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Education, Training and Productivity: Evidence from Thailand and Philippines

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Abstract

This paper investigates the relationship between education and training provided by the firm, both on the job and off the job, using a unique dataset drawn from a survey of Thai and Philippine employees conducted in the summer of 2001. We find sizable and statistically significant returns from training in both countries. In Thailand, We also find a negative and statistically significant relationship between educational attainment and on-the-job training (OJT) and a positive and statistically significant relationship between education and off-the-job training(OFFJT). In Philippine sample, we use total training hours instead and find that the impact of education on training incidence is positive for operators but negative among technicians and engineers.

We explain these results in terms of relative shifts in marginal cost and benefit schedules for training as we vary education attainment of workers. We find for OJT in Thailand that increased opportunity cost of training for the better educated outweighs the increased benefit from training. In the case of OFFJT, additional education not only augments the returns from training, but also reduces the net cost of training. For training in the Philippine samples, we find positive and significant effect of education, as well as the positive impact of education on training returns.

We also find strong positive correlation among technology, education, and training across sample industries in the two countries. These findings are reviewed with recent studies on training in developing countries and major implications are discussed.

Keywords: training, education, Thailand, Philippines
JEL: J24, J31

1. Introduction

Workplace training plays a key role in skill development and enhancement of labor productivity at firms. In spite of the obvious and compelling need to empirically examine the effect of work place training, the depth and width covered in the existing literature on training are limited. One major reason for the paucity of the research in this field is the lack of reliable data. By its very nature, trainings take place inside firms and other organizations. Some type of trainings are almost never documented and even the management of firms often know little about these activities. Much of the so called on the job training (OJT) are informal, ad hoc, spontaneous, and highly flexible. These characteristics make it extremely difficult to collect reliable and quantifiable information on these types of training. The data availability problem is even more severe in developing countries wherein solid empirical research in the area is of paramount importance. The data availability can be also a crucial factor by itself responsible for the apparent under investment in training in developing countries, especially among smaller firms as the lack of knowledge and proper guidance might well be an important reason for under-investment in training..

Setting aside these empirical problems, conventional model of human capital does not offer us much in guiding us how best to incorporate training as an integral part of human capital accumulation. We know very little, for example, whether or not training is a close substitute for education. If the answer depends upon specificity of training and education, we would like to know how they interact each other in the determination of productivity.

This paper tries to provide some review of recent empirical studies in this field, as well as to offer some of our own research outputs based upon the recent employee survey conducted in manufacturing firms in Thailand and Philippines.

In order to investigate empirically interactions among productivity, technology, education and training, both on the job and off the job, we need not only fairly extensive set of data, we also have to place the analysis in a comprehensive framework to incorporate all of these variables in a coherent manner. These issues are crucial in understanding the role of training in human capital development. Moreover, they are also relevant when we examine the role of education in skill developments. In economic development literature, much of the emphasis has been placed on education. According to Behrman [1987], the economic literature emphasizes strongly the importance of schooling in increasing productivity, improving health and nutrition and reducing fertility. Schooling can affect productivity both directly, by improving basic skills, and indirectly, by affecting training incidence. A positive association between education and training has two implications. On the one hand, if the more educated also receive more training, both on the job and off the job, an increase in the average level of educational attainment leads to even higher human capital and productivity. On the other hand, if the less educated receive less training, initial individual differences in the level of human capital are bound to widen in the labor market.

Even a casual inspection of workplace in a developing country reveals that incidence of training is crucially related to the employed technology as well as its changes. Adaptation and adoption of new technology embedded in a new equipment, new production method, new production line design, etc., are an integral part of regular operations of contemporary industries. Available evidence points out rather strongly that the speed of adoption and adaptation has been accelerating. In each of these instances, re-tooling and re-training of the workforce is a necessary ingredient for fast and smooth transition from the current to new technology. On the other hand, the capacity of a firm to absorb and adopt a new technology hinges upon the technical capability of the firm as they are embodied in its current human resource and accumulated technology.

In short, education, training, and technology adoptions all interact with each other in important way to shape the overall productivity and technical capability of a firm. Although it is clear that all of these factors do play some role, what is missing is reliable estimate on these magnitudes. We provide some of our own results in this paper. The paper is organized as follows. Section 2 reviews a small but growing literature on econometric studies on the impact of training. Our focus in the section is mainly, but not exclusively on those based on data from developing countries. In Section 3, we introduce a canonical model of training investment in order to highlight the relationship between education and training. Section 4 discusses the econometric specification. Section 5 presents the data. Empirical results are shown in Section 6. We also review our main findings in view of the relevant literature. A brief concluding remark follows.

2. Training at Workplace in Developing Countries

2.1 Incidence of Firm Level Training: Some stylized facts

In recent years, we have witnessed rapid accumulation of micro-data and empirical analysis on training, even among the developing countries[1]. Through these rapid advances in empirical works, we now have a handful of 'stylized facts' on training, against which we will compare later on

[1]Major studies in this area include Tan and Batra (1995), Aw and Tan (1993), Biggs, Shah, and Srivastava (1995), Schaffner (2001), and Tan and Lopez-Acevedo [2003]. Our own research project includes Yamauchi and Poapongsakorn (2002), Ariga and Brunello (2002), and Yamauchi (2002).

our own empirical work. By way of introducing and motivating major research agenda, we list out some of the more important stylized facts.

Stylized Facts #1: Larger firms tend to train more of their employees[2]

The positive correlation between the firm size and training investment is found almost universally, irrespective of the type of training, industry, or country affiliations. Although it is not clear if the size itself is a true causal factor that increases training investment, there are reasons to believe that the scale economy is significant in provision of firm level training[3]. To begin with, except for ad hoc, on the spot, informal, on-the-job training, all the training requires trainees to be pulled out of workplace to receive training. This is often a difficult arrangement to make for a small scale firms[4]. There also exist some important elements of fixed costs to run systematic training program at workplace. Most of large scale firms typically have in house training center, the set up of which clearly incur some fixed costs. Moreover, recent econometric studies on the impact of training on productivity indicates important comeplementarity between training and other high powered human resource management practices, such as job rotation, flexible task assignment, quality circle, etc. Implementation of these practices incurs some costs[5]. They also require professional staffs in human resource management.

Smaller scale firms are more likely to rely on external training programs provided by a variety of public and private training institution to train their employees. In house training can be provided more easily and effectively if the firm can provide internally the suitable instructors, which again points out important advantage for large scale firms with ample staffs.

Stylized Facts #2: Firms employing more advanced technology train more[6]

This correlation is again almost universal irrespective of firm size, industry affiliation, or country. To the extent that training generates skilled labor force, this can be understood simply as a corollary of technology-skill complementarity. The correlation can be interpreted in a somewhat different manner, however. If only complementarity of technology and skill is behind this finding, firms may not rely on training to get more skilled workers; instead, they can hire the qualified

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[2] See Blundell, et al. (1999), Lowenstein and Speltzer (1999). Tan and Lopez-Acevedo [2003] for developing countries,

[3] The distinction between scale economy in provision of training and that in benefit from training is often difficult and in most of the cases irrelevant as independent identifications of marginal cost and benefit schedules are virtually impossible anyway.

[4] As a matter of fact, for some of key variables, we have to use company record instead of direct interviews in Philippine survey precisely because surveyed firms found it difficult to pullout sample workers from workplace for long time for interviews.

[5] Ichinowski, et al [1997] is the most well known case study for the US steel plant, followed by many similar studies which are reviewed in Ichinowski [2003].

workers right away. The fact that they do train more suggests that firms employing more advanced technology requires set of skills and skilled workers not readily available at market place. If this is the case, the proper interpretation is the correlation of skill/technology specificity coupled with advancement of technology.

Stylized Fact #3: Firms adopting new technology train more[7]

Although similar to #2, empirically, the distinction between this and #2 is important. Firms often find it almost imperative to provide training when it undergoes important change in production technology. As a matter of fact, through our interviews with many plant managers of sample firms, we found that at some hi-tech firms, the most important task for plant engineer and technician group is to design and implement swift and smooth introduction of new technology. For example, at firms producing hard disk drives or its component, major design change occurs regularly, say, every 3 to 6 months. This often entails major reshuffle and re-design of production line, entire revision of specifications, quality control procedures, and testing. Reshuffling of production workers is routine.

Even at medium sized firms, replacement of capital equipments is not uncommon and it often entails some amount of re-training, often by the help of the supplier of new equipments. This type of training associated with technology change is intricately mixed, and, occur concurrently with learning process. In fact, most of the training is nothing but to help accelerate the learning by doing processes inherent in getting used to new work environment. A significant portion of training is conducted by supplier firms of major capital equipment shortly after its installment. As we will show later in Table 4, significant portion of training, especially OJT, are directly related to the changes in production technology.

Stylized Fact #4: The more educated people receive more training[8]

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[6] Lillard and Tan [1992].

[7] Tan and Lopez-Acevedo [2003], for example, shows that significant and growing share of training are provided by machine suppliers. Our interview results also confirm the significance of production and organizational changes on the incidence of training.

[8] Virtually, all the relevant empirical studies list the positive correlation between training and education. See, however, Lowenstein and Speltzer (1999) for the more detailed discussions on types of trainings and their relation to formal schooling. In a different strand of literature, which focuses on the concept of over-education, finds that overeducated individuals receive less OJT than individuals with less education. According to Sicherman [1990], this is evidence that education and OJT are substitutes in the production of human capital. Since over – educated workers are more likely to quit, employers have fewer incentives to train them. Hersch [1991] argues that the over-educated are less willing, or less able, to learn, which explains their higher marginal training costs and lower training incidence.

This is a common finding in most of developing countries, whereas evidence from developed countries is mixed. Many studies consider the positive correlation between formal education and training more or less self evident. After some thought, however, the issue is not so transparent. We come back to this important point later on in the analysis of our own data. A brief remark should suffice here. The point is that higher education makes worker productive not only in *receiving training*, but also *at work*. Since the cost of training includes at least foregone outputs he could have produced if he worked, the better educated workers are likely to cost more to train, which may or may not overcome their advantage of being a better learner. As we see later in more detail, another point to be noted is that the strong impact of education on training stems largely from its impact on selection of job and employer. Once we control for these factors, the direct impact of education on training is not typically robust and often negative. Although this caveat does not imply in any way the significance of education / training nexus, we should bear in mind that the nexus works primarily through allocating more educated people to more advanced and more technically demanding jobs, which in turn requires more training.

Stylized Fact #5: firms generally prefer to provide in house firm specific training, whereas employees often prefer to receive external and more general training

Although this is perhaps not qualified as a stylized fact (because most of studies do not consider this), it is nevertheless important that there exists potential conflicts of interests over different types of training. The difference in preference on the two sides is self explanatory. Workers prefer to be trained for skills which are more general and portable, perhaps with formal certificate. The added skills and credentials belong to those trained and they will retain them even after they move to different jobs. Firms actually often classify different types of training in such a way that some types of trainings are considered as a part of fringe benefit, rather than training. Examples include dispatching their employees to business schools abroad, or, sending them to an apprenticeship program provided by a parent company in a developed country. These are often considered as privileges, and, in some cases, employees must sign up for the contract that stipulates penalty for leaving firm within a certain period after they receive this type of training. Firms also prefer to train workers internally because they can tailor the program to suit their specific requirements. In our interviews with managers in charge of HRM, we often found out that significant portion of training activities are not so much on provision of any specific skills, but more on corporate culture, work ethics, team spirit, etc., some of which are close to a form of indoctrination. For example, in our Philippines survey, variety of seminars related to work behaviors, such as work ethics, company philosophy, company regulations and rules, etc., comprised the second largest share (15%) of total training hours, next to technical training (75%).

