop their preference based on what others have and want (Pavlopoulos, 2007, p. 16). Therefore, absolute measurements may be insufficient to portray the improvement of individuals. To the best of our knowledge, examining the impact of training participation on relative mobility has never been done before. Last but not least, we discover the heterogeneity of impact with respect to participants and programmes characteristics. The results provide a better understanding of which component is associated with greater success and hence can be used as a policy guideline to improve the effectiveness of human capital development by means of vocational training programme.

We are fortunate to get access to the Thailand Socio-economic Panel Survey which, to our knowledge, has never been used in any impact evaluation studies. This panel data set covers seven years and contains rich information of training and individuals' socioeconomic characteristics and thus allows us to address training impact as well as its heterogeneity in the short term, medium term and long term, and capture changes that occurred in both formal and informal sector. The remainder of the paper is structured as follows. Section two summarises previous findings of the impact of vocational training in both developed and developing countries. Section three outlines Thailand's context and detail of vocational training in Thailand. Section four describes data and methodology used in this study and the subsequent section presents the results of the empirical analysis. The last section concludes the results and discusses the policy implications.

2. Evidence on Vocational Training

During the past decades, many evaluation studies of vocational training have been carried out. However, these evaluations have been concentrated in developed nations (Cho et al., 2015; Hirshleifer et al., 2015), both in the USA and Europe. Many studies claim that training programmes in these countries, on average, have a positive but small impact on labour market outcomes in the short term but the long-term impact has been inconclusive. Kluve (2010) observes that 38 out of 70 training evaluations in Europe report a small but significant short-term positive impact on employment. Heckman et al. (1999) in reviewing evaluations of training programmes in North American and European countries conclude that training programmes have a moderate positive impact on participants' earnings, at best, but the impact is likely to dissipate in the long term. In contrast, Card et al. (2010), based on a meta-analysis, conclude that training programmes are likely to have a positive impact on earnings and employment in the medium and long term.

However, the results from developed countries may not be applicable in the context of developing countries due to the larger informal sector, greater skill gap, and weaker administrative capacity to implement the training programmes (Betcherman, Dar, & Olivas, 2004). Very little literature is available from the developing world, most of it comes from Latin America and the Caribbean (LAC) (Puerta, 2010). Ibarraran and Rosas Shady (2008) review evaluation studies of training programmes in seven Latin American countries. They conclude that, on average, the impact of training programmes in LAC is slightly larger than the results discovered in developed countries. Recent studies from LAC have also tried to address the long-term impact of training which has been a crucial gap in the literature. Attanasio et al. (2015) merge experimental data with administrative information to examine the longer-term impact of the Columbian training programme. They found that after ten years, the impact of training on earning and probability to work in the formal sector remained positive and significant. Another evaluation study by Ibarraran et al. (2015) claims that despite the disappointing impact on labour earnings and quantity of employment, the training programme in the Dominican Republic is found to increase the quality of employment, measured as the probability of being a formal employee, in the long run. Although evaluation studies from LAC give an insight into training impacts in the context of developing countries, most of the LAC programmes target the youth, and not the general working-age population.

Maitra and Mani (2013), instead of looking at youth, evaluate the impact of the training programme for women living in poor neighbourhoods in India. They conclude that participants are likely to work more and earn more relative to their non-participant counterparts. These positive effects are realised in both short term (6 months after the programme) and medium term (18 months after the training). Hirshleifer et al. (2015) attempt to examine the result of vocational training beyond the medium term by examining the impact of Turkey's training programme on the unemployed population in general and uncover changes up to three years after the programme. After merging experimental data with social security records, they find no statistically significant impact of training on earnings and employment. The impact on formality of employment is positive and significant but disappears within three years. Although this study sheds further light on the long-term impact of vocational training in developing country, the social security data they used does not capture changes that occurred in the informal sector. It might be the case that earnings actually increased but participants remained in the informal sector in which the data was not recorded. Therefore, the results may not represent the real impact of training in developing economies.

The existing evidence shows that the impact of vocational training varies from programme to programme. The main general conclusion emerging from the overall result is that the effectiveness of the programme depends considerably on characteristics of participants and types of training (see e.g. Heckman et al., 1999; Ibarraran & Rosas Shady, 2008). However, little evidence exists on what specific features drive such heterogeneous results (Betcherman et al., 2004; Maitra & Mani, 2013; McEntaffer, 2015).[2] Heterogeneity of effect by gender, among several individual characteristics, has received most attention. Many studies conclude that female participants, on average, do better than males especially in the long run (Greenberg et al., 2003; McEntaffer, 2015; Osikominu, 2013). Osikominu (2013) examines heterogeneity of training impact by pre-specified skill and education. He finds that participants with higher occupational skill and degree of education gain less in terms of earnings but more in terms of employment. By contrast, Hirshleifer et al. (2015) do not observe any variation of impacts with respect to gender, age, cognitive ability, education and personality traits (measured by work centrality and tenacity).

The existing evidence is much scarcer regarding heterogeneity due to programme characteristics. Greenberg et al., (2003) by means of a meta-analysis, found no significant variation of impact by programme cost, implying that more expensive training does not guarantee better outcome. Hirshleifer et al. (2015) observe only limited and non-robust heterogeneity by course length and quality of teacher. Strong heterogeneity is only found by type of provider. Training programmes tend to have more impact when they are provided by private provider, but this distinction is significant only in the short run.

3. Thailand's Context and Vocational Training Programmes

Thailand is a middle income country with a poverty rate of 8.6 percent in 2016 and a Gini coefficient, measuring the level of income inequality, of 0.5 in 2015 (National Economics and Social Development Board [NESDB], 2017a). In 2017, out of 56 million people aged 15 years or older, around 38 million are in the labour market. In other words, the labour force participation rate is around 68 percent (NESDB, 2017b). The unemployment rate has been very low at about one percent over the last decade (National Statistical Office [NSO], 2017b). However, like many other developing countries, the quality of employment has long been a critical issue. Thailand has a large informal economy and more than half of employment takes place in the informal sector. In 2016, around 55.6

[2] Some studies also try to provide evidence regarding the impact heterogeneity by means of a meta-analysis but their findings are based on Active Labour Market Policies as a whole, not only vocational training (see e.g. Card, Kluve, & Weber, 2015; Crépon & van den Berg, 2016).

percent of Thai workers are informal with uncertain earnings and no protection from social security (NSO, 2016).

Moreover, Thailand also faces the challenge of an ageing workforce as more than 50 percent of Thai workers are older than 40 years (NESDB, 2017b). The working age population is expected to decrease rapidly by 2040, and at a faster pace than in other developing countries in East Asia and Pacific (The World Bank, 2016). Furthermore, the average salary of workers in Thailand is low and the decrease in labour supply, due to factors such as an ageing population, does not seem to result in higher salary. In addition to the institutional factors that have contributed to this wage rigidity, the low quality of labour supply is also to be mentioned. In 2017, around 60 percent of Thai workers have education only at lower secondary level or below (NSO, 2017a). Therefore, an investment in human capital aiming to increase workers' skills, productivity and thus earning level has been the priority for the Thai government.

Although Thailand has managed to achieve most of the Millennium Development Goals on gender equality in 2015 (NESDB, 2015), the Thai labour market is not that friendly for women. As of April 2018, around 60 percent of women of working age participate in the labour force, compared to 77 percent of male labour force participation (NSO, 2018). Although the wage gap between male and female workers has narrowed over the past decades due to an improvement in skills and education of female workers, the gender wage gap remains large when informal and self-employed workers are taken into account (Warunsiri Paweenawat, Vechbanyongratana, & Yoon, 2017). The discrimination against women in a number of industries also resulted in a lower wage of female workers compared to their male counterparts (Bui & Permpoonwiwat, 2015).

The Department of Skill Development (DSD), under the Ministry of Labour, is the main agency delivering the public vocational training programme for the population in Thailand since 1960. Its objectives are to improve human capital, increase individual welfare and address structural skill mismatches in the labour market. DSD provides services through its 12 regional and 68 provincial training centres across the country. The training programme comprises pre-employment training, upgrade training and retraining, aiming to increase earnings and employability of participants. The duration of training varies from course to course, ranging from six hours to longer than two months. The training courses offered cover a wide range of skills and occupations such as computer, electronics, constructions, craft production and cooking. These courses are mostly delivered in the classroom setting. Some courses also offer a brief on-the-job training after classroom training. Target participants are those with low socioeconomic status such as informal labour, elderly and low income workers. However, the participation in a training programme is entirely voluntary. Between

2009 and 2013, the average number of participants was around 300,000 per year with dropout around two percent (DSD, 2016).

