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

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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 program. We also examine the heterogeneity of effects with respect to individual and program 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 program. 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

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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 programs and participants (Borkum et al., 2015; Maitra & Mani, 2013). An insight into impact heterogeneity is thus crucial to improve the effectiveness of training programs. Nevertheless, most of the studies to date have simply focused on the overall impact of a particular program. The most important questions, *for whom the training works best and which type of training is most effective,* have rarely been answered. Therefore, the existing body of literature is not informative for policy design. Moreover, the econometric evaluation of training programs 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 programs in developing economies.

The objective of this research is to fill these knowledge gaps by using a large-scale vocational training program 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 program 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

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[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 programs 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 program.

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 summarizes 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 evaluation 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 programs in these countries, on average, have a positive but small impact on labor 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 programs in North American and European countries conclude that training programs 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 programs 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 programs (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 programs in seven Latin American countries. They conclude that, on average, the impact of training programs 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 program. 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 labor earnings and quantity of employment, the training program 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 programs 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 program for women living in poor neighborhoods in India. They conclude that participants are likely to work more and earn more relative to their non-participant counterparts. These positive effects are realized in both short term (6 months after the program) 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 program on the unemployed population in general and uncover changes up to three years after the program. After merging experimental data with social security records, they found 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 program to program. The main general conclusion emerging from the overall result is that the effectiveness of the program 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 found a complimentary effect with respect to employment but a substitution effect with respect to earning. In other words, participants with higher occupational skill and degree of education receive less earning gains but more employment gains. 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 more scarce regarding heterogeneity due to program characteristics. Greenberg et al., (2003) by means of a meta-analysis, found no significant variation of impact by program 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 programs 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 Programs

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 0.45 in 2015 (National Economics and Social Development Board [NESDB], 2017a). In 2017, out of 56 millions people aged greater than 15 years, around 38 millions people are in the labor market. In other words, labor 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

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[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 Labor 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, there is also a challenge of aging 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 this decline of Thailand's working age population appears to be higher than other developing countries in East Asia and Pacific (The World Bank, 2016). Furthermore, the average salaries of workers in Thailand is low and the decrease in labor supply, due to factors such as an ageing population, does not seem to result in higher salaries. In addition to the institutional factors that have contributed to this wage rigidity, the low quality of labor supply is also one of the reasons. 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.

In addition, although Thailand has managed to achieve most of the millennium development goals on gender equality in 2015 (NESDB, 2015), Thai labor market is not that friendly for women. As of April 2018, around 60 percent of women of working age participate in labor force, compared to 77 percent of male labor force participation (NSO, 2018). Moreover, although the wage gap between male and female workers has been narrowed down 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 in to account (Warunsiri Paweenawat, Vechbanyongratana, & Yoon, 2017). Besides, there has been discrimination against women in a number of industries resulting in a lower wage of female workesrs compared to their male counterparts (Bui & Permpoonwiwat, 2015).

The Department of Skill Development (DSD), under the Ministry of Labor, is the main agency delivering the public vocational training program for the population in Thailand since 1960. Its objectives are to improve human capital, increase individual welfare and address structural skills mismatch in the labor market. DSD provides services through its 12 regional and 68 provincial training centers across the country. The training program 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 labor, elderly and low income workers. However, participation in training program is entirely on voluntary basis. 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 programs 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 programs are free of charge and some are partly subsidized 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 and 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 programs 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 NSO. The data set comprises of five waves of which the first wave was conducted in 2005. The survey in 2005 contains some questions in which the interviewers asked respondents to recall their information backward up to 12 months prior to the interview. For example, respondents were asked "Have you ever attended training program during the last 12 months?". Therefore, the survey in 2005 also contains some information 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 is 13.4 percent from 2005 to 2006, 12.3 percent from 2006 to 2007, 26.6 percent from 2007 to 2010 and 27.3 percent from 2010 to 2012.The overall attrition rate from the first wave in 2005 to the last wave in 2012 is 30 percent. This attrition rate 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 laborer 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 10,484 individuals per wave of which 406 observations are treated and 10,078 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 centered on income, also known as economic mobility and labor 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 per capita 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 household living expenses such as food, housing, clothing and transportation and are divided by household size. Expenditure mobility can directly reflect changes in an individual's living standard.