Having said these tendencies, we hasten to add that firms do indeed provide trainings which appear to be quite general. Many managers at human resource management department complained to us about the need to supply basic arithmetic and language skills to new employees, which they say should have been un-necessary if they had studied hard at schools prior to employment.

Stylized Fact #6: The Bottom Line?

After going through all these findings and cautionary notes, at the end of the day, you might ask: how much difference does it make to train a worker? Is it worth the money and the effort? Most of the empirical studies indicate that indeed the returns from training typically exceed comparable returns from education. Tan and Batra (1995), for example, indicate that the impact on firm level productivity 10% or more for 5 out of 6 countries they study. Our own study indicates somewhat more modest returns, but still higher than comparable returns from education as we see later. Setting aside the magnitudes, virtually all the existing studies on firm level training find statistically significant impact of training on various measures of productivity.

Although the fact that firm level training does enhance productivity may seem rather trivial and self evident, it should be contrasted against rather dismal assessment on most of public funded training programs. Grim assessments of publicly funded trainings problems are rather voluminous and we refer the interested reader to Heckman's survey [Heckman, LaLonde and J. Smith (1999)]. Suffice it here to say that the ineffectiveness of publicly funded training is found across different countries and over diverse training programs.

Two points are important in the comparison. First of all, most of publicly funded trainings are general and often those programs are outdated and ineffective, whereas private firms have every incentive and means to carefully select the content of training programs best suited for their own needs. Second, by its very nature, public trainings are provided to those with a variety of problems for skill advancement; many programs are designed specifically for particular groups such as school dropouts, or unemployed. Firms, on the other hand, do not have such mandate and freely select from its own employees to maximize the effect of training.

2.2. What are the agendas?

Having gone through quickly with the list of major stylized facts, three major themes will emerge. First of all, these stylized facts are mostly correlations among potentially endogenous variables. We need to supply them with structural interpretations, and, hopefully, with structural parameter estimates. For this purpose, we propose a very simple model of optimal training investment. Next, we build on this simple model to discuss how best to incorporate these stylized facts into the model. Last, we consider major deviations from canonical model.

2.2.1 Canonical model of training investment

We start with a canonical model of training investment which comprises of the following set of equations.

$$mb_i = \frac{\partial Q_i}{\partial K_i} = \varphi(E_i, Z_i^B) \quad (MB)$$

$$mc_i = \phi(I_i)c(E_i, Z_i^C) \quad (MC)$$

$$I = \phi^{-1}\left[\frac{\varphi(E_i, Z_i^B)}{c(E_i, Z_i^C)}\right] \quad (I)$$

The first equation (MB) is marginal benefit from training investment measured as the marginal effect of an increase in (training) human capital (*K*) on productivity (*Q*), whereas the second equation (MC) defines the marginal cost of training investment as a product of convex function of investment level (I_i) multiplied by a unit cost of investment, *c*. Hence the optimal investment is determined as an increasing function of the ratio of marginal benefit and unit cost of training (I). Note that in most of empirical studies, direct estimate or data on unit cost of training is almost never available and we typically end up estimating the first (MB) and the third (I) equation only. We also note that not only education (E_i), but also most other explanatory variables in both equations are likely to overlap, thus making separate identifications of these schedules empirically extremely difficult.

Even estimating the first and the third equations requires rather extensive list of variables and some heroic assumptions. Starting from the latter, we notice immediately that the marginal benefit itself is almost never directly observable[9]. There are two principal methods used in getting around the problem. First, most ideally, if the data covers not only training but also other crucial statistics on production, factor usage, factor prices, and other related data, we can estimate a production (or cost) function of sample firms and include some proxy for the training human capital at firm. The estimated marginal benefit is nothing but the estimated marginal impact of training human capital. Although this strategy is straightforward, it requires a host of data and data points. Model specifications are also often problematic, especially if we need to distinguish and incorporate interactions among education and training. Another popular approach, which we actually take in our own empirical study, is to assume that the unknown productivity of an employee is proportional to respective wage and focus on the individual worker. In that case, model is now translated into the marginal impact of training capital on wage. Then we estimate wage function including training human capital as one of its arguments to obtain the impact of training on wage, and hence on productivity.

The training investment equation is somewhat easier to estimate primarily because we have direct observation of the training level itself. Upon closer look, however, the identification of training investment equation as opposed to the marginal benefit equation, poses several important problems. First of all, unless we can identify the marginal cost separately, training investment function is a reduced form, and, the estimation falls short of giving us structural estimates of the underlying parameters. This is especially problematic because most of explanatory variables used in the investment equation can appear not only in marginal benefit [Z_i^B] but also in unit cost functions [Z_i^C]. For example, it is very popular to include variety of firm and industry characteristics as explanatory variables, such as firm size, industry affiliation, technology level, R&D investment, etc. Arguably, all of these factors can potentially explain not only variation in marginal benefit but also in costs as well. **To put it differently, anything that makes a worker more productive is likely to make her also more productive or efficient recipient of training.** Notice that this problem is independent from whether or not any of such explanatory variables are exogenous. The problem is further compounded by some of recent HRM practices that emphasize holistic approaches and integrate it to other spheres of management, such as Total Quality Management (TQM), which in a

[9] In some cases, we can use evaluation by supervisors of sample employees as a proxy for productivity. At establishment level, statistics such as defect rate or downtime (time length during which operation stopped during regular work hours) is sometime used as a proxy to measure the impact of training. Theses measures are often more direct and easier to document. The problem is that they do not lend themselves easily to monetary estimates of marginal benefits.

sense institutionalizes[10] such coherence in productivity and quality control at every aspect of corporate activity.

We now notice that most of the stylized 'facts' about training incidence is precisely on these reduced form equations. Among other things, the impact of education variable can appear in both sides of the investment equation. Firm size also can influence both cost and benefit of training. What about technology? Needless to say, technology can influence both cost and benefit of training, Moreover, an additional problem with technology (choice) is that it really is an endogenous variable: unless we have an effective empirical model on technology choice, especially one that spells out how the choice is related to training decision, the observed correlation is useful but falls short of allowing us to make any definitive statement. For example, it is very popular to associate the observed positive correlations among education, technology, and training with skilled biased technical changes. But it is far from obvious if observed co-variations allow us to draw such a conclusion.

2.2.2 Identifying Marginal Cost and Benefit Schedules

With some additional assumptions, we can, however, make some headway towards identifying shifts in marginal cost from marginal benefit schedule. One such candidate is capacity utilization rate or over time work hours which exhibit strong cyclicality. Such cyclicality has a strong impact on marginal cost of training primarily because it creates sizable swings in opportunity cost of training: we know that training intensity is highly counter-cyclical[11]. It seems reasonable to assume that such cyclical variation in productivity has no strong impact on expected returns from training. Independent information on the cost of training is of course gives us much needed information[12]. In some limited cases, public funding of some type of firm trainings provide us with an exogenous variations in subsidy provision, which can give rise to exogenous shifts in marginal cost schedule. Both Thailand and Malaysia have such subsidy program, although many suspect very

[10] Many of our sample firms in Thailand and Philippines recently received, or, was applying for accreditation of ISO 9000s, virtually all of them with the help form a few consulting firms. See Table 4.

[11] We experimented variety of regression specifications in earlier stage of research. Unfortunately, our data on over time work hours did not perform well as an instrument for cost of training.

[12] On the other hand, researchers often face important tradeoff between more detailed information and sample coverage. Requirement of cost data on training is often prohibitively costly or difficult for small scale firms and it may invites additional source of selection bias.

limited impact of the program[13]. Unfortunately, up to now, we know of no study exploiting this exogenous variation in cost.

There exist several candidate variables which we can safely assume to enter only in marginal benefit, and not in marginal cost schedule. One such candidate is a variety of information on employment stability as it directly influences the expected length of employment relation, and hence the expected marginal returns. The major problem is that these variables are endogenous and stability itself is likely to depend upon the amount of training. Admittedly, however, we can some time exploit arguably exogenous portion of separation behavior associated with, say, age, family background, etc.

Overall, identification of all these three equations is a formidable task in terms of data requirement and it is often advisable to continue to use reduced form approach, especially if the main objective of the research is to find important correlations among training and other variables of interests.

2.2.3 Why so many firms do not train workers?

Taken at face value, most of recent empirical studies on firm level training indicate large gains from firm level training. Hence it is puzzling that so many firms, especially in developing countries, seem to invest so little in training. Before we treat this apparent contradiction as something of a puzzle, however, several caveats are in order. First of all, it is practically impossible to have an accurate estimate of training cost. As a consequence, most of studies assume that the cost of training is the foregone wage of the person trained[14]. Otherwise it is impossible to come up with rate of returns simply from the estimate of the impact of training only. Most probably, this assumption generates general downward bias in the cost. Moreover, the degree of bias is likely to be larger for smaller firms. As a result, the lack of proper cost estimate tend to generate upward bias in the estimated returns, especially so among the smaller firms. As we have shown above, firm level training incurs fixed cost, which can be sizable for small scale firms. Moreover, as we noted above, several studies indicate that the effectiveness of training depends substantially upon other practices of human resource management. Firms with more advanced (and hence costly) set of human resource practices tend to have more training and have higher productivity. This suggests that not

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[13] In both Malaysia and Thailand, special tax provision for training expenses are provided. Apparently, the tax relief program is not working well primarily because (1) many firms do not have taxable operating income, (2) paper work necessary to be eligible for tax provision is voluminous and for small firms, it simply is not worthwhile to file for such provision. See Worldbank**

[14] If Mincerian wage function is estimated, the estimated coefficient on training (measured in foregone work hours) corresponds to the implied rate of returns from training.

only scale but also economy of scope may be important in provision of training. In sum, unless we can fully incorporate these factors, our estimates creates upward bias on the returns, especially for smaller scale firms.

Setting aside the cost factors, the estimation is likely to suffer from correlation of the residual with the explanatory variable, especially training, as we have noted above. Although we can always try to rectify the situation using instrumental methods, it is not entirely obvious how we can find a good instrument for training. Such a variable must be orthogonal to TFP and at the same time correlated with training. Panel data is likely to be far ore effective coping with the problem assuming (reasonably) that the firm specific residual is likely to be stable over time. Although desirable, constructing panel data for firms including training investment is not an easy task[15]. The fact that we have such few empirical studies using firm level data is ample demonstration of the cost involved in such a project.

At the end of the day, do we really know enough about the returns from training to recommend to small scale firms to increase investment in training? Our answer is a guarded, 'yes'. Our conclusion is guarded, primarily because we know so little on the realistic magnitude of fixed or quasi fixed cost of firm level training. It is tempting to jump to a policy conclusion and to recommend a coordination among smaller firms to build a training center. Given the diversity of training needs and difficulty in coordinating needs and supply of training services, such a conclusion is probably premature.