In addition to the DSD, many other government agencies also offer programmes related to vocational training. For example, the Ministry of Agriculture and Cooperatives provides agricultural and fishery training to farmers nation-wide. Local administrative units also provide skills training to their residents that fit the local context and community needs. Most of the programmes are free of charge and some are partly subsidised by the government. Although the government has been a major provider of vocational training courses, it has encouraged private institutions to participate in skills training provision through various measures. For example, there are a number of public-private partnership projects that provide training to the unemployed, laid off workers and new graduates (Smiti, 2009). Moreover, the government also offers low-cost credit from which poor and unemployed workers can borrow to finance their vocational training programmes offered by private providers (Jitsuchon et al., 2009).

4. Data and Methods

4.1 Data

In order to examine the impact of training and its heterogeneity, we require a data set that contains information of training participants (and non-participants) such as income, age, gender, education and employment status; and details of the training such as course content, course length and course provider. Moreover, as the outcome of interest is mobility, the data set needs to be longitudinal. The Thailand Socio-Economic Panel Survey (SES-Panel) is a nationally representative longitudinal survey conducted by the National Statistical Office (NSO). The data set comprises five waves, of which the first one was conducted in 2005. The survey in 2005 contains some questions in which the interviewers asked respondents to recall their information up to 12 months prior to the interview. For example, respondents were asked "Have you ever attended a training programme during the last 12 months?". Therefore, the survey in 2005 also contains information about the situation in 2004. This is also the case for the follow up surveys which were conducted in 2006, 2007, 2010 and 2012.

In this analysis, we use training participation in 2006 as the treatment variable, and 2005 as the baseline. Changes that occurred from 2005 to 2006, or within a year after the training, are perceived as a short-term effect. A change from 2005 to 2007 or between 1-2 years post-training is a medium-term effect. Lastly, changes that occurred between 2005 and 2010 (4-5 years after training) and 2005 and 2012 (6-7 years after training) are considered as long-term impacts.

The first survey in 2005 covered 6,000 households or 21,450 individuals from both rural and urban areas in all regions: Bangkok Metropolitan, Central, North, Northeast, and South. The attrition rate during 2005 to 2012 is 27.7 percent which is comparable to other surveys used in training evaluations in developing countries such as the Dominican Republic (38 percent) and Malawi (46 percent) (as cited in Hirshleifer et al., 2015, p. 8).

The data is trimmed by excluding all individuals below the age of 15 years because our analysis focuses on work-related issues and any worker aged less than 15 is perceived as an illegal child labourer in Thailand. Moreover, people who participated in a training before 2006 and those from the non-treatment group attending trainings after 2006 are also dropped from the analysis. We then balance the panel by keeping only observations that can be observed in all five waves. The final balanced sample size consists of 10,485 individuals per wave of which 406 observations are treated and 10,079 observations are non-treated. Table 1 provides summary statistics of the trimmed and balanced panel data set classified by training participation.

4.2 Defining and measuring upward mobility

Mobility studies are concerned with quantifying the movement of individuals or households' socioeconomic status between two or more points in time. The analyses can take place either in inter- or intra-generational contexts, however, due to data availability, this paper focuses on intra-generational mobility. Research on intra-generational socioeconomic mobility has centred on income, also known as economic mobility and labour market status, also known as social mobility (e.g. Fields, 2006; Fields et al., 2003; Rama et al., 2015). Concerning economic mobility, our outcomes of interest include both absolute income mobility, measured by directional movement or income level per capita in natural logarithm, and relative income mobility, measured by positional movement or changes in income ranking.[3] In short, an individual is moving upward if he/she achieves a higher income or moves to a higher income rank in a subsequent period. In addition to income mobility, we also include wage mobility and expenditure mobility in our evaluation. In this paper, wage refers exclusively to return from wage employment while income is the total of all returns from working including wage, agricultural income and business income for each individual. Household expenditures per capita include all living expenses such as food, housing, clothing and transportation divided by household size. Expenditure mobility can directly reflect changes in an individual's living standard.

[3] According to Fields's definition (2006), directional movement examines the direction and magnitude of income changes between two periods. Positional movement measures changes of the position in the income distribution.

Regarding labour mobility, most studies use the transition between labour market states such as inactivity, unemployment, self-employment, informal employment and formal employment to compute mobility across various positions (e.g. Tansel & Kan, 2011; Verme et al., 2014). In this paper, three indicators are used to reflect upward labour mobility. The first indicator is an improvement in labour force status which is categorised, in an ascending order, as inactivity, unemployment and employment. The second indicator is a transition to formal employment which measures the prospect of upward movement from being informally employed to a formal employee. The final indicator is an improvement in employment status which is categorised, in an ascending order, as unpaid family worker, informal self-employed/informal employee, formal self-employed/formal employee and employer. While the first indicator indicates the impact of training on employment prospects or the quantity of employment, the other two indicators are used to track changes in terms of quality of employment which is also a major problem of labour markets in developing countries.

4.3 Estimation Methodology

In this section, we describe the econometric models used to identify the treatment effect and its heterogeneity. Due to the fact that vocational training in Thailand is offered to the general working-age population and participation is on a voluntary basis, a problem of selection bias is likely to occur. As anticipated, the summary statistics in Table1 show that a person with higher socioeconomic status is more likely to attend the training. The treatment group has higher level of education, tends to be more employed and has higher wage, income and expenditure. Rigorous econometric methods for impact evaluation are thus necessary to address this potential problem of selection bias.

4.3.1 Treatment Effect

We employ two different methods to examine the aggregate impact of vocational training on upward mobility, i.e. difference in differences (DD) and endogenous switching regressions (ESR).

Following the method suggested by the World Bank Handbook on Impact Evaluation (Khandker, Koolwal, & Samad, 2010), we first estimate the propensity score to exclude outliers, who fall outside the common support region, from the analysis. The propensity score is calculated by probit model of the probability of participation in training conditional on observable characteristics of individuals or $P(X) = \Pr\{T = 1|X\}$ where T indicates training participation in 2006 which is equal to "1" for participant and "0" for non-participants (Khandker et al., 2010). X is a set of individual characteristics at baseline (2005) that are likely to influence training participation including age, gender, level of education, urban/rural setting, region (Bangkok Metropolitan, Central, North, Northeast, and South), employment status and health condition. By keeping only observations that remain in the common support region, the sample reduces to 9,681 observations, of which 397 observations are treated and 9,284 observations are non-treated. Table 1 provides baseline characteristics of these "on-common-support" observations categorised by their treatment status.

However, as can be seen from Table 1, there are still serious imbalances between participants and non-participants in various aspects including age, rural/urban setting, education, labour force status, wage and expenditure. Therefore, we further perform one-to-one nearest neighbour matching without replacement to ensure that treatment and control group become more comparable at the pre-intervention baseline. This nearest neighbour matching step reduces the sample size to 794 individuals of which half of the final matched observations belongs to the treatment group and the other half are the control group. The treatment and control groups are then more comparable as presented in Table 1.

After that, we apply the difference in differences regressions to both on-common-support observations and nearest neighbour matched samples to estimate the impacts of vocational training programmes in Thailand;

$$lny_{it} = a_0 + a_1 T_{i1} + a_2 t + a_3 T_{i1} t + a_4 X_{it} + u_{it} \tag{1}$$

where y_{it} is wage, income or expenditure. t is time which is equal to "0" in the year prior to training (2005) and "1" in the post-training year. X_{it} is a set of control variables including age, gender, level of education, location of living (urban or rural), region, employment status, household size (in case of expenditure), and borrowing status (to control for any potential confounding effect from having better access to physical capital). The coefficient of the interaction term between treatment and time (a_3) is the treatment effect (Khandker et al., 2010).