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[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 labor mobility, most studies use the transition between labor 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 labor mobility. The first indicator is an improvement in labor force status which is categorized, 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 categorized, 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 labor 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. propensity score matching with 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 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, location of living (urban or rural), region (Bangkok Metropolitan, Central, North, Northeast, and South), employment status and health condition. By keeping only observations that remain in the common support region, this propensity score matching step reduces the sample size to 9,683 of which 397 observations are treated and 9,286 observations are non-treated. Table 1 provides baseline characteristics of treatment and control group after this "on-common-support" matching.

However, as can be seen from Table 1, there are serious imbalances between treatment and control group in many baseline characteristics including education, labor force status and wage. Therefore, we further perform nearest neighbor matching without replacement to ensure that treatment and control group become more comparable at the pre-intervention baseline.[4] This nearest neighbor 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 put in control group. The treatment and control group are then more comparable as presented in Table 1.

After that, we apply the matched samples from each matching method, on-common-support matching and nearest neighbor matching, with the following difference in differences regressions to obtain impact of vocational training program in Thailand;

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

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. For the matched samples from the on-common-support matching tenchinique, as our treatment and control group are not comparable at baseline, we control for a number of factors including age, gender, level of education, location of living (urban or rural), region (Bangkok Metropolitan, Central, North, Northeast, and South), 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). For the nearest neighbor matched individuals, since several characteristics are already balanced at baseline, we only control for factors which were not used to calculate propensity score and thus may not be balanced, such as household size and borrowing status. The coefficient of the interaction term between treatment and time (a_3) is the treatment effect (Khandker et al., 2010).

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[4] We have also tried other matching methods such as radius matching and kernel matching. However, nearest neighbor matching without replacement gives us the balanced baseline while maintaining highest number of treated observations after matching.

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 labor market status. The dependent variable (g_{it}) takes the value "1" if an individual moves upward to higher ranking position, moves to a better labor 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.

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

Difference in differences 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 neighbor matching, gives us a more comparable treatment and control group before the program 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 which treatment status is given, 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): | $lny_{1it+2} = \beta_1 X_{1it+2} + u_{1it+2}$ | (3) |

$$lny_{1it+2} = \beta_1 X_{1it+2} + u_{1it+2} \quad (3)$$

Regime1 (participant):

$$lny_{2it+2} = \beta_2 X_{2it+2} + u_{2it+2} \quad (4)$$

Regime2 (non-participant):

$$y_{3it+1} = \pi Z_{it} + \varepsilon_{it+1} \quad (5)$$

Selection Equation:

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

$$Cov(u_{1it+2}, u_{2it+2}, \varepsilon_{it+1}) = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{12} & \sigma_{22} & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & 1 \end{bmatrix}$$

where t is time at baseline or year 2005, t+1 is time when training takes place or in year 2006 and t+2 is post-training period or in year 2006 (but after the training takes place), 2007, 2010 or 2012.

In equation (3), y_{3it+1} is a binary variable denoting training participation. If an individual participates in training program in 2006, y_{3it+1} will equal "1" and will be placed in regime1 (participant). Regime2 (non-participant) will be applied if y_{3it+1} takes the value "0". Z_{it} 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 one used to estimate propensity score in DD approach. The outcome equation (1) and (2), y_{1it+2} and y_{2it+2} are absolute wage, income or expenditure in the post-training period. X_{1it+2} and X_{2it+2} are control variables in the post-training year including age, gender, level of education, location of living (urban/rural), region, employment status, household size (in case of expenditure), and borrowing status.

Treatment effect is then calculated by the following equation;

$$\text{Average Treatment Effect} = \left[(\beta_1 X_{1it+2}) + \rho_{13}\sigma_1 \frac{\varphi(\pi Z_{it})}{\Phi(\pi Z_{it})}\right] - \left[(\beta_2 X_{2it+2}) - \rho_{23}\sigma_2 \frac{\varphi(\pi Z_{it})}{1-\Phi(\pi Z_{it})}\right] \quad (6)$$

where ρ_{13} and ρ_{23} are correlation coefficients of the error terms from the selection and each outcome equation. σ_1 and σ_2 are the standard error of residual of the outcome equations.