2.2.4 Potential market failure in training investment

An immediate objection to the canonical approach to model training investment in a manner described above is potential impacts of market failures. In particular, an employer and an employee may not be able to form a binding agreement in which they can fully internalize costs and benefits from training. This issue is nothing new and the potential source of inefficiency is well known. For example, if an employee invests in costly firm specific training, his investment decision depends upon (a) its impact on wage, as well as on (b) the probability that the employment is terminated in the future. Unless severance pay compensates in full for the loss incurred to this employee by layoff, employer is likely to lay off more than the optimal. By the same token, investment incurred by

[15] Tan and Lopez-Acevedo [2003] is a rare exception. Their results using panel of Mexican manufacturing firms and employees produce even stronger impact of training on wage and productivity, which is re-assuring, but somewhat surprising, in view of our concerns about the potential sources of the bias.

employer side may be ignored by employee when she makes decision on quit. To the extent that both sides of the contract anticipate these opportunistic behaviors of the other sides, their investment level is suboptimal.

Unfortunately, the empirical modeling and estimation of the impact of market imperfection on training investment is made difficult for several reasons[16]. First of all, identifying empirically the nature of market imperfection is often impossible without invoking a set of stringent conditions. For example, a model of monopoly labor union would predict that union bargaining power can be used to police moral hazard by employers in training /wage decision by curtailing optimistic behavior of employers to take advantage of firm specific nature of training investment. On the other hand, the same bargaining power on the labor side might as well aggravate the underinvestment in training, if for example, the incumbent workers resist implementation of new technology and production methods (and training necessary for implementation) in fear that such a change might result in the loss of their jobs.

According to conventional human capital model, the impact of training on productivity and worker earnings should depend crucially upon whether or not training is general or firm specific. If it is general, and the market is competitive, full impact of productivity is reflected in wage, whereas the wage increase due to firm specific training should be smaller compared to the gain in productivity. As far as we know, there is no direct evidence on this important issue. The problem in testing such prediction stems from difficulty in empirical distinction between general and specific training[17]. One piece of related evidence is that the estimated impact of training on productivity is generally larger than the impact on wage, which is at least consistent with an interpretation that some of trainings are not general.[18] Our own results do not offer any supporting evidence on this crucial prediction. If anything, our estimation shows higher returns from OJT than from OFFJT, not consistent with the prediction above. At the same time, we also find that both OJT and OFFJT contain types of trainings both general and specific.

One area that has met some empirical support is the impact of job security or stability on training, and vice versa. The available evidence is strong and unanimous pointing out that stability of employment enhances training. The crucial question, namely, if and to what extent the apparently

[16] See Leuven [2002].

[17] Lowenstein and Speltzer [1999] finds no significant difference in returns from training on worker wage between general and specific trainings.

[18] See Blundell, et al [1999] for general assessment.

costly separations are due to market failure, cannot be answered in any reliable manner in empirical research.

The issue of poaching (of workers) received much attention, especially during the pre-crisis years in East Asia wherein alarming number of popular magazines reported growing incidences of worker poaching, especially among professional jobs. A popular folklore would put it that firms are often discouraged from training investment in fear that the trained workers will reap the gain by quitting the current job to take up a higher paying one elsewhere. Notice first of all that the story itself, even if factual, does not necessarily imply any market failure. Indeed if workers find it so easy to get a better paid job once trained, he has every reason to invest his own money to do so and there will be no market failure. The most of poaching incidences seem to be concentrated in limited number of skilled and professional jobs in countries or economies wherein rapid increase in demand for those workers outpaces the supply responses. The poaching problem can be cast in a model of labor market imperfection, for example, Acemoglu's seminal paper generates 'high training low turnover, and low training high turnover' equilibria. The issue of poaching is essentially those of (pecuniary) externalities, and, as such, it requires careful empirical modeling of the labor market, not of individual firms or employees[19].

3. The model

In this section, we develop a simple model of training investment along the line that we indicated in the last section. We consider an economy populated by individuals who differ in their educational attainment. Each individual is employed by a firm for *P* periods of time and then retires. For simplicity, training takes place exclusively during the first period and is decided by the employer. At the end of each period the employee can quit at the exogenous rate q. We assume linear preferences and let earnings *W* be proportional to output per head *Y*. Individual earnings are described by the Mincerian earnings function

$$\ln W_t = a_0 + a_1 E + a_2 X + a_3 T_{t-1} + a_4 E T_{t-1} + \varepsilon_{Wt} \qquad [1]$$

[19] Schaffner [2001] compares training incidences in sample firms in United States and Columbia, and, surprisingly finds that controlling for other attributes, Columbian workers receive more training than the comparable American workers. She attributes this difference to the higher separation rate in Columbia which necessitates more intensive re-training, due to higher depreciations of skills associated with turnovers.

where X is a vector of individual and aggregate characteristics, including tenure and experience, E is years of schooling, T is the stock of training received by each employee and $\varepsilon_{Wt} = \eta_{Wt} + \mu$, where μ is a time invariant individual effect and η is random noise. In this standard specification, education and training influence earnings both directly and indirectly, by affecting job allocation to different occupations and positions in the job hierarchy. We assume that all the benefits of training are fully captured by [1].

With linear preferences the optimal level of training is obtained by maximizing total output net of training costs. Let output per capita at time t be a function of the years of education and of the stock of training accumulated during the previous period

$$Y_t = Y(E, T_{t-1}) \qquad [2]$$

where

$$T_t = I_t + T_{t-1} \qquad [3]$$

and I is the flow investment of training.

Following Ben Porath [1964] and Heckman, Lochner and Cossa [2002], a key component of the cost of skill formation is foregone production. Training today reduces current production but increases future production. Total training costs C are proportional to output per head during the first period, Y_1, and depend also on the investment flow, on educational attainment and on individual (unmeasured) talent. Therefore, we have

$$C = \phi(I, E, \mu) Y_1 \qquad \text{r} \qquad [4]$$

where $\phi'_I > 0$, $\phi''_I > 0$ and ϕ'_E can take either sign[20]. The convexity of the cost function ϕ with respect to the investment flow captures the assumption that adjustment costs are convex. When ϕ'_E is negative, higher education improves the efficiency of training and reduces output losses, either because it increases learning skills and the speed of learning, as suggested by Thurow and

[20] One prime to denote the first derivative and two primes for the second derivative.

Rosen, or because it reduces the non-pecuniary costs of training, such as psychic costs[21]. The opposite occurs when ϕ'_E is positive. Notice that [4] incorporates the effect of education on training cost over and beyond the indirect impact through its effect on output, Y_1. In other words, we measure the impact of education on cost of training relative to the hypothetical case in which education does not improve or reduce the learning efficiency of employees at training. For example, if ϕ'_E is zero, and the direct impact of education on productivity is positive, hourly opportunity cost increases as the foregone output increases, whereas the learning ability as measured by ϕ does not change at all and the overall impact of education on training will be negative.

Defining β as the discount factor, net output from the match of a firm with an employee is

$$V = Y_1 - \phi(I, E, \mu)Y_1 + \sum_{s=1}^{P} \beta^s (1-q)^s Y_{1+s} \qquad [5]$$

In this specification, the costs of training are incurred during the first period and the benefits are reaped from the second period onwards. The optimal training flow *I* is given by the following first order condition

$$-\phi'(I, E, \mu)Y_1 + \sum_{s=1}^{P} \beta^s (1-q)^s \frac{\partial Y_{1+s}}{\partial I} = 0 \qquad [6]$$

Letting $W_1 = \gamma_1 Y_1$ and $W_{1+s} = \gamma_2 Y_{1+s}$ we ca re-write [6] as[22]

$$-\phi'(I, E, \mu)\frac{W_1}{\gamma_1} + \frac{1}{\gamma_2} \sum_{s=1}^{P} \beta^s (1-q)^s \frac{\partial W_{1+s}}{\partial I} = 0 \qquad [7]$$

Next, we model the costs of training per unit of output ϕ as

[21] To illustrate with an example, somebody with relatively high education working in a production job and receiving OJT from a senior but less educated employee can experience frustration and psychic costs, which reduce the effectiveness of training. In this case higher education increases the non-pecuniary costs of training.

[22] We assume that the employer and the employee have the same discount factor and normalize the profits and earnings in the event of exogenous separation to zero.

$$\phi = \frac{\psi}{\nu} e^{\lambda E + \nu I - \mu} \qquad [8]$$

where λ captures the pecuniary and non-pecuniary effects of education on the efficiency of training and we assume that individuals with higher unmeasured talent are cheaper to train. A negative value of λ implies that education improves learning skills, reduces and reduces training costs.

We simplify the model further by assuming an infinite lifetime and that the flow of marginal benefits proportional to marginal benefits one period ahead of the investment, with ϱ as the factor of proportionality. Thus we have

$$\frac{\psi}{\gamma_1} e^{\lambda E + \nu I - \mu} W_1 = \frac{\beta(1-q)}{1-\rho\beta(1-q)} \frac{1}{\gamma_2} \frac{\partial W_2}{\partial I} = R \frac{\partial \ln W_2}{\partial I} W_2 \qquad [9]$$

where $R = \frac{\beta(1-q)}{1-\rho\beta(1-q)}$.

Using the Mincerian function [1] and the fact that $\ln \frac{\partial \ln W_2}{\partial I} = \ln(a_3 + a_4 E) \approx \ln a_3 + \frac{a_4}{a_3} E$, we can take the logs of both sides of [9] and obtain

$$-\mu + \lambda E + \nu I = c + \ln R + \ln a_3 + \frac{a_4}{a_3} E + \ln \frac{W_2}{W_1} \qquad [10]$$

where c is a constant term. Letting $\ln R = \delta_o + \delta_1 Z$, where Z is a vector of variables affecting the flow of marginal benefits, we can re-write [10] as

$$I = \frac{c + \delta_0 + \delta_1 Z + \ln a_3 + \frac{a_4}{a_3} E - \lambda E + \mu + \Delta \eta_W}{\nu - a_3 - a_4 E} \qquad [11]$$

The denominator in [11] must be positive to guarantee that the slope of the marginal cost function is steeper than the slope of the marginal benefits function, a condition for the stability of equilibrium[23]. Differentiation of [11] with respect to *I* and *E* yields

$$\frac{\partial I}{\partial E} = \frac{1}{\nu - a_3 - a_4 E}\left[\frac{a_4}{a_3} - \lambda + a_4 I\right] \qquad [12]$$

Both the marginal costs and the marginal benefits of training are affected by educational attainment, but marginal costs are affected relatively more if $\frac{a_4}{a_3} + a_4 I < \lambda$. In this case the investment in training declines with educational attainment.

This framework can be extended to cover the case of two types of training. Denoting investment flows and stocks of OJT as *O* and *J* and flows and stocks of OFFJT as *F* and *K*, the Mincerian earnings function with two types of training can be written as

$$\ln W_t = a_0 + a_1 E + a_2 X + a_3 K_{t-1} + a_4 E K_{t-1} + a_5 J_{t-1} + a_6 E J_{t-1} + \varepsilon_{W\,t} \qquad [13]$$

and the optimal decision to invest in each type of training is given by the following two equations[24]

$$F = \frac{c + \delta_o + \delta_1 Z + \ln a_3 + \frac{a_4}{a_3} E - \lambda_F E + (a_5 + a_6 E) O + \mu + \Delta\eta_W}{\nu_F - a_3 - a_4 E} \qquad [14]$$

$$O = \frac{c + \delta_o + \delta_1 Z + \ln a_5 + \frac{a_6}{a_5} E - \lambda_O E + (a_3 + a_4 E) F + \mu + \Delta\eta_W}{\nu_o - a_5 - a_6 E} \qquad [15]$$

[23] The slopes of the log marginal cost functions and benefits (net of the opportunity costs of training) are respectively ν and $a_3 + a_4 E$.