We also use the probit model to examine the impact of training on the probability of positive movement of the position in the wage, income and expenditure distribution, and labour market status. The dependent variable (g_{it}) takes the value "1" if an individual moves upward to higher ranking position, moves to a better labour market status, or maintains the highest status. On the other hand, g_{it} takes the value "0" if an individual experiences downward mobility or remains stuck in the low status.

$$\Pr\,(g_{it} = 1) = \Phi(c_0 + c_1 T_{i1} + c_2 t + c_3 T_{i1} t + c_4 X_{it} + \nu_{it}) \tag{2}$$

The difference in difference method is supposed to be valid as long as the unobservable characteristics that may influence upward mobility are time invariant. In other words, participant and non-participant groups must have a parallel trend in their outcomes (Khandker et al., 2010). We are convinced that the parallel trend assumption is plausible as the propensity score matching in the first step, particularly the nearest neighbour matching, gives us a more comparable treatment and control group before the programme starts. Moreover, during 2005 to 2012, there are no macroeconomic nor policy changes, to our knowledge, that affects the treatment and control group differently. However, since vocational training in Thailand is based on voluntary registration, some unobservable factors such as motivation and aspiration in life that affect both outcomes and decision to participate are likely to change over time. Therefore, we employ another method to examine the aggregate impact of vocational training in Thailand.

Unlike DD for which treatment status is given, the endogenous switching regressions (ESR) approach assumes that selection into treatment is endogenous; hence unobservables that influence training participation are not independent of unobservables that affect outcomes (Maddala, 1983). Accordingly, ESR can address selection that is due to both observable and unobservable factors. Individuals, based on certain characteristics, are self-selected into two different regimes: participants and non-participants. The outcome equations are then estimated separately according to their regime, meaning that covariates are allowed to affect the outcome differently. Consequently, the unobservables in the selection (or choices) of training participation are taken into account in outcome equations and the possible selection bias is thus addressed. The model consists of two outcome equations and a selection equation that determines which regime applies.

Drawing from Maddala (1983) and Cameron and Trivedi (2005, p. 556), the impact of vocational training on absolute income, wage and expenditure mobility is estimated by the following regressions;

Regime1 (participant):

$$lny_{1it+1} = \beta_1{}'X_{1it+1} + u_{1it+1} \tag{3}$$

Regime2 (non-participant):

$$lny_{2it+1} = \beta_2{}'X_{2it+1} + u_{2it+1} \tag{4}$$

Selection Equation:

$$y_{3it} = \pi' Z_{it-1} + \varepsilon_{it} \tag{5}$$

$$y = \begin{cases} lny_{1it+1} \text{ if } y_{3it} > 0 \\ lny_{2it+1} \text{ if } y_{3it} \leq 0 \end{cases}$$

where t-1 is time at baseline or year 2005, t is time when training takes place or in year 2006 and t+1 is post-training period or in year 2006 (but after the training takes place), 2007, 2010 or 2012, the error terms in equations (3), (4) and (5) have mean zero and variance-covariance matrix

$$Cov(u_{1it+2}, u_{2it+2}, \varepsilon_{it+1}) = \begin{bmatrix} \sigma_{11} & \cdot & \sigma_{1\varepsilon} \\ \cdot & \sigma_{22} & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & 1 \end{bmatrix}$$

where the variance of the error term in the selection equation (5) or σ_{ε}^2 is assumed to be equal to 1 for reasons of identification. $\sigma_{11}$and σ_{22} denote the variances of the error terms in the outcome equations (3) and (4). $\sigma_{1\varepsilon}$ and $\sigma_{2\varepsilon}$ are the covariances of the error terms in equation (3), and (4) respectively, with equation (5). The covariance between the error terms in equations (3) and (4) cannot be identified and is therefore reported as a dot because lny_{1it+1} and lny_{2it+1} are never observed at the same time.

In equation (5), y_{3it} is a binary variable denoting training participation. If an individual participates in training programme in 2006, y_{3it+1} will equal "1" and will be placed in regime1 (participant). Regime2 (non-participant) will be applied if y_{3it} takes the value "0". Z_{it-1} are baseline characteristics used to model selection into training including age, gender, level of education, location of living (urban or rural), employment status, region and health condition. These variables are the same set as the ones used to estimate propensity score in DD approach. The outcome equation (3) and (4), y_{1it+1} and y_{2it+1} are absolute wage, income or expenditure in the post-training period. X_{1it+1} and X_{2it+1} are control variables in the post-training year, most of which are used as explanatory variables in the DD regression for the on-common-support matched samples, including age, gender, level of education, rural/urban setting, region, employment status, household size (in case of expenditure), and borrowing status. Following Heckman et al. (2001) and Di Falco et al. (2011), the treatment effect on the treated evaluated at the means of the variables is then calculated by equation (6)[4] as follows;

$$\text{Treatment Effect on the treated} = ({\beta_1}' - {\beta_2}')\bar{X}_{1it+1} + (\sigma_{1\varepsilon} - \sigma_{2\varepsilon})\frac{\varphi(\pi'\bar{Z}_{it-1})}{\Phi(\pi'\bar{Z}_{it-1})} \quad (6)$$

where bars over the variables denote averages. For the impact on relative and labour mobility, outcome variables are coded as binary variables. The dependent variable takes the value "1" if individuals experience upward mobility or maintain the highest status and "0" otherwise. We now have a bivariate probit model with

$$y_{it+1}^{*} = {\beta_1}'X_{1it+1} + v_{1it+1}$$

[4] It is worth nothing that individual-specific components have not been taken into account.

$$y_{3it}^{*} = \pi' Z_{it-1} + \varepsilon_{it}$$

where $y_{it+1}^{*} = 1[y_{1it+1}^{*} > 0]$ represents upward mobility and $y_{3it}^{*} = 1[y_{3it}^{*} > 0]$ represents training and where v_{1it+1} and ε_{it} follow a bivariate normal distribution with variances equal to 1 and correlation equal to ϱ.

Using a conditional distribution from a bivariate distribution (Greene, 2012) and following Lokshin and Sajaia (2011, p. 371), the effects of the vocational training programme on the treated for relative and labour mobility evaluated at the means of the variables are obtained by equation (7)[5] as follows.

$$P(upward\ mobility\ |training) - P(upward\ mobility\ |not\ training) = \frac{P(upward\ mobility\ \cap\ training)}{P(training)} - \frac{P(upward\ mobility\ \cap\ not\ training)}{P(not\ training)}$$

$$\text{Treatment effect of the treated} = \frac{\Phi_2(\beta_1' X_{1it+1}, \pi' Z_{it-1}, \sigma_{1\varepsilon}) - \Phi_2(\beta_2' X_{2it+1}, \pi' Z_{it-1}, \sigma_{2\varepsilon})}{\Phi(\pi' Z_{it-1})} \quad (7)$$

The same set of regressors (X_{1it+1} and X_{2it+1}) used in the case of absolute mobility are also used in the two outcome equations but we further include some control variables at baseline (X_{1it-1} and X_{2it-1}) to account for environmental changes during the two periods of time.

4.3.2 Impact Heterogeneity

As mentioned at the beginning, the main objective of this study is to generate evidence that is informative for training policy design and implementation. We aim to examine impact heterogeneity and give answers to the question: do certain types of participant benefit more and do particular types of training work better than others? Equation (8) is used to estimate heterogeneity of impact by individual and programme characteristics.

$$lny_{it} = \alpha_0 + \alpha_1 T_{i1} + \alpha_2 t + \alpha_3 T_{i1} t + \alpha_4 X_{it} + \gamma T_{i1} t I_{i0} + \delta T_{i1} t P_{i1} + v_{it} \quad (8)$$

Equation (8) is extended from equation (1) by adding the interaction of treatment, time, and individual characteristics at baseline ($T_{i1} t I_{i0}$) and the interaction of treatment, time and programme characteristics($T_{i1} t P_{i1}$) to the DD regression. The difference-in-difference effect is now a linear function of the variables included in I_{i0} and P_{i1}. In this equation, y_{it} is wage, income or household

[5] Like in equation (6), in this equation, we do not control for any individual-specific unobserved effect.

expenditure per capita. T is treatment variable and t is time which is equal to "0" in the year prior to training (2005) and "1" in the post-training year. I_{i0} includes variables for individual characteristics before the start of training, i.e. baseline characteristics, including gender, living area (urban or rural), age, education and labor force status (inactive, unemployed or employed). I_{i0} also includes variables indicating tenacity measured by whether the individual attends more than one training course (multiple training) and whether he/she participates in two consecutive years, both 2006 and 2007 (repeated training). P_{i1} consists of variables related to the training programme, including type of course, type of provider, course length, financial supporter, and training costs. The nearest neighbour matched observations are used to estimate heterogeneity of impact where treatment and control group are made comparable.