For the impact on relative and labor 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. The probit model is used to estimate equation (3) and (4), and treatment effect is obtained by equation 7.

$$\text{Average Treatment Effect} = \Phi\left[(\beta_1 X_{1it+2}) + \rho_{13}\frac{\varphi(\pi Z_{it})}{\Phi(\pi Z_{it})}\right] - \Phi\left[(\beta_2 X_{2it+2}) - \rho_{23}\frac{\varphi(\pi Z_{it})}{1-\Phi(\pi Z_{it})}\right] \tag{7}$$

The same set of regressors (X_{1it+2} and X_{2it+2}) 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} and X_{2it}) 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? Equations 8 is used to estimate heterogeneity of impact by individual and program characteristics.

$$lny_{it} = \alpha_0 + \alpha_1 T_{i1} + \alpha_2 t + \alpha_3 T_{i1}t + \alpha_4 X_{it} + \gamma T_{i1}tI_{i0} + \delta T_{i1}tP_{i1} + v_{it} \tag{8}$$

Equation (8) is extended from equation (1) by adding the interaction of treatment, time, and individual characteristics at baseline ($T_{i1}tI_{i0}$) and the interaction of treatment, time and program characteristics ($T_{i1}tP_{i1}$) to the DD regression. In this equation, y_{it} is wage, income or expenditure. 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 program, including type of course, type of provider, course length, financial supporter, and training costs. The matched observations from nearest neighbor matching method is used to estimate heterogeneity of impact as treatment and control group are more comparable using this method.

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 labor mobility using on-common-support matching with a difference in difference (DD) approach. We find that vocational training has no statistically significant impact 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 decrease to 11.1 percent. Nevertheless, these positive and significant results do not persist in the long run.

In line with absolute mobility outcomes, we do not observe any statistically significant impact of vocational training on the probability of positive wage and income rank change. However, although the impact on 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 labor 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 labor 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 neighbor 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, and labor mobility. The only exception is the impact on absolute expenditure mobility in the short and medium term. While the on-common-support matching finds that training participation can significantly contribute to higher 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.

The results obtained with the nearest neighbor matching and DD approach are also robust when we consider the results obtained by endogenous swichting 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 labor mobility when we take into account the endogeneity of decision to participate in training program.

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 program but the impact only materializes 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 effective in terms of wage and income mobility. All things considered, it is difficult to conclude at what age should people 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 labor 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 labor market.

We also examine whether attending more than one training program within a year, yields better outcomes. The result suggests that we cannot reject the null hypothesis of equality between participants attending only one program and those attending more than one program, implying that having participants to attend multiple programs does not necessarily foster the program 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 do not appear to persist after 2007 when the repeated training does not take place.

5.3   Heterogeneity by program characteristics

Table 6 presents heterogeneity of training effect by program characteristics. With regard to types of training, we categorize 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 the 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 program. 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 program 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 program characteristics, by performing DD with various matching methods such as radius matching and running equation (8) with various specification 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 analyze 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 matching and nearest neighbor matching methods to confine treatment and control group. In comparison to on-common-support matching, nearest neighbor matching reduces risk of bias at the expense of higher variance due to smaller sample size. To thoroughly assess the impact of training we therefore conduct another different method i.e. endogenous switching regressions (ESR). While DD assumes that treatment assignment is given and relies 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 vocational training in Thailand fails to move participants upward 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 labor 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 results 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 large argricultural 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 houshold'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 realized when a DD approach with on-common-support matching 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 program 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 program fails to move participants upwards to a higher expenditure ranking. This finding highlights the importance of using both absolute and relative indicators in program 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 unfavorable labor 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 realize 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 labor change. Furthermore, employers may use training participation to indicate greater productivity of employees or job applicants. Since the role of this signaling and screening effect may become less important in the long run, the impact of training is relatively more favorable in the short term.

As we have discussed, participation in vocational training does not lead to higher wage, income or labor 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 program 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 effort on improving these marginalized 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 labor 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, occupational segregation and unfair hiring practices due to protective legislations for women (Hansatit, 2014). Therefore, structural and institutional barriers preventing women from a decent and well-paid job need to be removed.