[24] Recall that $\ln \frac{W_2}{W_1} = a_3 F + a_4 EF + a_5 O + a_6 EO$. We define λ_F, λ_O, ν_F and ν_O as the parameters of the training cost function ϕ in the case of OFFJT and OJT respectively.

which suggests that the decisions to undertake OJT and OFFJT are interrelated. We can solve [14] and [15] and express both types of investment flow as functions of the vector *Y* and of educational attainment *E* as follows

$$F = b_{0F} + b_{1F}Z + b_{2F}E + \varepsilon_F \quad [16]$$

$$O = b_{0O} + b_{1O}Z + b_{2O}E + \varepsilon_O \quad [17]$$

The theoretical model predicts that the investment in training and educational attainment are correlated. This correlation can be positive or negative, depending on whether the effects of education on the marginal benefits of training prevail on the effects on marginal costs, which include both the opportunity costs of training and the costs associated to learning the required skills. In the next section, we discuss how to apply this model to our sample of employees in Thailand and Philippines.

4. **The empirical setup**

The theoretical model described in the previous section is composed of three equations: the Mincerian wage function [13] and a first order condition such as [10] for each type of training. In our empirical investigation using Thailand samples, we use a limited information approach, which consists of estimating separately [13] and the two quasi – reduced form equations [16] and [17][25], and also estimate as a simultaneous system the wage growth equation, two training equations and an equation for educational attainment. For Philippines, we only have data for the total amount of training and use instead [13] and a reduced form equation, as well as simultaneous system comprising of training, education and wage growth.

Starting with the former approach, our information on training is available either as a dummy variable (did the individual experience any training event during the reference period) or as a continuous variable (the average number of hours of training per month) with left censoring at zero hours. Assuming that the errors ε_F and ε_O are normally distributed, we use either a probit or a

[25] They are quasi – reduced forms because education is potentially endogenous.

tobit model to study training incidence. In the former case we explicitly take into account the existence of contemporaneous correlation between errors by using a bivariate probit.

A feature of the error term in [16] and [17] is that it includes unmeasured individual talent μ, which is correlated to educational attainment if the more talented are also more likely to be better educated, a plausible assumption. Therefore, our training equations can be treated as limited information simultaneous limited dependent variable models, as in Smith and Blundell (1986), and the correlation between education and unmeasured ability can generate a simultaneous equation bias.

We deal with the potential endogeneity of education as follows. First, we assume that unobserved ability is partly the consequence of the genetic and environmental contributions of the family (see Willis [1986] and Plug and Vijverberg [2003]) and include in the training equations the father's, mother's and oldest sibling's education. We also add province of birth dummies, because the local environment matters in the development of individual talent. After conditioning on family background and the province of birth, however, residual ability could still be correlated with educational attainment. Therefore, we need instrumental variables. Let educational attainment E be given by

$$E = \pi Z^{E} + \varepsilon_{E} \qquad [18]$$

where Z^{E} is a vector of exogenous variables, which includes at least one variable omitted from the training equations. Our key instruments for educational attainment are the number of siblings in the household, the age of the father at birth and the position at birth in the household (oldest, youngest or intermediate son or daughter). Other instruments are the second and third power of age and the interactions of age, the number of siblings and the father's age at birth with a gender dummy. These instruments, together with family background and province of birth, are included in the vector Z^{E}.

The number of siblings is not obviously correlated with individual ability but affects the resources per capita available in the household for investment in education. The position and the age of the father at birth capture household preferences in the decision to provide education to the off-spring. For instance, very young fathers may value education of the offspring relatively less than more senior parents. Moreover, the older son/daughter can have priority in the allocation of the resources devoted by the household to education. We fit years of education on the variables included in the vector Z^E and use the Bound F-test to verify whether the selected instruments are jointly significant in the first stage regression. Following Smith and Blundell [1986], we compute the residuals from the regression and add them to the explanatory variables in [16] and [17]. Intuitively, these residuals control for the endogenous component of years of schooling. If the associated coefficient is not statistically significant, there is evidence that education is weakly exogenous.

Turning to the Mincerian equation [13], this equation associates log individual earnings to a vector of individual and aggregate characteristics, educational attainment and the stock of accumulated training. The use of lagged rather than current training is motivated by the nature of our data. As explained more in detail in the next section, our information on individual wages refers to the month of January of each year and our information on training refers to the previous calendar year[26]. Since the error term ε_W includes individual unmeasured characteristics which are correlated to education and training, we exploit the panel structure of our data and use a fixed-effects estimator to eliminate these time invariant characteristics.

Taking first differences of [13] and using the first order conditions for *F* and *O*[27] we obtain the following system of three (two for Philippines) equations

$$O_t = \frac{1}{\nu_O}\left[c + \delta_o + \delta_1 Z + \ln a_5 + (\frac{a_6}{a_5} - \lambda_F)E + \ln\frac{W_{t+1}}{W_t} + \mu\right] \quad [19]$$

$$F_t = \frac{1}{\nu_F}\left[c + \delta_o + \delta_1 Z + \ln a_3 + (\frac{a_4}{a_3} - \lambda_F)E + \ln\frac{W_{t+1}}{W_t} + \mu\right] \quad [20]$$

$$T_t = \frac{1}{\nu_P}\left[c + \delta_o + \delta_1 Z + \ln a_3 + (\frac{a_4}{a_3} - \lambda_T)E + \ln\frac{W_{t+1}}{W_t} + \mu\right] \quad [20p]$$

[26] For instance, wages in January 2000 are regressed on training accumulated from the start of the observation period to 1999.
[27] These conditions are

$-\mu + \lambda_F E + \nu_F F = c + \ln R + \ln a_3 + \frac{a_4}{a_3}E + \ln\frac{W_2}{W_1}$ for OFFJT and

$$\ln \frac{W_{t+1}}{W_t} = a_2 \Delta X + a_3 F_t + a_4 EF_t + a_5 O_t + a_6 EO_t + \Delta \eta_{Wt} \quad [21]$$

$$\ln \frac{W_{t+1}}{W_t} = a_2 \Delta X + a_3 I_t + a_4 EI_t + \Delta \eta_{Wt} \quad [21p]$$

Treating [19] and [20] as linear regressions, we estimate [18]-[21] by three stages least squares, using as instruments the variables in the vectors *Z*, Z^E and ΔX. For Philippines, we use [18], [20p] and [21p] .

5. **The data and preliminary explorations**

5.1 Survey Data

The survey data that we use in this paper was conducted in the summer of 2001 in Bangkok and Manila. Our samples are employees of large manufacturing firms in Thailand and the Philippines. These employees filled a questionnaire especially designed to elicit information on earnings, education, training and family background. The availability of information on the last three variables is an important feature of these data. Failure to control for family connections and ability could lead to spurious associations between schooling, training and earnings. The employee survey on which our data are based covers firms belonging to four industries: food processing, auto parts, hard disk drive makers and computer parts (mainly ICs). The latter two industries are high tech and dominated by foreign subsidiaries. Both sample countries are one of the principal production and assembly locations for hard disk drives and related components, and this industry is one of the major exporters for both countries (see Doner and Brimble [1998]). The former two industries use more mature production technologies and majority samples are domestic firms. Despite being hi-tech, HDD and IC/PC firms are also fairly labor intensive, and production are increasingly get outsourced into the sample countries from abroad to take advantage of the favorable price of labor. In the HDD industry, production involves mainly head stack and head gimbals assembly, which are very labor intensive. In the auto parts industry, we have firms producing car air-conditioner and compressors, variety of electric parts, body press, and other parts. In the food industry, majority of Thai sample

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$-\mu + \lambda_O E + \nu_O O = c + \ln R + \ln a_5 + \frac{a_6}{a_5} E + \ln \frac{W_2}{W_1}$ for OJT.

firms produce canned sea food, fruits and vegetables, fresh fruits juice and soft drinks, whereas Filipino sample firms include soft drink bottling, meat product processing, as well as firms producing canned foods.

The selection of these industries provides a reasonable coverage of the industry in sample countries without pretending to produce a statistically representative sample of the spectrum of the industry. Due to budgetary and time constraints, we have restricted our attention to firms with plants located in the Greater Bangkok area for Thailand and Metro Manila and vicinity in the Philippines. Firms in the four industries were approached and asked too cooperate to the survey. Overall, 20 firms in Thailand and 27 firms in the Philippines agreed to cooperate. Total sample size is 1,867 for Thailand and 2,001 for the Philippines[28].

Our employee samples are essentially limited to those at production facilities; majority of sample employees are operators, technicians and engineers. We stratified employment in each firm by age and education and randomly sampled employees within each cell, using larger weights for engineers and technicians to secure enough observations of workers in this category.

We relegate the description of the survey questionnaire to the Appendix. Let us note here one crucial aspect of the questionnaire. In order to create longitudinal data on training and earnings, we asked Thai sample workers retroactively incidence of training and earnings for the four year period (1998-2001). In the Philippine survey, we obtained the data on training and wages directly from sample firms. We come back to this point later on. The timing of these retrospective questions is framed to generate predetermined variables. To illustrate, monthly wages were asked with reference to January of each year, and the questions on the occurrence of training referred to the full year. Therefore, training in 1999 could be considered as predetermined with respect to wages in 2000, which were measured in January 2000.

While we acknowledge that recall data are affected by different types of measurement error (see Beckett et al [2001]), we stress that many of these questions are qualitative (requiring only a yes or no answer). We also stress that the relative short span of recall is likely to reduce the relative importance of these errors.

Overall, our sample provides a snapshot of events for an important group of employees in the two countries. It is not, however, a statistically representative sample, both because of the selection of industries and because of the endogenous selection associated with the participation of firms to

[28] As we see later on, we build a panel consisting of observations for 1998-2001. We lose one observation per employee by taking logs and we also lose many samples due to the lack of wage or training data.

the project. These limits need to be weighted against the advantages, which include the collection of detailed current and retrospective information on family background, education and different types of training. This information is not readily available from nationally representative labor surveys.

5.2 Overview of the Survey Data

As we indicated above, sample workers in our data deviate from the national average, even from the averages for manufacturing sector employees in respective countries. To begin with, sample firms in our data set are large. Median employment size of sample firms is 511 for Thailand and 598 for Philippine. Unless the selection into these firms are random, our survey data deviates in important manner from the population averages. They are mostly paid better than averages of comparable jobs in respective countries.

Among other differences, we note that our sample is substantially better educated. Table 1 shows for Thailand and Philippines the distribution of employment by education and industry in the sample (columns 1 to 4) and in the total labor force. The share of employees with primary education in our sample is close to zero in three industries out of four and significantly different from zero only in the food processing industry[29].

Table 1. Distribution of employees by education. By industry and overall.