5. Results

This section discusses the results of the estimations presented in the previous section. We begin with the overall treatment effects of vocational training on upward mobility. We then examine the heterogeneity of impacts with respect to pre-specified individual characteristics and types of training.

5.1 Impacts on upward mobility

Table 2 presents the impact of vocational training in Thailand on absolute, relative and labour mobility using on-common-support observations with a difference in difference (DD) approach. According to the results, we do not find any statistically significant impact of vocational training on neither absolute wage nor income mobility in any of the time horizons. However, participation in training increases absolute expenditure mobility, and hence individual's living standards, by 11.3 percent within a year after training. This result is significant at the 10 percent level. A similar effect is found in the medium term when the impact slightly decreases to 10.7 percent. Nevertheless, these positive and significant results do not persist in the long run.[6]

In line with absolute mobility outcomes, we observe no significant impact of vocational training on the probability of positive wage and income rank change. However, although the impact on

[6] We also estimate equation (1) and (2) using the whole sample without on-common-support restriction and nearest neighbour matching (10,485 individuals of which 406 observations are treated and 10,079 are non-treated). Our control variables in this case include both the variables used in the calculation of propensity score (probit model) and those used in the difference-in-differences regressions. The results are similar to what we obtain from the on-common-support observations.

expenditures is positive and significant, the impact is not large enough to move participants upward to a higher expenditure ranking position. The effectiveness of training on upward labour mobility is also disappointing. There is no statistically significant evidence, for any time duration, that training participation contributes to more employment, measured as the transition to a higher labour force status. Likewise, no positive impact is found on the quality of employment, neither for the transition to formality nor for the upward movement to a higher employment status.

As a robustness check, we estimate the results by conducting DD on the nearest neighbour matched samples. As presented in Table 3, we find consistent results between the two matching methods as both models find no significant impact of training on wage and income, both absolute and relative terms, and labour mobility. The only exception is the impact on absolute expenditure mobility in the short and medium term. While the on-common-support observations show that training participation significantly contributes to higher household expenditure, the impact on expenditure vanishes when we address the statistically significant differences between participants and non-participants before examining the impact of vocational training. In addition, we also estimate the results using other matching methods such as radius matching. We find that most of the results from nearest neighbour matching are in line with radius matching. Hence, we consider that our results are robust to different matching technique.

The results obtained with the nearest neighbour matching and DD approach are also robust when we consider the results obtained by endogenous switching regression (ESR) which are presented in Table 4. As can be seen, vocational training does not play a part in fostering upward absolute, relative and labour mobility when we take into account the endogeneity of decision to participate in training programme.

5.2 Heterogeneity by participant characteristics

The heterogeneous effect across population subgroups is presented in Table 5. As can be seen, our findings on the heterogeneity by gender is different from previous studies, which claim that female participants benefit more from training especially in the long run (see e.g. Greenberg et al., 2003; McEntaffer, 2015; Osikominu, 2013). In our case, we find that male participants, on average, do better than their female counterparts in the short term, medium term and long term, for wage and expenditure mobility. However, no significant variation is found when the outcome of interest is income mobility. We also find that vocational training is more effective in fostering wage and expenditure mobility for those living in urban area. In the medium term (2005-2007), however, urban residents seem to benefit less from training in terms of income but the impact is significant only at the 10 percent level.

The variation across age groups is mixed. We find some evidence indicating that when the dependent variable is absolute wage mobility, participants aged 25-39 appear to benefit most from the programme but the impact only materialises in the short run. When we consider income and expenditure mobility, participants aged 40-59 benefit most from training in the short and medium term. In the long run, the elderly (60 and above) appear to be the least affected in terms of wage and income mobility. All things considered, it is difficult to conclude at what age people should attend vocational training. The only conclusion we can derive is that vocational training appears to be the least effective for youth (aged 15-24) in the short and medium term and for elderly in the long term.

There is a complimentary effect between initial human capital, measured by degree of education, and training. The overall finding suggests that participants with a higher degree of education, especially vocational education and higher education, do better than those that have attended only primary school or less. The results are particularly compelling when the dependent variable is wage mobility as the magnitude of the impact is highest for all time horizons. These findings contrast sharply with pervious findings from Germany which, with respect to earnings, report a substitution effect between education and training (Osikominu, 2013). Concerning heterogeneity by labour force status, we do not observe a significant difference between participants who are already employed before the start of training and those who are not. However, participants who are economically inactive before the training appear to benefit less than those who have already been active in the labour market.

We also examine whether attending more than one training programme within a year, yields better outcomes. The result suggests that we cannot reject the null hypothesis of equality between participants attending only one programme and those attending more than one programme, implying that having participants to attend multiple programmes does not necessarily foster the programme impact on upward mobility. Finally, we further examine if there is any significant difference between those attending the training only in 2006 and those attending in two consecutive years (2006 and 2007). We find that participants who attend training in both years do better in all absolute mobility indicators but the impact on income and expenditure mobility does not appear to persist after 2007 when the repeated training does not take place.

5.3 Heterogeneity by programme characteristics

Table 5 also presents heterogeneity of training effect by programme characteristics. With regard to types of training, we categorise the courses into four main categories including agriculture, manufacturing and construction, services, and computer. Participants that have attended a computer training course do considerably better than others especially when it comes to wage mobility. Regarding the role of training duration, our findings are somewhat similar to Card et al. (2010) who report that longer courses do not differ from shorter courses. We find that although longer training courses appear to be more effective than shorter courses, in terms of expenditure mobility, in the long run, the evidence is weak as the positive result is significant only at the 10 percent level and does not persist beyond five years post-training. Considering the role of training provider, in line with Hirshleifer et al. (2015), we find that the training has a stronger impact when offered by private institutions in comparison to government agencies. However, private providers are found to significantly differ from public providers only if the outcome variable is expenditure mobility. When we consider wage and income mobility, a partnership between public and private agencies in training provision leads to a larger impact in the medium term.

With regard to heterogeneity by financial supporter, we cannot find statistically significant evidence that participants who finance themselves are different from those attending the training for free. Unsurprisingly, training participants who are financed by their employers appear to be more effective in terms of upward wage mobility in the short, medium and long term. The reason might be that employers know what skills they need and develop career paths based on the skills obtained from vocational training. However, this heterogeneity does not persist beyond 4-5 years after the programme. Last but not least, we examine the role of training costs in driving upward mobility. Our findings are comparable to Greenberg (2003) in that there is almost no significant variation of impact by programme cost. The only exception is in 2005-2010 during which we find a positive and significant association between training cost and upward income mobility. The magnitude of the impact is small, however.

We check the robustness of the results, in both heterogeneities by participant and programme characteristics, by performing DD with various matching methods such as radius matching and running equation (8) with various specifications such as removing treatment (T) and time (t) variables as well as adding/removing control variables. We find that most of the results are robust to different matching methods and specifications.

6. Conclusions and Policy Implications

Vocational training is, and will continue to be, an important policy tool to increase human capital, improve individual welfare and move people upward. However, its effectiveness has been inconclusive. This paper provides the first quantitative evaluation of vocational training in Thailand using a unique panel data set to analyse the training impact on upward mobility in the short, medium and long term. We use various treatment effect methods that work under different assumptions. Starting from propensity score matching with difference in differences (DD), we use both on-common-support observations and nearest neighbour matched observations to confine treatment and control group. In comparison to the on-common-support restriction, the nearest neighbour matching reduces the risk of bias at the expense of higher variance due to smaller sample size. To thoroughly assess the impact of training, we also apply endogenous switching regressions (ESR). While DD assumes that treatment assignment is given and relies for its accuracy on the parallel trend assumption, ESR allows for endogenous treatment, that is, when treatment assignment is not independent of outcomes.

Despite the different assumptions, all approaches suggest a common conclusion, which is that there is no credible evidence for the positive impact of Thailand vocational training programme on upward mobility of participants in terms of earnings and employment, both in absolute and relative terms. The result is quite disappointing but not so much different from many previous training evaluation studies which found only modest impacts, at best. The unpromising results of training effectiveness in Thailand might be due to a mismatch between skills acquired from training and labour market demand. The quality of a training is also an important issue which hampers trainings to facilitate upward mobility.