Moreover, training should be more customized 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 programs need to provide up-to-date skills for senior participants so that they can stay in the labor force and contribute to national economic and social development especially in the era of aging 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 program 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 program (Cedefop, 2016). Regarding participants who are inactive before the start of training, simply providing vocational skills may not be sufficient. Other

active labor market policies such as employment counselling and job search assistance are needed to complement the training program. Our results also show that repeated training is associated with better upward mobility outcomes. Accordingly, the same training program, 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 program 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 labor. As private providers and the cooperation of public and private 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 programs. Furthermore, improving a connection with businesses may also help widen employment opportunity for training participants, thereby enhancing the effectiveness of training program. Last but not least, the empirical results imply that training is more effective when it is sponsored by employers. Therefore, the government should incentivize 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 program.

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 centers and groups of participants. Moreover, 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.

Table 1: Baseline Statistics by Treatment and Control Groups

	Before Matching			After Matching					
				On-Common-Support matching			Nearest Neighbor Matching		
	Treatment	Control	Standardized Differences	Treatment	Control	Standardized Differences	Treatment	Control	Standardized Differences
Number of Observations	406	10,078		397	9286		397	397	
Age (years)	40.94	43.08	0.15	40.94	42.58	-0.12	40.94	40.5	0.04
Gender (% of female)	55	55	0.003	55	55	-0.001	55	53	0.04
Location (% of rural)	70	64	0.12	70	65	0.01	70	71	0.02
Education (%)									
Primary and below	47.10	64.50	0.36*	47.10	64.00	-0.34*	47.10	47.10	0.00
Secondary	19.90	21.60	0.04	19.90	21.90	-0.05	19.90	19.90	0.00
Vocational	9.60	6.80	0.10	9.60	7.00	0.09	9.60	8.30	0.04
Higher Education	23.40	7.10	0.47*	23.40	7.20	0.46*	23.40	24.70	0.03
Labor force status (%)									
Inactive	83.90	71.60	0.30*	83.90	72.90	0.27*	83.90	84.60	0.02
Unemployed	6.00	5.40	0.03	6.00	5.50	0.02	6.00	5.30	0.03
Employed	10.10	23.00	0.35*	10.10	21.50	-0.32*	10.10	10.10	0.00
Wage (THB per month per capita)	6,732.06	3,077.50	0.38*	6,732.06	3,134.38	0.37*	6,732.06	5,530.16	0.10
Income (THB per month per capita)	11,788.16	9,681.30	0.08	11,788.16	9,842.70	0.07	11,788.16	10,767.66	0.05
Household Expenditure (THB per month per capita)	3,899.00	2,965.61	0.21*	3,899.00	2,984.10	0.20	3,899.00	3,226.58	0.17

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 program are in the treatment group while those do not attend are put in the control group. An absolute value of a standardized difference that is larger than 0.2, a cut-off of a small effect size suggested by Cohen (1988), is considered as imbalance. * denotes that imbalance between treatment and control group.

Table2: Impacts of Training by On-Common-Support Matching and Difference in Differences (DD)

		2005-2006	2005-2007	2005-2010	2005-2012
Absolute Mobility	Wage	0.0936 (0.1665)	-0.0781 (0.1602)	0.0412 (0.1668)	-0.0262 (0.1733)
	Income (wage + farm income + non-farm income)	0.1307 (0.1714)	0.0953 (0.1745)	0.2417 (0.1659)	0.1630 (0.1637)
	Expenditure	0.1130* (0.0628)	0.1112* (0.0630)	-0.0311 (0.0587)	-0.0369 (0.0587)
Relative Mobility	Wage rank	0.0122 (0.0221)	0.0072 (0.0209)	0.0036 (0.0188)	0.0101 (0.0189)
	Income rank	-0.0081 (0.0374)	0.0074 (0.0371)	-0.0266 (0.0383)	0.0009 (0.0382)
	Expenditure rank	-0.0040 (0.0364)	-0.0047 (0.0362)	-0.0013 (0.0360)	-0.0053 (0.0357)
Labor Mobility	**Labor force status** inactivity → unemployed → employed	-0.0090 (0.0358)	-0.0106 (0.0353)	0.0016 (0.0369)	0.0009 (0.0308)
	Formality of employment informal employed → formal employed	-0.0134 (0.0356)	-0.0091 (0.0349)	-0.0083 (0.0351)	-0.0212 (0.0354)
	Employment status unpaid family worker --> informal self-employed/informal employee --> formal self-employed/formal employee --> employer	-0.0020 (0.0326)	-0.0031 (0.0311)	-0.0041 (0.0343)	-0.0135 (0.0359)