Thailand

	(1)	(2)	(3)	(4)	(5)
Primary	0.40	0.00	0.04	0.03	0.75
Lower Secondary	0.19	0.11	0.27	0.26	-
Upper Secondary	0.24	0.46	0.37	0.36	0.16
Tertiary	0.17	0.45	0.32	0.35	0.09

Notes: secondary: lower and upper secondary education aggregated together in the national average; (1): foodstuffs; (2): electronics; (3): auto components; (4): HDD components; (5) national average (Source: OECD[2002]).

[29] It should be noted also that a large portion of sample workers from the food industry are contract workers. Especially at firms producing canned fruits and vegetables, production itself is highly seasonal and factories operate only in harvest season. Nevertheless most of sample workers have been repeating the seasonal contract for many years and they are close to regular employees.

Table 1 (continued) Philippines

	(1)	(2)	(3)	(4)	(5)
Primary	0.07	0.00	0.00	0.00	0.43
Secondary	0.71	0.55	0.65	0.72	0.45
Tertiary	0.22	0.45	0.35	0.28	0.11

Notes: secondary education requires 4 years to complete in the country; (1): foodstuffs; (2): electronics; (3): auto components; (4): HDD components; (5) national average (Source: OECD[2002]).

In Thailand as a whole, this share is as high as 75 percent. On the other hand, college graduates are 44 percent of all employees in the computer parts industry and only 9 percent in the national average. These drastic differences are accounted by the fact that we are selecting industries with more than 100 employees, where the average age of employees is close to 28 years. Moreover, the national average includes agricultural employment, where average educational attainment is very low. Similar comparison with the labor force for the Philippine sample reveals that the sample employees are substantially better educated than the national average but the difference is somewhat smaller, primarily because Filipino labor force is on average more educated than the Thai.

Table 2 and 3 present the summary statistics of the main variables in the survey for the year 2001, separately for males and females (Table 2), and operators and engineers and technicians (Table 3). In both countries and sexes, the average ages are 28 to 30 years. Average tenure as of 1998 at the current employer is between 3 to 4 years. In the Philippines, male average is slightly higher but in Thailand female average tenure is slightly higher.

Previous work experience (*exp98,*prior to joining the current firm) is around 2 years for Thailand and 1 to 1.5 years for the Philippines. In both countries, the majority of sample workers do not have any prior job experience. Female samples are predominantly operators[30] (77% in the Philippines and 94% in Thailand), whereas more than 30% of male sample workers are technicians/engineers.

Table 2. Means and standard deviations of the main variables by gender. 2001 Thailand

	Mean	Standard Dev	Mean	Standard Dev
	Males		Females	
# obs :	690		1047	
Wage	14386	(8237)	9347	(5260)
Ten98	2.59	(3.54)	3.29	(3.60)
Exp98	2.17	(3.44)	2.27	(3.72)
DOJT	0.55	(0.49)	0.67	(0.46)
DOFF	0.67	(0.46)	0.58	(0.48)
FOJT	2.62	(6.66)	3.18	(7.49)
FOFF	1.57	(3.04)	0.87	(1.56)
SOJT	8.95	(22.26)	11.63	(25.9)
SOFF	6.07	(12.59)	3.93	(6.49)
E	12.90	(2.59)	10.67	(3.05)
Age	28.26	(5.34)	28.09	(6.31)
Njobs	1.11	(1.38)	0.92	(1.09)
Sibli	3.12	(2.18)	3.36	(2.23)
Feduc	0.26		0.18	
Meduc	0.15		0.09	
Seduc	0.21		0.09	

Notes: wage: nominal monthly wage in baths; ten98 = tenure in 1998; exp98 = previous labor market experience in 1998; DOJT = dummy equal to 1 if any OJT training occurred in year h; DOFF = dummy equal to 1 if any OFFJT training occurred in year h; FOJT= average duration of OJT in hours per month; FOFF = average duration of OFF in hours per month; SOJT= sum of OJT from 1998 to year h; SOFF = sum of OFF from 1998 to year h; E = years of education; njobs= number of jobs held before current job; feduc= education of the father (1: higher than primary; 0: primary or less); meduc = education of the mother (1: higher than primary; 0: primary or less); seduc = education of the oldest sibling (% with college degree); sibli = number of siblings.

Average years of attained education are about 13 years for males and to 11 years for females in Thailand. There exists virtually no gender difference in average education in the Filipino samples and the average is about 12 years. Note that the Philippine high school system requires only 4 years so that high school graduates have 10 years of education. Notice that there are more females than males in the sample, which partly reflects the already mentioned fact that females take the largest share of labor in export-oriented firms in both countries.

In Thailand, slightly more than 14 percent of the interviewed employees started their first job with the current employer after 1998. A similar proportion has previous labor market experience started their current job after 1998. The situation is very similar also among Philippine sample employees. For these individuals we set experience net of tenure before labor market entry and

[30] Operators include team leader and supervisor (at factory), as well as regular operators.

tenure (*ten98*) before the current job spell at zero. The vast majority of the employees in the survey are composed of stayers, who have started their current spell and their labor market experience before 1998. For this group, tenure and experience are equal to tenure and experience in 1998 plus a linear trend. While we can estimate this trend with panel data, we cannot distinguish between tenure, experience and aggregate labor market effects. There exists no major gender difference in number of previous jobs held (*njobs*) in both countries, but Philippine sample averages (1.91 and 1.76) are substantially higher than Thai averages, 1.11 and .92.

Table 2 (continued) Philippines

	Mean	Standard Dev	Mean	Standard Dev
	Males		Females	
# obs :	774		1208	
Wage	10603	(5022)	9762	(3523)
Ten98	2.91	(4.48)	2.43	(4.19)
Exp98	1.65	(3.13)	1.11	(2.55)
DTRAIN	0.748	(0.43)	0.677	(0.47)
FTRAIN	1.85	(8.04)	1.97	(6.71)
STRAIN	3.06	(9.24)	3.45	(8.68)
E	11.96	(1.98)	11.67	(1.79)
Age	30.84	(8.16)	27.02	(5.71)
Njobs	1.91	(1.35)	1.76	(1.39)
Sibli	4.33	(2.51)	4.90	(4.15)
Feduc	0.71		0.59	
Meduc	0.69		0.56	
Seduc	0.64		0.44	

Notes: wage: nominal monthly wage excluding bonus in pesos; DTRAIN = dummy equal to 1 if any training occurred in each year ; FTRAIN= average duration of training hours per month; STRAIN= sum of TRAIN from 1998 up to the current year ; For ten98, exp98, E, njobs, feduc, meduc, seduc, and sibli see the notes for Thailand.

In Thailand, we collect information both about on the job (*OJT*) and off the job (*OFFJT*) training provided by the firm after probation. The former includes training carried in the workplace by senior employees, supervisors or instructors and focuses on the performance of daily tasks. While we explicitly exclude learning by doing and learning from watching others, we include learning by oneself with guidance from supervisors[31].

[31] Informal training is difficult to measure. See the discussion in Barron et al, 1997, and Lowenstein and Spletzer, 1994. Interviews with human resource managers in the selected firms made clear that learning by oneself with guidance from supervisors is fairly common among junior technicians and engineers, who need to get used to the firm – specific technology and organization of production by going over manuals and other technical material.

Table 3. Means and standard deviations of the main variables, by job. 2001.
Thailand

	Mean	Standard Dev	Mean	Standard Dev
	Production		Tech+Eng	
# obs :	1465		272	
Wage	10157	(5945)	17755	(8851)
Ten98	3.20	(3.86)	2.01	(2.73)
Exp98	2.35	(3.74)	1.58	(2.76)
DOJT	0.64	(0.48)	0.54	(0.49)
DOFF	0.61	(0.48)	0.68	(0.46)
FOJT	3.00	(7.17)	2.70	(7.21)
FOFF	1.02	(1.84)	1.82	(3.82)
SOJT	10.83	(24.92)	9.13	(22.74)
SOFF	4.47	(9.12)	6.47	(10.95)
E	11.02	(3.00)	14.44	(1.50)
Age	28.22	(6.22)	27.85	(4.06)
Njobs	0.99	(1.22)	1.02	(1.23)
Sibli	3.36	(2.23)	2.93	(2.06)
Feduc	0.19		0.33	
Meduc	0.09		0.21	
Seduc	0.10		0.33	

Notes: see Table 2.

Philippines

	Mean	Standard Dev	Mean	Standard Dev
	Production		Tech+Eng	
# obs :	1356		304	
Wage	9166	(2877)	13722	(6814)
Ten98	2.87	(4.38)	1.63	(3.53)
Exp98	0.95	(2.24)	2.02	(3.38)
DTRAIN	0.67	(0.47)	0.81	(0.40)
FTRAIN	1.61	(3.61)	3.11	(12.11)
STRAIN	4.84	(8.20)	7.78	(10.59)
E	11.20	(1.73)	13.21	(1.24)
Age	28.22	(7.26)	28.74	(5.86)
Njobs	1.77	(1.44)	1.86	(1.23)
Sibli	4.99	(4.09)	4.05	(2.46)
Feduc	0.58		0.76	
Meduc	0.55		0.75	
Seduc	0.43		0.78	

Notes: see Table 2.

The latter, *OFFJT,* is training carried out off the job and organized by the firm either in or outside the premises, and either during or after standard working hours. While OJT is provided mainly by senior workers in the same unit, team leaders and foremen (72% of the total), OFFJT is supplied mainly by instructors from professional training centres and from outside the company (86% of the total) and concerns both daily tasks, instruction for the operation of machines and tools, quality control and standards and safety regulations.

For each type of training, we asked whether the employee has had any training during the reference period (the year), a simple (0,1) dummy, and about training intensity. We call the former variable *DOJT* for on the job and *DOFF* for off the job training. For each individual, training intensity (*FOJT* for on the job and *FOFF* for off the job) is obtained as the product of the number of training events in each month by the average intensity of each event, measured in hours. Starting with training incidence, we find that in 2001, 55% of the males in the sample have undertaken some OJT in 2001, compared to 67% of the females. Interestingly, the opposite holds for OFFJT, with 67% of the males and 58% of the females receiving it. In the case of training intensity, we find similar differences by gender and type of training. The number of hours of training per month is 2.62 for males and 3.18 for females in the case of OJT and 1.57 for males and 0.87 for females in the case of OFFJT. Therefore, males experience longer OFFJT and shorter OJT than females. Similar results hold for cumulated training *SOJT* and *SOFF*, obtained by summing up average monthly hours from 1998 to 2001.

In Philippine survey, data on training and wage are collected directly through firm documents and records. As a consequence, Philippine data on these variables do not suffer from the usual problems associated with retrospective panel survey. On the other hand, Philippine data on training may under-report informal on the job training to the extent they may not be recorded in formal firm documents. We therefore suspect that Philippine training data may under-report the training, especially those informal OJT. We hence only use the sum of monthly average training hours (*TRAIN*) as our training variable. Tables 2 and 3 for Philippines show that the average total training hours is about a half of Thai average: about 1.9- to 2 hours per month. Across gender, females actually receive slightly more training than males.

Turning to family background, we present in the table the father's (*feduc*) and mother's education (*meduc*), the education of the oldest sibling (*seduc*) (next to oldest if the employee is the oldest) and the number of siblings (*sibli*). For ease of presentation, the information on the former two variables is recoded to generate two (0,1) dummies, with 0 referring to primary education or less and 1 referring to higher education. The education of the oldest sibling is expressed as the percentage of individuals with a college degree. It turns out that male employees, who have higher educational attainment than females, have also a "better" family background, since both parents and the oldest sibling have on average higher education and the number of siblings is smaller. We find similar gender differences in Philippine samples: education attainments of male employee family members are uniformly better than the female counterparts, although the average education attainment of sample workers do not differ much between male and female.