The only significant impact of training is obtained when the outcome variable is expenditures. This inconsistent result between wage/income, and expenditures might be due to the nature of the survey data which this analysis is drawn from. In an economy with a large agricultural and informal sector like in Thailand, it is more likely that wage and income are understated (Haughton & Khandker, 2009). Respondents may be incapable to estimate or recall their accurate wage and income. Moreover, they may be reluctant to report their actual earnings (ibid). If we also consider that expenditures may better reflect a household's or individual's standard of living, expenditures might be a more reliable indicator in this case (Christiaensen, Scott, & Wodon, 2002).

However, this desirable result on expenditures is only realised when a DD approach with on-common-support observations is employed. In other words, vocational training is found to foster absolute expenditure mobility when we ignore the significant differences between treatment and control group at baseline or disregard the endogeneity of decisions to participate in a vocational training. The potential explanation might be that people who voluntarily participate in a training programme are more likely to succeed even without training due to their superior characteristics especially the unobservable ones such as motivation and ability. Therefore, once we take these factors into account by ensuring that treated and controlled observations are comparable from the start or applying the endogenous approach, the positive and significant impact vanishes. Moreover, although the impact on the level of expenditures is positive and significant, the training programme fails to move participants upwards to a higher expenditure ranking. This finding highlights the importance of using both absolute and relative indicators in programme evaluation.

In addition, the significant impact of training on absolute expenditure mobility does not appear to sustain in the long run. This finding is interesting as vocational training is normally predicted to have small or negative short-term effects but become more positive in the long run. The reason is that during training, participants may spend less time and effort on working and finding jobs resulting in prolonged unemployment and unfavourable labour market outcomes in the short run (Card et al., 2015). This lock-in effect is found empirically in Card et al. (2010), Attanasio et al. (2015), Ibarraran et al. (2015). The reverse finding in Thailand, which is in line with Heckman et al. (1999) and Hirshleifer et al. (2015), is probably because the training length, in general, is not long enough to realise the lock-in effect. Moreover, the training content might be so specific that the return to such a training course may disappear in the long run when technology and demand for labour change. Furthermore, employers may use training participation to indicate greater productivity of employees or job applicants. Since the role of this signalling and screening effect may become less important in the long run, the impact of training is relatively more favourable in the short term.

As we have discussed, participation in vocational training does not lead to higher wage, income or labour mobility. The significant impact on expenditure mobility appears only in absolute terms, but it is not robust to different evaluation methods and disappears in the long run. Therefore, further analysis is needed to fully understand the impact of training and to design more effective policies that mitigate the potential negative effects and enhance the positive impact of training on upward mobility. One possible way of doing so is to examine impact heterogeneity to discover what programme and participant characteristics are associated with greater (and lesser) success.

According to the results, among several groups of participants, women, rural residents, youth (aged 15-24) and elderly (60 and above), low-educated workers, and economically inactive persons are found to benefit less from vocational training. Therefore, policies to foster upward mobility need to target their efforts on these marginalised groups. With regard to the heterogeneity by gender, training courses have to be more female friendly by offering skills training for jobs that are suitable for female workers. However, the limited opportunities for women in Thailand's labour market may not be overcome simply by providing vocational training. There might also be factors that hinder women from advancing their career such as perception of women in traditional Thai society, family commitments, and occupational segregation. Moreover, protective legislations for women such as mandated maternal benefit may lead to unfair hiring practices against women because it increases the cost of employment of women (Hansatit, 2014). Therefore, structural and institutional barriers preventing women from a decent and well-paid job also need to be removed.

Moreover, training should be more customised to serve different age groups. For the youth, in addition to the classroom training, a different training setting that provides hands-on experience such as apprenticeship and on-the-job training may be more effective for the transition from school to work. It is also more common for seniors to remain working even after retirement. Some people may continue their primary occupation after their retirement and some may choose different vocations. In any case, vocational training programmes need to provide up-to-date skills for senior participants so that they can stay in the labour force and contribute to national economic and social development especially in the context of an ageing population.

The strong complimentary effect between education and training suggests that investment in formal education, both in terms of quantity and quality, should continue to be priority. However, for those who have already dropped out and are unlikely to get back to the formal education system, vocational training must take into account participants' prior knowledge and experience. The training programme must also address their barriers to learning as the low educated participants may lack motivation and encounter some impeding factors such as family obligations that prevent them from achieving success in training programme (Cedefop, 2016). Regarding participants who are inactive before the start of training, simply providing vocational skills may not be sufficient. Other active labour market policies such as employment counselling and job search assistance are needed to complement the training programme. Our results also show that repeated training is associated with better upward mobility outcomes. Accordingly, the same training programme, probably with more advanced contents, should be offered to the same participants every year or on a regular basis.

Our analysis also suggests a number of important policy implications with respect to programme features. As can be seen, a computer training course has larger effects compared to other types of training. This is not surprising as computer skills have become an essential requirement for career advancement in Thailand during the past decades. Therefore, computer skills training should be offered more. At the same time, other types of training such as agriculture, manufacturing and services, should be redesigned to better fit the current country context and keep up with the demand for labour. As private providers and public-private partnerships are found to be more effective than the courses offered by government agencies alone, the government should continue to support private institutions and consider working more with them in designing and providing skill development programmes. Furthermore, improving a connection with businesses may also help widen employment opportunity for training participants, thereby enhancing the effectiveness of training programme. Last but not least, the empirical results imply that training is more effective when it is sponsored by employers. Therefore, the government should incentivise employers to support their employees both by funding the training cost and providing opportunity for job promotion based on skills that employees can be equipped by attending the training programme.

The presented results and conclusions are derived from the rigorous methods with the justified assumptions. However, we must admit that there are some limitations in this study, mainly due to the lack of data, which call for further research. First, as we do not have data for the quality of training, we cannot ensure that the quality of training courses delivered are consistent across training centres and groups of participants. Second, as we mentioned earlier, vocational training in Thailand has been offered for decades. Due to data availability, however, we can only control for the year 2005, which is used as the baseline, and make sure that during the past 12 months, at least, before the training takes place, not any person in our sample participates in vocational training. There might be the case that subjects in the control group did participate in vocational training long before 2005 resulting in the bias which cannot be addressed by the current data set.

Finally, although our disappointing results on the impact of training programmes are in line with existing literature and several explanations can be used to justify the result, the zero impact, which we find, might simply be because our sample size is too small. Unlike previous training evaluation studies in developing countries, which analyse the impact based on administrative data, this study makes use of survey data to ensure that changes that occur in the informal sector are captured in the analysis. Unfortunately, in the dataset we use, only a small number of training participants were surveyed. Hence, we may have difficulty discerning the training impact resulting in an unpromising outcome of Thailand's vocational training programme.

Table 1: Baseline Statistics by Treatment and Control Group

	Unmatched Observations			On-Common Support Observations			Nearest Neighbour Matched Observations		
	Treatment	Control	p-value for equal means	Treatment	Control	p-value for equal means	Treatment	Control	p-value for equal means
Number of Observations	406	10,079		397	9,284		397	397	
Age (years)	40.90	43.71	0.001***	40.95	42.58	0.033**	40.95	40.54	0.637
Gender (% of female)	54.68	55.85	0.642	54.66	54.74	0.975	54.66	52.90	0.619
Location (% of rural)	69.95	64.83	0.034**	69.77	65.18	0.059*	69.77	71.54	0.586
Education (%)									
Primary and below	46.55	61.22	0.000***	47.10	63.95	0.000***	47.10	48.36	0.723
Secondary	19.70	20.61	0.659	19.90	21.90	0.345	19.90	18.64	0.653
Vocational	9.36	6.53	0.025**	9.57	6.98	0.049**	9.57	8.31	0.535
Higher Education	23.40	6.70	0.000***	23.43	7.17	0.000***	23.43	24.69	0.679
Labour force status (%)									
Employed	83.01	69.78	0.000***	83.88	72.95	0.000***	83.88	84.64	0.770
Unemployed	5.91	5.34	0.615	6.05	5.55	0.672	6.05	5.79	0.881
Inactive	9.85	23.79	0.000***	10.08	21.50	0.000***	10.08	9.57	0.812
Wage (THB per month per capita)	6,651.18	2,963.31	0.000***	7,465.44	3,135.05	0.000***	7,465.44	7,237.65	0.831
Income (THB per month per capita)	12,156.44	9,330.38	0.066*	11,788.16	9,844.68	0.227	11,788.16	10,557.34	0.418
Household Expenditure (THB per month per capita)	3,857.55	2,880.11	0.000***	4,122.19	2,984.64	0.000***	4,122.19	3,892.83	0.503

Source: Own estimations based on Thailand Socio-Economic Panel Surveys 2005

Notes: Summary statistics presented here are trimmed by excluding observations below the age of 15 years and keeping observations that can be observed in all five waves (balanced panel). Treatment and Control groups are classified by training participation in 2006 in which those attending the programme are in the treatment group while those do not attend are put in the control group. p-value is derived from t-test for an equality of means which $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.001$ denotes imbalance between treatment and control group.