Notes: The total number of observations after matching is 9,683 of which 397 observations are treated and 9,286 observations are non-treated. The impact on absolute mobility is obtained by equation (1) and impact on relative and labor mobility is 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. Average marginal effects are reported for relative and labor mobility. Standard errors in parentheses and $^* p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.001$

Table3: Impacts of Training by Nearest Neighbor Matching and Difference in Differences (DD)

		2005-2006	2005-2007	2005-2010	2005-2012
Absolute Mobility	Wage	-0.1875 (0.2414)	-0.3014 (0.2331)	-0.1404 (0.2237)	-0.1159 (0.2412)
	Income (wage + farm income + non-farm income)	0.1451 (0.2317)	-0.0079 (0.2301)	0.0735 (0.2184)	0.0899 (0.2243)
	Expenditure	0.1617 (0.1064)	0.1022 (0.1050)	0.0047 (0.0986)	0.0224 (0.0971)
Relative Mobility	Wage rank	0.0028 (0.0464)	0.0111 (0.0346)	-0.0074 (0.0310)	0.0026 (0.0247)
	Income rank	-0.0156 (0.0525)	0.0125 (0.0524)	-0.0370 (0.0520)	-0.0099 (0.0534)
	Expenditure rank	-0.0005 (0.0500)	-0.0005 (0.0502)	0.0012 (0.0498)	-0.0028 (0.0500)
Labor Mobility	**Labor force status** inactivity → unemployed → employed	0.0011 (0.0343)	-0.0011 (0.0317)	-0.0003 (0.0328)	0.0002 (0.0357)
	Formality of employment informal employed → formal employed	0.0028 (0.0573)	0.0013 (0.0583)	0.0017 (0.0583)	-0.0024 (0.0590)
	Employment status unpaid family worker --> informal self-employed/informal employee --> formal self-employed/formal employee --> employer	0.0054 (0.0219)	0.0010 (0.0413)	-0.0258 (0.0423)	-0.0080 (0.0444)

Notes: The total number of observations after 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 impact on relative and labor mobility is obtained by equation (2). Control variables such as household size (in case of expenditure), and borrowing status are included but not shown here. Average marginal effects are reported for relative and labor 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	0.23286	-0.0499	0.23450	-0.5191
		(0.9616)	(0.6416)	(0.9025)	(1.0548)
	Income (wage + farm income + non-farm income)	0.2382	0.3586	0.1997	-0.0633
		(0.7386)	(0.6146)	(0.5806)	(0.9600)
	Expenditure	0.2837	0.1984	0.0726	0.2337
		(0.3720)	(0.3604)	(0.4352)	(0.4988)
Relative Mobility	Wage rank	0.1708	0.0431	0.0901	0.0591
		(5.2430)	(0.6880)	(1.5841)	(0.8264)
	Income rank	0.2266	0.1186	0.1234	0.1766
		(7.9957)	(1.3139)	(1.531)	(2.877)
	Expenditure rank	0.2024	0.0092	0.0252	0.0253
		(0.5983)	(0.9502)	(1.0193)	(1.9200)
Labor Mobility	**Labor force status** inactivity → unemployed → employed	0.1177	-0.0627	0.1461	0.1203
		(0.4333)	(0.5067)	(0.7858)	(0.1229)
	Formality of employment informal employed → formal employed	-0.3477	-0.1180	0.0237	-0.0634
		(0.4334)	(0.3650)	(0.3237)	(3.2066)
	Employment status unpaid family worker --> informal self-employed/informal employee --> formal self-employed/formal employee --> employer	0.0592	0.3928	0.1196	-0.1557
		(0.4043)	(0.4866)	(0.3892)	(0.3895)