Table 3 shows the means of the same variables separately for production workers, inclusive of team leaders and foremen, and for technicians and engineers. As expected, the latter group is better educated than the former and receives more formal OFFJT and less OJT than shop floor employees. In the questionnaire we also ask whether OFFJT training was carried out in the firm premises or outside it, either in a training center, at a supplier or at a parent firm. It turns out that training outside the firm premises is more frequent for technicians and engineers and for employees with longer tenure and higher education. In summary, less experienced and less educated female workers in the production line receive more OJT, and more experienced and better educated male workers in technical and engineering jobs receive more OFFJT. In Philippines, the difference between operator and engineer/technicians groups is much larger: the latter group receives almost twice (3.11 versus 1.61) as much training and three years of additional education. Although the average age is about the same, engineer/technician group has more than twice previous work experience but their average tenure at the current employer is much shorter (1.63, versus 2.87 years for operator group). To some extent, the larger difference can be attributed to the lack of data on informal training, which is likely to under-estimate training hours of operators more than those for engineer/technicians. Longer experience and shorter tenure of the latter group are consistent with the popular perception that engineers with college education tend to move more frequently.

In Thailand, we asked for year 2001 and 2000 types of trainings each sample worker received for OFFJT and OJT. They are shown in Table 4[32]. We notice immediately that trainings immediately related to the current tasks are the most common, especially so among OJT. To the extent these trainings are directly related to their daily tasks, they are likely to contain at least some element of firm specific training. In this sense, even significant portion of OFFJT are firm specific. On the other hand, even in OJT, 20 to 25% of those received some OJT were trained on 'general

[32] For Philippines, we have record on each episode of training and they are not amenable to easy classification. We find, however, that many training are rather general, such as, instruction on computer program (e.g., Excel).

skill improvement', which can be hardly firm specific. In short, although there is some tendency that more firm specific trainings are conducted as OJT than OFFJT, the distinction is not very clear cut. Another notable finding is significant share of trainings related to introduction of new product, new machine, or new production line. These figures indicate that major technology change is indeed associated with additional training investment.

Table 4. Types of Training Received: Thailand
(1) OFFJT Incidence[33]

Job Groups	Operators	Tech/Engineers	Administration
# Samples	3576	740	420
New Worker Orientation	25.7%	1.1%	0%
Daily Task	47.4	23.2	21.9
Safety	58.4	47.0	3.5
Machine Maintenance	14.0	27.6	18.1
New Product	13.8	14.2	16.2
New Machine	8.8	11.4	7.6
New Product Line	1.6	1.6	1.9
General Skill Improvement	15.3	9.2	9.5
Finance and Accounting	1.0	0.5	2.9
Marketing	1.0	0.5	3.8
Work Efficiency	9.7	13.5	23.8
Management & Leadership	8.5	14.6	32.4
ISO, HACCP	31.7	28.6	39.0
Others	25.5	23.2	13.3

We conclude this section by discussing how years of education vary with family background, the number of siblings and the position in the household at birth[34]. Average years of schooling in the Thai sample are equal to 11.56. This average falls to 11.29 in if the father has at most primary education and increases to 12.55 if the father has higher education. A similar gap exists when we focus on the mother's education. The relationship between position in the household and years of education varies with gender. The percentage of male individuals aged between 21 and 30 with at least 12 years of education is 66.8% for the oldest in the household, 60% for the youngest and 54.5%

[33] Figures are % share of sample workers who received each type of training within each year among those who received some type of OFFJT. Multiple answers allowed.

[34] The importance of family background for education in East Asian countries is discussed by Wossmann, 2003.

for those in intermediate position. These percentages for females in the sample fall dramatically to 21%, 24.9% and 15.7% respectively.

Table 4 (continued) (2) OJT Incidence

Job Groups	Operators	Tech/Engineers	Administration
# Samples	3752	584	224
New Worker Orientation	1.9%	4.1%	5.4%
Daily Task	83.4	70.5	76.8
Safety	45.8	39.7	28.6
Machine Maintenance	26.6	34.9	19.6
New Product	16.6	13.7	14.3
New Machine	18.6	28.8	21.4
New Product Line	27.2	17.8	28.6
General Skill Improvement	26.3	21.9	26.8
Others	18.6	15.1	17.9

Turning to the number of siblings, Table 5 shows how the distribution of educational attainment varies with the number of siblings. It is clear that the percentage of individuals with low educational attainment is significantly higher in Thailand when the number of siblings is larger, which suggest stronger competition for household resources. The same correlation exists, but, the impact of sibling is smaller on education attainment in Philippines. It should be noticed also that Filipino samples have far larger number of siblings (average in excess of 4 for female and close to 5 for male), reflecting the major difference in birth rates between the two countries.

Table 5. Distribution of employees by education and number of siblings.

Thailand

	E<9	E=9	E=12	E>12
S: 0-1	6.18	14.61	40.73	38.48
S: 2	8.21	19.57	33.09	39.13
S: 3	8.84	24.39	36.59	30.18
S: >3	19.34	23.43	33.96	23.27

Note: S: number of siblings; E: years of schooling

Table 5 (continued) Philippines

	E<10	E=10	E=12	E>=14
S: 0-1	0.00	27.78	11.11	61.11
S: 2	0.00	28.69	22.71	48.61
S: 3	1.89	30.82	24.84	42.45
S: >3	2.17	45.61	26.85	25.37

Notes: E=10 corresponds to high school, 12 to vocational college, and 14 to 4 year colleges. See also footnote for Thailand above.

6. The results

6.1 Training Incidence

The vector *Z* in the training equations [16] and [17] is expected to capture variations in the turnover rate and in the discount factor. For both countries, we proxy turnover with firm dummies, the number of jobs held before the current job (*njobs*), tenure (*ten98*) and experience (*exp98*) at the start of the observation period, and two dummies indicating whether the first (*fjquiw*) and the previous (*pjquiw*) jobs were quitted because of better job prospects, and the discount factor with gender, a dummy for marital status (*marry*) and the number of children in the household (*child*). Since our data cover the years 1998-2001, we also add a linear and a quadratic trend to capture the influence of aggregate effects[35].

We implement the weak exogeneity test suggested by Smith and Blundell, 1986, by regressing years of education on the vector Z^E and by computing the residuals *RES*. Since the Bound test statistic is equal to 5.15, we can reject the null hypothesis of no (joint) statistical significance of the additional instruments at the 1 percent level of confidence. Similarly, our regression results on Philippine data can safely rejects the null[36].

Next, we run the bi-probit model for DOJT and DOFF and the tobit model for FOJT and FOFF after adding RES to each model and test whether the residuals are statistically significant. In the affirmative case, we reject the hypothesis that education is weakly exogenous in the training incidence equations. It turns out that the estimated coefficients of the residuals are statistically

[35] These trends also capture the time varying effects of experience and tenure.
[36] Results from the first stage regression are available from the authors upon request.

significant at the 0.05 level of confidence when training is measured as a dummy variable and not statistically significant in the case of training intensity. Therefore, in the former case we reject the weak exogeneity of education. In the case of Philippines, education residuals are not significant in any of regressions on *DTRAIN* and *FTRAIN*.

Table 6 and 7 show our estimates when training is measured as a (0,1) dummy and as training hours respectively. For both measures of training available in the data, we present results for the full sample (former two columns) and for the sub-sample of production workers (latter two columns) for Thailand. Our estimates unambiguously show that, independently of the measure of training, individuals with higher education are less likely to receive OJT and more likely to receive OFFJT. We also find that the probability of receiving OJT declines with age and tenure and with the number of previous jobs. On the other hand, the probability of receiving OFFJT is higher among older workers with higher tenure. Both types of training are less likely for individuals living in households with a higher number of children. We interpret this as evidence that more risk averse employees and/or employees with a heavier load of parental duties receive less training from the employer.

These findings do not change in a qualitative way when we consider only the sub-sample of production workers. Therefore, the nature of the relationship between education and training does not depend on the type of occupation in Thailand. We also ask whether the relationship between education and training intensity varies with gender by adding to the set of explanatory variables the interactions between years of education and the gender dummy. It turns out that these interactions are never statistically significant for OJT. In the case of OFFJT, the positive relationship with education is significantly lower among female employees. Therefore, the complementarity between education and OFFJT is significantly stronger for male workers.

In the case of Philippines, results are more mixed. Although education is significant and positive in *DTRAIN* regression, and, also on training hours (***FTRAIN***) regressions for entire sample and operators, the impact is marginally significant and negative for technicians and engineers group.

Our estimates use four years of retrospective data. A drawback of these data is that they introduce measurement error, as respondents may suffer from recollection problems, which are expected to increase with the period of time between the training spell and the interview and with the detail of the training question (see Leuven, 2002). To minimize the influence of these measurement errors and check the robustness of our results, we replicate Tables 6 and 7 in a sub-sample which retains only the observations for 2000 and 2001. It turns out that the relationship between education and training in the shorter sample is negative for OJT and positive for OFFJT, as in the longer sample. More in detail, we find that the estimated coefficient of schooling in the training intensity equation is equal to –0.609 - with standard error equal to 0.094 – for OJT and to 0.126 – with standard error equal to 0.033 – for OFFJT.

Table 6. Bivariate probit estimates of training incidence. DOJT and DOFF Thailand

	DOJT	DOFF	DOJT	DOFF
Ten98	-0.013 (0.007)	0.021* (0.008)	-0.020* (0.008)	0.020* (0.009)
Exp98	-0.015 (0.007)	0.007 (0.007)	-0.017 (0.008)	0.006 (0.008)
Marry	0.009 (0.025)	0.015 (0.026)	0.004 (0.029)	-0.001 (0.028)
Sex	-0.013 (0.071)	-0.066 (0.072)	0.021 (0.082)	-0.120 (0.086)
Njobs	-0.031 (0.022)	-0.041 (0.022)	-0.002 (0.026)	-0.035 (0.025)
Age	-0.013* (0.005)	0.020* (0.006)	-0.003 (0.006)	0.022* (0.006)
Fjquiw	0.098* (0.046)	0.182* (0.047)	-0.027 (0.049)	0.175* (0.052)
Pjquiw	0.044 (0.066)	-0.015 (0.066)	0.009 (0.070)	-0.006 (0.072)
Child	-0.074* (0.032)	-0.117* (0.032)	-0.073* (0.034)	-0.097* (0.035)
E	-0.150* (0.033)	0.110* (0.035)	-0.131* (0.036)	0.125* (0.038)
RES	0.097* (0.033)	-0.085* (0.035)	0.083* (0.037)	-0.102* (0.039)
Ξ	0.352* (0.026)		0.349* (0.028)	
Nobs	5350	5350	4495	4495

Notes: see Table 2. The former two columns refer to the full sample and the latter two columns to operators . Standard errors in parentheses with $p<0.05$ = ~, $p<0.01$ = *. Nobs: number of observations. Each regression includes firm dummies, family background variables, a linear and a quadratic term. Fjquiw: whether first job was quitted because of better wage prospects; pjquiw: whether previous job was quitted because of better wage prospects; sex: gender dummy (1: male); marry: marital status dummy; ten98: tenure in 1998; exp98: labor market experience in 1998; child: number of children in the household; ξ=correlation between training error terms.