Table2: Impacts of Training by Difference in Differences with On-Common-Support Observations

		2005-2006	2005-2007	2005-2010	2005-2012
Absolute Mobility	Wage	0.094 (0.166)	-0.078 (0.160)	0.041 (0.167)	-0.026 (0.173)
	Income (wage + farm income + non-farm income)	0.131 (0.171)	0.096 (0.175)	0.241 (0.166)	0.163 (0.164)
	Expenditure	**0.113*** **(0.063)**	**0.107*** **(0.063)**	-0.031 (0.059)	-0.037 (0.059)
Relative Mobility	Wage rank	0.008 (0.024)	0.008 (0.022)	0.002 (0.020)	0.011 (0.020)
	Income rank	-0.013 (0.038)	-0.004 (0.038)	-0.031 (0.039)	-0.006 (0.037)
	Expenditure rank	-0.006 (0.037)	-0.007 (0.036)	-0.008 (0.036)	-0.005 (0.036)
Labour Mobility	**Labour force status** inactivity → unemployed → employed	-0.009 (0.036)	-0.011 (0.035)	0.002 (0.037)	0.001 (0.031)
	Formality of employment informal employed → formal employed	-0.013 (0.036)	-0.009 (0.035)	-0.008 (0.035)	-0.021 (0.035)
	Employment status unpaid family worker --> informal self-employed/informal employee --> formal self-employed/formal employee --> employer	-0.011 (0.038)	-0.007 (0.037)	-0.006 (0.038)	-0.019 (0.039)

Notes: The total number of observations after matching is 9,681 of which 397 observations are treated and 9,284 observations are non-treated. The impact on absolute mobility is obtained by equation (1) and impacts on relative and labour mobility are obtained by equation (2). Control variables namely age, gender, level of education, location of living (urban or rural), region, employment status, household size (in case of expenditure), and borrowing status are included but not shown here. Marginal effects are reported for relative and labour mobility. Standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table3: Impacts of Training by Difference in Differences with Nearest Neighbour Matched Observations

		2005-2006	2005-2007	2005-2010	2005-2012
Absolute Mobility	Wage	0.180 (0.248)	0.081 (0.238)	0.187 (0.233)	0.132 (0.252)
	Income (wage + farm income + non-farm income)	0.140 (0.227)	0.025 (0.226)	0.232 (0.215)	0.328 (0.222)
	Expenditure	0.106 (0.106)	0.082 (0.107)	-0.012 (0.099)	0.016 (0.097)
Relative Mobility	Wage rank	0.002 (0.039)	0.005 (0.039)	-0.009 (0.035)	0.004 (0.026)
	Income rank	-0.015 (0.052)	-0.009 (0.052)	-0.051 (0.050)	-0.001 (0.053)
	Expenditure rank	0.001 (0.048)	-0.000 (0.049)	0.001 (0.049)	0.001 (0.049)
Labour Mobility	**Labour force status** inactivity → unemployed → employed	-0.003 (0.034)	-0.019 (0.164)	-0.0002 (0.034)	0.001 (0.035)
	Formality of employment informal employed → formal employed	0.002 (0.058)	0.016 (0.149)	-0.001 (0.058)	-0.001 (0.060)
	Employment status unpaid family worker --> informal self-employed/informal employee --> formal self-employed/formal employee --> employer	0.002 (0.058)	0.014 (0.149)	-0.002 (0.058)	-0.001 (0.060)

Notes: The total number of observations after one-to-one nearest neighbour matching is 794 of which 397 observations are treated and 397 observations are non-treated. The impact on absolute mobility is obtained by equation (1) and impacts on relative and labour mobility are obtained by equation (2). Control variables such as household size (in case of expenditure), and borrowing status are included but not shown here. Marginal effects are reported for relative and labour mobility. Standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table4: Impacts on Upward Mobility by Endogenous Switching Regression (ESR)

		2005-2006	2005-2007	2005-2010	2005-2012
Absolute Mobility	Wage	0.034 (0.459)	-0.253 (0.364)	0.263 (0.470)	-0.312 (0.715)
	Income (wage + farm income + non-farm income)	0.297 (0.342)	0.329 (0.633)	-0.093 (0.492)	0.277 (0.366)
	Expenditure	0.441 (0.392)	0.277 (0.271)	0.303 (0.191)	0.180 (0.168)
Relative Mobility	Wage rank	-0.013 (0.070)	-0.499 (0.370)	-0.456 (0.374)	-0.737 (1.709)
	Income rank	0.466 (0.6693)	-0.301 (0.584)	0.760 (0.843)	0.502 (2.366)
	Expenditure rank	0.020 (0.119)	0.509 (0.353)	-0.348 (6.650)	-0.588 (0.630)
Labour Mobility	**Labour force status** (inactivity → unemployed → employed)	0.216 (0.435)	0.130 (0.214)	0.070 (0.787)	0.064 (0.347)
	Formality of employment (informal employed → formal employed)	-0.201 (0.216)	-0.152 (0.195)	0.350 (0.790)	0.143 (0.942)
	Employment status (unpaid family worker --> informal self-employed/informal employee --> formal self-employed/formal employee --> employer)	-0.309 (0.344)	-0.182 (0.319)	0.324 (0.676)	0.135 (0.437)

Notes: The total number of observations is 10,485 of which 406 observations are treated and 10,079 observations are non-treated. The effects of the treatment on the treated evaluated at the means of the variables are reported. The impact on absolute mobility are obtained by (3)-(6) while the impact on relative and labour mobility are estimated by equation (3)-(5) and (7) Control variables namely age, gender, level of education, location of living (urban or rural), region, employment status, household size (in case of expenditure), and borrowing status are included but not shown here. Marginal effects are reported for relative and labour mobility. Standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table5: Heterogeneity of Effect by Participant and Programme Characteristics