Notes: The total number of observations is 10,484 of which 406 observations are treated and 10,078 observations are non-treated. The impact on absolute mobility are obtained by (3)-(6) while the impact on relative and labor 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. Average marginal effects are reported for relative and labor mobility. Standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table5: Heterogeneity of Effect by Participant Characteristics

	2005-2006			2005-2007			2005-2010			2005-2012		
	wage	income	exp	wage	income	exp	wage	income	exp	wage	income	exp
Female	-0.697*	-0.266	-0.183*	-0.902**	0.177	-0.232**	-0.920**	0.112	-0.264**	-0.388	0.229	-0.164*
	(0.414)	(0.293)	(0.0985)	(0.419)	(0.295)	(0.0950)	(0.417)	(0.290)	(0.0917)	(0.423)	(0.304)	(0.0912)
Rural	-1.040**	0.109	-0.273**	-1.040**	0.676*	-0.0924	-1.351**	0.365	-0.162	-1.855***	0.477	-0.311**
	(0.488)	(0.344)	(0.116)	(0.493)	(0.347)	(0.113)	(0.501)	(0.348)	(0.109)	(0.506)	(0.364)	(0.109)
Age (15-24=base)												
25-39	1.499*	1.802**	0.736***	0.970	1.440**	0.409**	-0.296	-0.224	0.191	-0.752	-0.273	0.135
	(0.848)	(0.600)	(0.204)	(0.851)	(0.598)	(0.195)	(0.859)	(0.597)	(0.189)	(0.870)	(0.626)	(0.188)
40-59	0.705	1.953**	0.849***	0.436	1.823**	0.543**	-0.954	-0.167	0.442**	-1.510*	-0.676	0.321*
	(0.878)	(0.621)	(0.211)	(0.883)	(0.621)	(0.202)	(0.889)	(0.618)	(0.196)	(0.901)	(0.648)	(0.195)
60 and up	-1.307	1.570**	0.812**	0.455	1.567**	0.369	-2.329**	-2.127**	0.0971	-2.199*	-2.473**	-0.0057
	(1.105)	(0.782)	(0.270)	(1.113)	(0.783)	(0.259)	(1.120)	(0.778)	(0.247)	(1.137)	(0.818)	(0.246)
Education (primary and below =base)												
secondary	-0.560	0.211	0.432**	1.134*	1.082**	0.555***	0.965	0.502	0.366**	0.679	0.214	0.465***
	(0.610)	(0.431)	(0.141)	(0.613)	(0.431)	(0.136)	(0.601)	(0.418)	(0.132)	(0.611)	(0.439)	(0.132)
vocational	1.979**	1.065*	0.841***	3.078***	1.816**	0.790***	3.182***	0.894	0.629***	3.788***	1.452**	0.675***
	(0.786)	(0.556)	(0.185)	(0.789)	(0.555)	(0.180)	(0.792)	(0.550)	(0.174)	(0.805)	(0.579)	(0.173)
higher educ	3.114***	1.481**	1.100***	3.805***	1.992***	1.084***	3.709***	1.000**	0.895***	4.568***	1.502**	0.848***
	(0.667)	(0.471)	(0.156)	(0.669)	(0.471)	(0.152)	(0.673)	(0.467)	(0.148)	(0.683)	(0.491)	(0.147)
Labor force status (employed=base)												
unemployed	-0.192	-0.844	-0.301	0.164	-0.640	-0.169	0.360	-0.421	-0.289	-0.102	-0.785	-0.293
	(0.828)	(0.585)	(0.191)	(0.820)	(0.577)	(0.187)	(0.826)	(0.574)	(0.182)	(0.840)	(0.604)	(0.181)
inactive	-2.892***	-3.681***	-0.187	-1.708**	-3.267***	-0.416**	-0.701	-2.553***	-0.348**	-0.721	-1.932***	-0.249
	(0.766)	(0.541)	(0.182)	(0.759)	(0.534)	(0.174)	(0.780)	(0.542)	(0.169)	(0.776)	(0.558)	(0.168)
Multiple training (training more than one course)	0.906	0.774	0.195	0.334	0.435	0.216	0.337	0.331	-0.0652	0.261	-0.707	0.109
	(0.892)	(0.630)	(0.204)	(0.876)	(0.616)	(0.196)	(0.908))	(0.630)	(0.194)	(0.897)	(0.645)	(0.193)
Repeated training (training in both year2006 and 2007)				0.909**	0.497*	0.263**	0.744*	0.242	0.0523	0.394	0.228	0.0327
				(0.428)	(0.301)	(0.0975)	(0.431)	(0.300)	(0.0945)	(0.436)	(0.314)	(0.0939)