Table 6 (continued) Philippines

	DTRAIN	DTRAIN
ten98	0.173* (0.028)	0.133* (0.038)
exp98	-0.030 (0.018)	-0.015 (0.026)
Marry	0.098 (0.106)	-0.004 (0.155)
Male	-0.102 (0.104)	0.070 (0.184)
Njobs	-0.058 (0.031)	-0.058 (0.038)
Age	0.002 (0.016)	0.012 (0.021)
Fjquiw	0.060 (0.088)	0.281~ (0.130)
Pjquiw	0.082 (0.137)	0.293 (0.263)
Child	-0.091 (0.058)	-0.092 (0.084)
E	0.331* (0.077)	0.255~ (0.110)
RES	-0.008 (0.025)	-0.039 (0.037)
Nobs	1563	873

See notes for Thailand table.

Table 7. Tobit estimates of training intensity.
Dependent variables: FOJT and FOFF
Thailand

	FOJT	FOFF	FOJT	FOFF
Age	-0.077	0.070*	-0.044	0.062*
	(0.046)	(0.018)	(0.048)	(0.019)
Njobs	-0.704*	0.057	-0.651*	0.018
	(0.183)	(0.069)	(0.205)	(0.075)
Pjquiw	0.207	-0.230	-0.003	-0.339
	(0.519)	(0.200)	(0.567)	(0.210)
Fjquiw	-0.338	0.128	-1.090*	0.069
	(0.358)	(0.139)	(0.388)	(0.146)
Child	-0.661~	-0.418*	-0.401	-0.326*
	(0.263)	(0.103)	(0.277)	(0.105)
Ten98	0.043	0.031	0.026	0.023
	(0.063)	(0.024)	(0.066)	(0.024)
Exp98	-0.028	-0.015	-0.005	-0.009
	(0.062)	(0.023)	(0.064)	(0.023)
Marry	0.064	0.305*	-0.133	0.216*
	(0.202)	(0.078)	(0.221)	(0.082)
Sex	-0.077	0.205	0.281	0.099
	(0.565)	(0.217)	(0.642)	(0.239)
E	-0.862*	0.266*	-0.805*	0.281*
	(0.264)	(0.102)	(0.285)	(0.107)
RES	0.285 (0.267)	-0.145 (0.103)	0.254 (0.287)	-0.151 (0.108)
Nobs	5331	5331	4391	4476
R-sq	0.03	0.041	0.032	0.052

Notes: See Table 5

Table 7 (continued) Philippines

	FTRAIN	FTRAIN	FTRAIN
Sample	**All**	**Operators**	**Eng/Tech**
Age	.022	-.029	.799~
	(.08)	(.05)	(.39)
Njobs	-.289	-.056	-.015
	(.24)	(.12)	(1.09)
Pjquiw	-.143	1.080	-5.096
	(1.31)	(.95)	(3.76)
Fjquiw	.286	.893~	-3.187
	(.73)	(.45)	(2.55)
Nchild	.370	.263	.162
	(.34)	(.19)	(1.21)
Ten98	.366*	.207*	.202
	(.12)	(.06)	(.56)
Exp98	-.319*	-.168~	-.683
	(.13)	(.08)	(.43)
Marry	1.523~	.891*	2.436
	(.63)	(.36)	(2.32)
Male	.280	-.963*	.010
	(.54)	(.32)	(.67)
E	1.401*	1.304*	-2.293~
	(.26)	(.16)	(1.04)
RES	-.292	.136	-.748
	(.22)	(.09)	(0.94)
Nobs	3534	2337	579
R-sq	0.032	0.62	0.017

Notes: See Table 5

6.2 The Mincerian equation

Our measure of earnings is monthly net earnings including overtime pay. Training at time t is defined as the sum of average monthly hours of training from 1998 to the calendar year immediately before. For example, we regress wages in 2000 on training undertaken up to 1999. Since information on training before 1998 is not available, we use as proxies tenure and labor market experience. As for the training equations, we pool the available information and use firm dummies, a linear and a quadratic trend. The vector *X* includes also age, age squared, a gender and a marital status dummy and the dummy *CHANGE*, equal to 1 if the individual changes employer during the sample period. This dummy captures the individual–firm match effect. The use of a fixed -effects estimator implies that the coefficients associated to time invariant variables, such as education, tenure and experience in 1998, cannot be estimated. Table 8 presents our results for the full sample (column (1)) and for the sub-sample of production workers (column (2)).

The Wald test in the table shows that the interactions between educational attainment and training are statistically significant. Evaluated at sample mean years of education, the estimated percentage increase in (monthly) wages following a one - unit increase in the hours of monthly training is $\frac{\partial \ln W}{\partial SOJT}$ = 0.0025 for OJT and $\frac{\partial \ln W}{\partial SOFF}$ = 0.0004 for OFFJT. The p-value of the Wald test of the hypothesis that the estimated effect is not significantly different from zero - reported within brackets in the table - shows that this effect is precisely estimated only in the case of OJT. Similar results hold in the sub - sample of production workers.

For Philippines, we again divided the sample into operators and engineer/technician groups. Consistent with training incidence regressions, we find that the returns from training increases for the better educated operator group, whereas the returns are smaller for the better educated engineer/technician group.

Are these returns low? To answer this question, suppose that an additional year of education requires about 1000 hours of instruction[37]. This is equivalent to about 83.3 hours per month. If we increase the monthly hours of OJT and OFFJT by a similar amount, monthly earnings would increase by 20.8% [83.3 x 0.0025] and 3.3% respectively. According to Psacharopoulos, 1994, the private returns to an additional year of education in Thailand is close to 10 percent, about half the size of the returns to an additional year of OJT and about three times the size of the returns to OFFJT. These returns are significantly lower than those estimated for the US by Frazis and Lowenstein, 1999, who find that 40 hours of training yield a return similar to one year of education, but broadly in line with the rate of return in the range between 16 and 26 percent reported for the US by Carneiro and Heckman, 2003[38].

[37] The mean number of hours of instruction received per year by pupils older than 14 in the US was 1032 in 1991. Source: OECD, Education at a Glance, Paris 1992.

[38] We do not include in the computation of the returns to OJT and OFFJT the return to tenure and labor market experience, because upward sloping earnings profiles are not necessarily generated by investments in human capital.

Table 8. Fixed – effects regression of the Mincerian equation Thailand

	(1)	(2)
C HANGE	0.053 (0.030)	0.048 (0.035)
SOJT	-0.003 (0.002)	-0.003 (0.002)
SOFF	-0.018 (0.009)	-0.012 (0.010)
E*SOJT	0.0005~ (0.0002)	0.0005~ (0.0003)
E*SOFF	0.0016~ (0.0007)	0.0012 (0.0008)
Time	0.166* (0.049)	0.204* (0.056)
Time2	-0.023* (0.008)	-0.031* (0.009)
Wald	[.002]	[.023]
$\frac{\partial \ln W}{\partial SOJT}$	.0025 [.0003]	0026 [.0007]
$\frac{\partial \ln W}{\partial SOFF}$	.0004 [.842]	.0005 [.847]
Nobs	5962	3849
R-squared	0.03	0.023

Notes: see Table 5. CHANGE: takes 1 if sample workers worked at firms different from current one.Standard errors within parentheses, p-values within brackets; Wald: joint test of statistical significance of interactions

Table 8 (continued) Philippines

	Log(wage)	**Log(wage)**	**Log(wage)**
	All	**Operators**	**Eng/Tech**
Tenure	.0139*	.0185*	.0196*
	(.002)	(.002)	(.002)
Strain	-.0111~	-.0149~	.0686*
	(.004)	.006	(.018)
Train*E	.00114*	.00161*	-.00464*
	(.0003)	(.0005)	(.0013)
$\frac{\partial \ln W}{\partial STRAIN}$	.0030 (.0016)	.0041 (.0018)	.0078 (.0022)
Nobs	3287	2327	459
R-sq	.023	.102	.076

Notes: See Table 5; *Strain*: cumulative training hours per month.

Similar computation yields substantially higher returns from training among Filipino samples: our point estimate for the entire sample shows .0030*83.3=25%, and 34%, 65%, respectively for operators and engineers. Ironically, the higher returns from training is matched with a very small amount of training in the country.

Marginal returns to training vary significantly with educational attainment. In the case of OJT, for example, they increase from close to zero for individuals with primary education to 0.0012 for individuals with junior high school to 0.0037 for individuals with a college degree. Therefore, private returns to training are higher for the groups that are less likely to be trained, a result already found in the literature (see OECD, 1999). Results for Philippines are similar in the sense that marginal returns from training varies greatly, positively with education attainment for operators, and negatively for engineer/technicians.

As for the training incidence equations, we check whether our results are driven by the measurement error associated to retrospective data by replicating the fixed - effects estimates in a sub-sample consisting of the last two years in the dataset. It turns out that in the shorter sample the returns to OJT and OFFJT are equal to 0.0042 (p-value of the Wald test that the estimated effect is not significantly different from zero: 0.003) and 0.003 (p-value of the test: 0.49) respectively.

A theme in this literature is that training with the current employer should yield lower wage growth than training with the previous employer, because of imperfect competition in the labor market (see Lowenstein and Spletzer, 1999). One way to check whether this effect is present in our data is to exclude from the wage regressions the individuals who have been trained in another firm before joining the current firm. If we do so, we find that the returns to training in the full sample fall from 0.0025 to 0.0021 in the case of OJT and from 0.0004 to -0.001 (not statistically significant) in the case of OFFJT, in line with the literature.

6.3 The structural model

We estimate the system (18)-(21) by 3SLS and present the estimated coefficients of the key parameters in Table 9. In these estimates, we focus exclusively on average monthly hours of training and specify the two training incidence equations as linear probability models. We use the results to compute the percentage increase in monthly earnings following a one – unit increase in the (monthly) hours of training and find that it is equal to 0.0031 – not statistically significant – in the case of OJT and to 0.024 – statistically significant – in the case of OFFJT. While the former effect is in line with the fixed - effects estimates in section 6.2, the latter effect is much larger and closer to the findings by Frazis and Lowenstein discussed above.

Table 9. 3SLS estimates of the model (18)-(21)
Thailand

Parameters	Coefficients	Parameters	Coefficients
a_3	0.025 (.036)	λ_F	-.062 (.098)
a_4	-.0001 (.002)	λ_O	.019 (.193)
a_5	-.036* (.010)	$\frac{\partial \ln W}{\partial SOJT}$	.0031 (.0026)
a_6	.0033* (.0009)	$\frac{\partial \ln W}{\partial SOFF}$	.0240* (.009)
$\frac{\partial FOJT}{\partial E}$	-.231	$\frac{\partial FOFF}{\partial E}$	.197

Philippines (1)

Parameters	Coefficients	Parameters	Coefficients
a_3	-.0998* (.036)	$\frac{\partial FTRAIN}{\partial E}$	1.129
a_4	.00836* (.0029)	$\frac{\partial \ln W}{\partial STRAIN}$	.0041 (.13)
λ_T	-1.199~ (.56)		

We also solve the system of equations to compute how training intensity (in hours per month) varies with educational attainment and find that a marginal increase in the years of schooling – evaluated at sample average education – reduces OJT hours and increases OFFJT hours. This result is clearly consistent with the estimates reported in sub-section 6.1.