	2005-2006			2005-2007			2005-2010			2005-2012		
	wage	income	exp	wage	income	exp	wage	income	exp	wage	income	exp
Participant Characteristics												
Female	-0.704*	-0.265	-0.184*	-0.902**	0.179	-0.231**	-0.950**	0.113	-0.264**	-0.393	0.216	-0.165*
	(0.422)	(0.287)	(0.098)	(0.426)	(0.295)	(0.097)	(0.421)	(0.292)	(0.091)	(0.430)	(0.303)	(0.091)
Rural	-1.029**	0.106	-0.272**	-1.040**	0.678*	-0.098	-1.312**	0.363	-0.162	-1.843***	0.506	-0.308**
	(0.498)	(0.339)	(0.115)	(0.502)	(0.347)	(0.116)	(0.506)	(0.351)	(0.108)	(0.514)	(0.362)	(0.108)
Age (15-24 = base)												
25-39	1.524*	1.943**	0.737***	0.971	1.445**	0.399**	-0.255	-0.225	0.191	-0.749	-0.266	0.136
	(0.865)	(0.610)	(0.202)	(0.866)	(0.599)	(0.200)	(0.867)	(0.601)	(0.188)	(0.884)	(0.622)	(0.187)
40-59	0.745	1.943**	0.851***	0.438	1.830**	0.528**	-0.914	-0.169	0.442**	-1.500	-0.654	0.324*
	(0.895)	(0.610)	(0.209)	(0.900)	(0.622)	(0.207)	(0.897)	(0.622)	(0.195)	(0.916)	(0.645)	(0.194)
60 and up	-1.284	1.563**	0.809**	0.456	1.569**	0.350	-2.279**	-2.129**	0.097	-2.197*	-2.470**	-0.005
	(1.127)	(0.767)	(0.268)	(1.133)	(0.784)	(0.265)	(1.130)	(0.784)	(0.246)	(1.156)	(0.813)	(0.244)
Education (primary and below = base)												
secondary	-0.535	0.203	0.436**	1.135*	1.083**	0.552***	0.977	0.502	0.366**	0.680	0.217	0.465***
	(0.622)	(0.423)	(0.140)	(0.624)	(0.432)	(0.140)	(0.607)	(0.421)	(0.132)	(0.621)	(0.437)	(0.131)
vocational	1.980**	1.064*	0.840***	3.078***	1.815**	0.789***	3.196***	0.894	0.629***	3.786***	1.447**	0.674***
	(0.801)	(0.545)	(0.183)	(0.804)	(0.556)	(0.185)	(0.799)	(0.554)	(0.173)	(0.818)	(0.576)	(0.172)
higher educ	3.101***	1.485**	1.090***	3.802***	1.984***	1.069***	3.652***	1.002**	0.895***	4.557***	1.477**	0.845***
	(0.680)	(0.463)	(0.155)	(0.682)	(0.472)	(0.156)	(0.679)	(0.471)	(0.147)	(0.694)	(0.489)	(0.147)
Labour force status (employed = base)												
unemployed	-0.198	-0.844	-0.303	0.164	-0.641	-0.171	0.371	-0.421	-0.289	-0.094	-0.765	-0.291
	(0.844)	(0.575)	(0.189)	(0.836)	(0.578)	(0.191)	(0.834)	(0.578)	(0.180)	(0.854)	(0.601)	(0.180)
inactive	-2.937***	0.775	-0.202	-1.712**	-3.272***	-0.421**	-0.736	-2.551***	-0.348**	-0.728	-1.950***	-0.251
	(0.781)	(0.619)	(0.180)	(0.773)	(0.535)	(0.178)	(0.787)	(0.546)	(0.168)	(0.789)	(0.555)	(0.167)
Multiple training (training more than one course)	0.902	0.775	0.194	0.335	0.438	0.215	0.410	0.328	-0.065	0.261	-0.707	0.109
	(0.909)	(0.619)	(0.202)	(0.892)	(0.617)	(0.201)	(0.916)	(0.635)	(0.193)	(0.912)	(0.642)	(0.192)
Repeated training (training in both year2006 and 2007)				0.911**	0.503*	0.263**	0.779*	0.241	0.052	0.398	0.238	0.034
				(0.436)	(0.302)	(0.100)	(0.435)	(0.302)	(0.094)	(0.443)	(0.312)	(0.093)

	2005-2006			2005-2007			2005-2010			2005-2012		
	wage	income	exp	wage	income	exp	wage	income	exp	wage	income	exp
Programme Characteristics												
Type of Course (agriculture = base)												
Manufacturing and construction	-0.147 (0.641)	0.137 (0.437)	-0.059 (0.149)	0.534 (0.638)	-0.485 (0.441)	-0.063 (0.148)	0.982 (0.633)	0.223 (0.439)	0.161 (0.137)	0.451 (0.645)	-0.456 (0.454)	0.040 (0.136)
services	0.206 (0.806)	0.381 (0.549)	-0.084 (0.185)	0.505 (0.820)	-0.395 (0.567)	-0.011 (0.188)	1.423* (0.811)	0.144 (0.562)	0.195 (0.175)	1.013 (0.824)	-0.390 (0.580)	0.021 (0.174)
computer	2.457** (0.892)	0.462 (0.607)	0.257 (0.207)	2.903** (0.897)	0.074 (0.620)	0.275 (0.204)	3.729*** (0.892)	0.986 (0.618)	0.542** (0.194)	2.612** (0.910)	-0.093 (0.640)	0.347* (0.193)
Length (less than a week = base)												
more than a week	0.607 (0.778)	-0.029 (0.530)	-0.173 (0.181)	0.869 (0.784)	0.513 (0.542)	-0.058 (0.182)	0.559 (0.782)	0.043 (0.542)	0.022 (0.169)	0.465 (0.801)	0.520 (0.564)	0.064 (0.169)
more than a month	1.098 (0.907)	0.169 (0.617)	0.167 (0.208)	1.339 (0.916)	0.544 (0.633)	0.318 (0.206)	0.679 (0.914)	0.038 (0.633)	0.331* (0.198)	1.501 (0.934)	0.859 (0.657)	0.194 (0.197)
Provider (government = base)												
private	0.557 (0.617)	0.374 (0.420)	0.301** (0.142)	0.083 (0.628)	0.539 (0.434)	0.380** (0.144)	0.172 (0.623)	0.439 (0.432)	0.261* (0.135)	0.178 (0.637)	0.447 (0.449)	0.186 (0.134)
both	0.299 (1.023)	1.053 (0.696)	-0.050 (0.233)	2.237** (1.029)	1.419** (0.711)	0.319 (0.238)	1.032 (1.027)	0.719 (0.712)	0.266 (0.222)	0.725 (1.052)	1.217 (0.740)	0.052 (0.221)
Financial Supporter (free = base)												
self-support	-0.329 (1.067)	-0.139 (0.726)	-0.025 (0.244)	-0.984 (1.081)	0.102 (0.748)	-0.033 (0.243)	-1.001 (1.079)	-1.193 (0.748)	-0.309 (0.233)	-0.896 (1.105)	-0.467 (0.777)	-0.231 (0.233)
employer	1.288** (0.557)	0.554 (0.379)	-0.005 (0.127)	1.087* (0.565)	0.440 (0.391)	0.034 (0.126)	1.128** (0.559)	0.060 (0.387)	0.078 (0.121)	0.685 (0.572)	-0.132 (0.402)	0.000 (0.120)
Training cost	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.0004* (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Reference (α_3)	-1.442 (2.041)	1.246 (1.389)	-1.186** (0.472)	-3.019 (2.072)	0.033 (1.433)	-1.307** (0.472)	-1.543 (2.069)	2.750* (1.434)	-1.257** (0.452)	-0.906 (2.118)	3.410** (1.490)	-0.905 (0.449)

Notes: The total number of observations after matching is 794 of which 397 observations are treated and 397 observations are non-treated. The results are obtained by equation (8). Control variables such as household size (in case of expenditure), and borrowing variable are included but not shown here. Standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Reference:

Attanasio, O., Guarín, A., Medina, C., & Meghir, C. (2015). *Long Term Impacts of Vouchers for Vocational Training: Experimental Evidence for Colombia*. National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w21390

Betcherman, G., Dar, A., & Olivas, K. (2004). *Impacts of active labour market programs: New evidence from evaluations with particular attention to developing and transition countries*. Social Protection, World Bank. Retrieved from http://info.worldbank.org/etools/docs/library/251019/day6DiscussionPaperSeries0402April6Se1.pdf

Borkum, E., Mamun, A., Marco, L., & Mubeen, M. K. (2015). Evaluation of the Vocational Training Grant Fund in Namibia: Baseline Report (No. 40233.241). Mathematica Policy Research.

Bui, M.-T. T., & Permpoonwiwat, C. K. (2015). Gender Wage Inequality in Thailand: A Sectoral Perspective. *International Journal of Behavioral Science*, *10*(2), 19–36.

Cameron, A. C., & Trivedi, P. K. (2005). Microeconometrics: Methods and Applications. Cambridge, UK: Cambridge University Press.

Card, D., Kluve, J., & Weber, A. (2010). Active Labour Market Policy Evaluations: A Meta-Analysis. *The Economic Journal*, *120*(548), F452–F477. https://doi.org/10.1111/j.1468-0297.2010.02387.x

Card, D., Kluve, J., & Weber, A. (2015). What Works? A Meta Analysis of Recent Active Labour Market Program Evaluations. *IZA Discussion Paper*, *IZA DP No.9236*. Retrieved from http://ftp.iza.org/dp9236.pdf

Cedefop (2016*). Improving career prospects for the low-educated: the role of guidance and lifelong learning*. Luxembourg: Publications Office. Cedefop research paper; No 54. http://dx.doi.org/10.2801/794545

Cho, Y., Mobarak, A. M., Orozco, V., & Wolfson, D. (2015). Gender Differences in The Effects of Vocational Training: Constraints on Women and Dropout Behavior. Retrieved from http://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-6545

Christiaensen, L., Scott, C., & Wodon, Q. (2002). *Poverty Measurement and Analysis* (MPRA paper No. 45362). The World Bank. Retrieved from https://mpra.ub.uni-muenchen.de/45362/1/MPRA_paper_45362.pdf

Crépon, B., & van den Berg, G. J. (2016). Active Labour Market Policies. *Annual Review of Economics*, *8*(1), 521–546. https://doi.org/10.1146/annurev-economics-080614-115738

Department of Skill Development. (2016). Summary Statistics of Vocational Training Program (in Thai). Retrieved from http://www.dsd.go.th/DSD/Stat

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

Fields, G. S., Cichello, P. L., Freije, S., Menendez, M., & Newhouse, D. (2003). Household Income Dynamics: A Four-Country Story. *The Journal of Development Studies*. https://doi.org/10.1080/00220380412331293757

Fields, G. S. (2006). *The Many Facets of Economic Mobility*. Cornell University ILR School.