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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table6: Heterogeneity of Effect by Program Characteristics

	2005-2006			2005-2007			2005-2010			2005-2012		
	wage	income	exp	wage	income	exp	wage	income	exp	wage	income	exp
Type of Course (agriculture=base)												
Manufacturing and construction	-0.110 (0.629)	0.129 (0.445)	-0.0460 (0.150)	0.536 (0.626)	-0.478 (0.441)	-0.0533 (0.144)	0.981 (0.627)	0.224 (0.435)	0.161 (0.138)	0.456 (0.634)	-0.446 (0.456)	0.0408 (0.137)
services	0.229 (0.791)	0.376 (0.559)	-0.0774 (0.186)	0.508 (0.805)	-0.383 (0.567)	-0.00976 (0.184)	1.364* (0.803)	0.146 (0.558)	0.195 (0.176)	0.456 (0.634)	-0.394 (0.583)	0.0205 (0.175)
computer	2.461** (0.875)	0.462 (0.619)	0.256 (0.208)	2.904*** (0.880)	0.0794 (0.619)	0.269 (0.200)	3.726*** (0.884)	0.986 (0.614)	0.542** (0.195)	2.611** (0.895)	-0.0940 (0.644)	0.346* (0.194)
Length (less than a week = base)												
more than a week	0.614 (0.763)	-0.0309 (0.539)	-0.167 (0.182)	0.870 (0.770)	0.515 (0.542)	-0.0465 (0.177)	0.571 (0.775)	0.0425 (0.538)	0.0217 (0.170)	0.473 (0.788)	0.538 (0.567)	0.0661 (0.170)
more than a month	1.078 (0.890)	0.174 (0.629)	0.160 (0.209)	1.340 (0.899)	0.544 (0.633)	0.318 (0.201)	0.726 (0.905)	0.0368 (0.629)	0.331* (0.199)	1.505 (0.919)	0.867 (0.661)	0.195 (0.198)
Provider (government=base)												
private	0.569 (0.606)	0.371 (0.428)	0.308** (0.143)	0.0853 (0.616)	0.545 (0.434)	0.391** (0.140)	0.196 (0.617)	0.438 (0.429)	0.261* (0.136)	0.181 (0.627)	0.452 (0.451)	0.187 (0.135)
both	0.299 (1.003)	1.054 (0.709)	-0.0479 (0.235)	2.238** (1.010)	1.422** (0.711)	0.320 (0.232)	1.027 (1.018)	0.719 (0.707)	0.266 (0.224)	0.717 (1.035)	1.200 (0.744)	0.0502 (0.223)
Financial Supporter (free=base)												
self-support	-0.333 (1.046)	-0.138 (0.740)	-0.0217 (0.246)	-0.983 (1.061)	0.104 (0.747)	-0.0171 (0.238)	-1.007 (1.069)	-1.193 (0.742)	-0.309 (0.235)	-0.890 (1.087)	-0.453 (0.782)	-0.229 (0.234)
employer	1.306** (0.547)	0.549 (0.386)	-0.0004 (0.128)	1.089* (0.555)	0.444 (0.391)	0.0364 (0.123)	1.151** (0.553)	0.0591 (0.384)	0.0779 (0.122)	0.682 (0.562)	-0.137 (0.404)	-0.0005 (0.121)
Training cost	0.00001 (0.0003)	0.0001 (0.0002)	0.00001 (0.0001)	0.0003 (0.0003)	0.0003 (0.0002)	0.00002 (0.0001)	-0.0001 (0.0003)	0.0004* (0.0002)	0.0001 (0.0001)	-0.0004 (0.0003)	0.0001 (0.0002)	0.0001 (0.0001)

Notes: The total number of observations after matching is 9,785 of which 402 observations are treated and 9,383 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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

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