Greenberg, D. H., Michalopoulos, C., & Robins, P. K. (2003). A meta-analysis of government-sponsored training programs. *Industrial & Labour Relations Review*, *57*(1), 31–53.

Greene, W. H. (2012). *Econometric Analysis* (Seventh Edition). Pearson Education Limited.

Hansatit, P. (2014). A study on gender inequality in Thailand◎: career experience of Thai female managers. Southern Cross University, Lismore, NSW. Retrieved from https://epubs.scu.edu.au/cgi/viewcontent.cgi?article=1403&context=theses

Haughton, J., & Khandker, S. R. (2009). *Handbook on Poverty and Inequality*. Washington, DC: The World Bank. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/11985/9780821376133.pdf?sequence=1

Heckman, J., Lalonde, R.J. and Smith, J.A. (1999). 'The economics and econometrics of active labour market programs', in (O.C. Ashenfelter and D. Card eds.), Handbook of Labour Economics, Vol. 3, Part A, pp. 1865–2097, Amsterdam: Elsevier.

Heckman, J., Tobias, J. L., & Vytlacil, E. (2001). Four Parameters of Interest in the Evaluation of Social Programs. *Southern Economic Journal*, *68*(2), 210. https://doi.org/10.2307/1061591

Hirshleifer, S., McKenzie, D., Almeida, R., & Ridao-Cano, C. (2015). The Impact of Vocational Training for the Unemployed: Experimental Evidence from Turkey. *The Economic Journal*, *126*(597), 2115–2146. https://doi.org/10.1111/ecoj.12211

Ibarraran, P., & Rosas Shady, D. (2008). Evaluating the impact of job training programmes in Latin America: evidence from IDB funded operations. *Journal of Development Effectiveness*, *1*(2), 195–216.

Ibarrarán, P., Kluve, J., Ripani, L., & Rosas, D. (2015). Experimental evidence on the long-term impacts of a youth training program. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2655085

Jitsuchon, S., Planpraphan, J., Vajragupta, Y., & Methakunavut, N. (2009). *Social Investment under the Changes in Social Structure and Transformation to a Knowledge-Based Society (in Thai)*. Thailand Development Research Institute. Retrieved from http://tdri.or.th/research/social-investment/

Khandker, S., Koolwal, G., & Samad, H. (2010). *Handbook on Impact Evaluation: Quantitative Methods and Practices*. The World Bank. https://doi.org/10.1596/978-0-8213-8028-4

Kluve, J. (2010). The effectiveness of European active labour market programs. *Labour Economics*, *17*(6), 904–918. https://doi.org/10.1016/j.labeco.2010.02.004

Lokshin, M., & Sajaia, Z. (2011). Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors. *The Stata Journal*, *11*(3), 368–385.

Maddala, G. S. (1983). Limited-Dependent and Qualitative Variables in Econometrics. Cambridge, UK: Cambridge University Press.

Maitra, P., & Mani, S. (2013). Learning and earning: Evidence from a randomized evaluation in India. *Fordham University, Department of Economics, Discussion Paper Series, 2*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2341125

McEntaffer, M. J. (2015, August). *The Promise of Worker Training: New Insights into the Effects of Government Funded Training Programs*. University of Nebraska.

National Economics and Social Development Board, Office of the Prime Minister. (2015). *Thailand Millennium Development Goals 2015 (in Thai)*. Retrieved from http://passthrough.fw-notify.net/download/261956/http://social.nesdb.go.th/social/Portals/0/MDG%20Thailand%2020150825.pdf

National Economics and Social Development Board, Office of the Prime Minister. (2017a). Social and Quality of Life Database System - *Poverty and Income Distribution (in Thai)*. Bangkok, Thailand. Retrieved January 3, 2018 from http://social.nesdb.go.th/SocialStat/StatDefault_Final.aspx

National Economics and Social Development Board, Office of the Prime Minister. (2017b). Social and Quality of Life Database System – *Thailand Labour Force (in Thai)*. Bangkok, Thailand. Retrieved June 4, 2018 from http://social.nesdb.go.th/SocialStat/StatSubDefault_Final.aspx?catid=2

National Statistical Office, Ministry of Information and Communication Technology. (2016). *Informal Labour in 2016 (in Thai)*. Bangkok, Thailand. Retrieved April 23, 2017 from http://service.nso.go.th/nso/web/survey/surpop2-2-4.html

National Statistical Office, Ministry of Information and Communication Technology. (2017a). *Summary report on Thailand labour force survey as of January 2017 (in Thai).* Retrieved 19 February, 2018 from http://service.nso.go.th/nso/nsopublish/themes/files/lfs60/reportJan.pdf

National Statistical Office, Ministry of Information and Communication Technology. (2017b). *The Labour Force Survey (in Thai)*. Bangkok, Thailand. Retrieved April 23, 2017 from http://service.nso.go.th/nso/web/statseries/statseries04.html

National Statistical Office, Ministry of Information and Communication Technology. (2018). *Summary report on Thailand labour force survey as of April 2018 (in Thai)*.

Osikominu, A. (2013). Quick Job Entry or Long-Term Human Capital Development? The Dynamic Effects of Alternative Training Schemes. *The Review of Economic Studies*, *80*(1), 313–342. https://doi.org/10.1093/restud/rds022

Pavlopoulos, D. (2007). *Wage Mobility Patterns in Europe*. Tilburg University. Retrieved from https://pure.uvt.nl/portal/en/publications/wage-mobility-patterns-in-europe(916ddc9e-ef9c-45ad-bc4b-4cb6e6cbad99).html

Puerta, M. L. S. (2010). *Labour Market Policy Research for Developing Countries: Recent Examples from the Literature What do we know and what should we know?* Citeseer. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.163.1431&rep=rep1&type=pdf

Rama, M., Beteille, T., Li, Y., Mitra, P., & Newman, J. L. (2015). *Addressing Inequality in South Asia*. The World Bank. Retrieved from https://openknowledge.worldbank.org/handle/10986/20395

Smiti, P. (2009). *Thailand's Perspective on Skills Training in the Workplace*. Department of Skill Development, Ministry of Labour. Retrieved from http://www.ilo.org/wcmsp5/groups/public/@asia/@ro-bangkok/documents/meetingdocument/wcms_120566.pdf

Tansel, A., & Kan, E. O. (2011). Labour Mobility Across the Formal/Informal Divide in Turkey: Evidence From Individual Level Data. Retrieved from http://ssrn.com/abstract=1978291

The World Bank. (2016). Thailand Economic Monitor - June 2016: Aging Society and Economy. Retrieved from http://www.worldbank.org/en/country/thailand/publication/thailand-economic-monitor-june-2016-aging-society-and-economy

Verme, P., Barry, A. G., Guennouni, J., & Taamouti, M. (2014). Labour Mobility, Economic Shocks, and Jobless Growth: Evidence from Panel Data in Morocco. *The Poverty Reduction and Economic Management Department, Middle East and North Africa Region, The World Bank*, Policy Research Working Paper 6795.

Warunsiri Paweenawat, S., Vechbanyongratana, J., & Yoon, Y. (2017). *Is Thailand's labour market really woman friendly? Revisiting the declining gender wage gap*. Presented at the Labour and Human Capital, Bank of Thailand, Bangkok, Thailand. Retrieved from https://www.pier.or.th/wp-content/uploads/2017/08/workshop2017_Labor_Jessica.pdf

Woolard, I., & Klasen, S. (2005). Determinants of Income Mobility and Household Poverty Dynamics in South Africa. *Journal of Development Studies*, *41*(5), 865–897. https://doi.org/10.1080/00220380500145313

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