Table 9 (continued) Philippines (2)

Parameters	Coefficients	Parameters	Coefficients
a_{3op}	-.125~ (.054)	$\lambda_T eng$	-.705 (.28) ~
$a_4 op$	.0115* (.0046)	$\frac{\partial FTRAIN}{\partial E}\vert_{opr}$	-.0022
$a_3 eng$	.0308 (.13)	$\frac{\partial \ln W}{\partial STRAIN}\vert opr$	.0093 (.017)
$a_4 eng$	-.00219 (.010)	$\frac{\partial FTRAIN}{\partial E}\vert_{eng}$	.628
$\lambda_T op$	-.0682 (.28)	$\frac{\partial \ln W}{\partial STRAIN}\vert_{eng}$	.0012 (.002)

One of the key results is that the relationship between education and training depends on the type of training and is negative in the case of OJT and positive in the case of OFFJT. In this section we focus on the former finding, which is less in line with the current literature. The fact that individuals with lower education receive more OJT may be attributed to the difficulties that Thai firms have in hiring properly educated workers, who are in scarce supply. With rapid growth and the limited human capital provided by schooling, our results suggest that firms in this country have been forced to hire poorly educated workers and train them on the job to make them productive in their assigned tasks.

We can examine how the marginal costs and benefits of training vary with educational attainment by differentiating the first order conditions associated to OJT and OFFJT with respect to education. We obtain that $\frac{\partial O}{\partial E} < 0$ if

$$\frac{a_6}{a_5} + a_6 O + a_4 F < \lambda_O \qquad [22]$$

and $\frac{\partial F}{\partial E} > 0$ if

$$\frac{a_4}{a_3} + a_6 O + a_4 F > \lambda_F \qquad [23]$$

Similarly, for overall training in Philippines, we have

$$\frac{\partial I}{\partial E} > 0 \text{ if}$$

$$\frac{a_4}{a_3} + a_4 I > \lambda_T \qquad [23p]$$

These expressions show how log marginal benefits - net of the opportunity costs of training - and log marginal costs associated to the efficiency of training vary with educational attainment. Education increases training incidence or intensity if it raises the net marginal benefits of training - the left hand side of [22] and [23] - more than the marginal costs ϕ'_E - the right hand side of [22] and [23].

All the parameters in [22] and [23] can be retrieved from the estimates of the structural model[39]. We use these estimates to evaluate, at the sample averages of the relevant variables, the left hand sides of [22] and [23] and find that they are equal -0.084 and 0.005 respectively, which implies that one year of additional schooling reduces the *net* marginal benefits of OJT by 8.4 percent and increases the *net* marginal benefits of OFFJT by 0.5 percent. Turning to the estimates of parameters λ_F and λ_O, we find that the former is negative and equal to -0.062 (standard error: 0.098) and the latter is positive and equal to 0.019 (standard error: 0.193). Albeit imprecise, these results suggest the possibility that education improves the efficiency of learning off the job and reduces the efficiency of learning on the job. The relevant literature has often emphasized that the better educated are either easier to train or better at learning new skills. This intuition is confirmed in our dataset when we consider more formal and less practical training, that is conducted offsite in a classroom, but does not apply for more practical training on the job.

Philippine results are shown for two separate cases: one for the entire sample, and another in which we separately estimates the coefficients on training and product of education and training for the two groups. Starting from the entire sample case, our results are largely comparable to earlier stage regression results. Our estimation shows that additional year of education decreases the net marginal benefits by .03, but, it also increases in learning efficiency and the reduction in cost from additional education. The end result is the positive impact of education on training. Turning to the lower panel, we estimate separately the coefficients for operator and engineer groups. For operator group, the left hand side declines by .0704 by additional year of education, which dominates the favorable impact of education on the marginal cost, .0682. The end result is slightly negative impact of education on training. For technician/engineer group, the decline in net benefit, .077, is dominated by a large reduction in marginal cost, .705, such that the impact of education on training is positive. Notice also that both estimates indicate positive but varied impact of training on wage. These results on the impact of education on training for operator and engineer groups differ diagonally from those given in Table 7.

6.4 Technology and training

Our survey covers wide variety of information on employees and employers. Due, however, to the limited size of the firm level data (although our survey covers roughly 4000 employees, sample firm size is less than 50), we cannot investigate in any systematic manner the impact of technology and technology change on training. On the other hand, given the large inter-industry variations in training within manufacturing sector, we suspect that technology and training tend to be highly positively correlated.

Table 10 Inter industry variations in Training, Education, and Wage

Industry	Food	Auto parts	HDD	IC/PC
Thai (OJT)	.74	.76	.86	1.59
Thai (OFFJT)	.82	1.00	.80	1.40
Thai (edyear)	9.94	11.93	12.22	12.99
Philippines	.30	.67	.82	1.95
Ph.(edyear)	10.89	11.68	12.03	12.34

Notes: training figures are shown as the ratio to the entire sample average; edyear is the average number of schooling.

Thai Sample Relative wages (Normalized by average wage for operators in food industry)

Industry	Food	Auto parts	HDD	IC/PC
Operator	1.0000	1.2776	1.4789	1.1467
Foreman	1.0961	2.2054	2.0229	1.6539
Supervisor	1.4574	2.3674	2.4401	2.4353
Manager	2.2041	2.2925	2.7095	3.3967
Technician	1.2656	1.7075	1.9344	1.6940
Engineer	2.0167	2.3283	3.4981	3.0923

[39] We cannot evaluate separately how the marginal benefits and opportunity costs of training vary with education because we lack estimates of the parameter a_1, which measures the effect of time invariant education on log earnings.

Table 10 (continued) Filipino Sample Relative wages
(Normalized by average wage for operators in food industry)

Industry	Food	Auto parts	HDD	IC/PC
Operator	1.0000	1.4178	1.4508	1.5495
Foreman	1.0799	1.4411	2.1159	1.5453
Supervisor	0.9118	1.6489	1.8095	1.8786
Manager	1.1981	1.5207	2.1479	2.0288
Technician	1.0058	1.2951	1.9898	1.7154
Engineer	1.0481	2.0015	2.3846	2.1552

Table 10 shows the industry variations of training and wages in the two countries. The inter-industry variations in training intensity are very similar between the two countries: in both countries, the average training is lowest in food processing, followed by auto-parts, hard disk drive, and electronics (integrated circuits and computer parts) is the highest. This ordering matches exactly in terms of education years. The major difference lies in the magnitude of variations. Training intensity variation is much larger in Philippines than in Thailand. Notice that HDD and electronics industries are almost totally export oriented and many of them are subsidiaries of multinational major players in the industry. Not surprisingly, training programs are highly standardized across countries.

Inter industry wage structure is also shown in lower panel in Table 10. We notice again similar inter-industry variations: in both countries, average wage follows the same ordering as training intensity, except perhaps for the fact that the two export industry wage structure are similar. The difference between the two countries is that wage variations across industry and job are much larger in Thailand than in Philippines. The variance for the normalized wage for Philippines shown in Table is .184, whereas the variance for the Thai samples is .484. This difference mirrors closely the contrasting overall performances of manufacturing sector in the two countries. In Philippines, manufacturing sector has been stagnant for more than a decade and the share in GDP continues to decline. The latest figure for year 2000 is 22.4, more than 3% smaller than 1970 figure, 25.7%. During the same 30 year period, Thailand manufacturing share in GDP increased from 15.9 to 32.0%. Stagnation of manufacturing industry coupled with heavy international competition forced wage compression, and manufacturing sector wage now falls substantially behind service sector wage, especially for college graduates. In short, more compressed wage structure in Philippines, highly correlated industry variations in wage and training investment are all consistent with positive correlation between training, education, technology, and productivity.

Using our survey data, Yamauchi and Poapongsakorn (2003) estimated fixed effect regression on wage growth. They found that the impact of training is negatively influenced by the fixed capital investment rate, their proxy for technical change, but, estimated coefficients are not significant. The results, taken at face value, seem to indicate that trainings induced by new capital equipment are needed to start up new system. As such, it is possible that additional training does not generate extra productivity above and beyond what can be predicted from the installment of new machinery. The point here is that such new machinery will not be productive without such trainings.

On the other hand, technical change, as measured by net capital investment for each sample firm/year, clearly has positive impact on off the job training incidence of sample workers of respective firms, whereas the impact on OJT is insignificant and negative for Thailand. In the case of the Philippines, we have significant positive impact only on returns from training among engineers and technicians, and returns on operators as well as training incidences are all positively influenced by capital growth rates (but not statistically significant)[40].

7. Conclusions

The results reported in this paper are largely consistent with many of recent studies on training conducted in developing countries, but not without some additional findings and discrepancies. First of all, our results confirm statistically significant returns from training which is comparable or superior to returns from education. Compared to the past study, however, our study covers informal on the job training at Thai sample firms. Our study shows that the dominant shares of training at sample firms are informal OJT. Our estimation demonstrates also that the average return from OJT is statistically significant and sizable. OJT is especially important for operators.

Our survey also shows that the association between general training to OFFJT, and firm specific training to OJT, are, at best, statistically weak and can be even misleading. The results on the impacts by education are mixed and we suspect that interactions between education and training are much more complex than what conventional wisdom suggests. The nature of interaction seems to differ substantially between formal OFFJT and informal OJT. The positive correlation is much

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[40] These regression results (not shown) are available from authors upon request.

stronger for OFFJT than in OJT. In a sense, this is not surprising. OFFJT is much closer to regular course work at schools and we naturally expect that the better educated are better learners at this type of training. On the other hand, OJT is found to be more of substitutes for formal education. We also found for Philippine samples that training investment is positively influenced by education for overall sample, whereas the coefficients estimated separately for operator and engineer groups generate mixed results and no definitive conclusion emerged.

We add here one cautionary note on our finding. Throughout the regression analysis, we used job, and industry or firm dummies to control for job and industry/firm characteristics. It is evident, however, that allocation of a worker to a job/industry/firm is not exogenous. In particular, it is highly correlated with education. We find in our data, for example, in earnings regression, estimated returns from education is reduced to less than a half of the estimate without job and industry controls. One obvious implication is that the ultimate impacts of education on training and productivity are mainly through allocation to jobs and industries. In view of the earlier discussion on the research methodology and review of recent literature, the current state of our knowledge, including our own, falls short of structural estimation of relevant parameters to be used for important policy analysis. In particular, identification of cost of training is a major empirical challenge, without which most of candidates policies submitted to enhance training cannot be evaluated properly.

Once we control for job and industry, the direct impact of education on training or productivity is rather limited. This suggests potentially important role of the overall balance in level and type of education between what school system provides and what is needed at workplace. Highly compressed pay structure and relatively small amount of training among Philippine samples might well be a reflection of the stagnant industry growth and glut of university graduates of the country. In any case, many of Philippine regression results are conflicting each other and the nature of interactions between education and training in the country remains something of a mystery. On the other hand, comparison of the two countries certainly provides additional support to the view that the interactions among education, training, and technology relies upon the overall balance of education supply and demand. Steeper pay structure and higher level of training in Thailand is consistent with high economic growth and rapid industrial development of the country. The large premium on professional jobs does reflect scarcity of college graduates.

In this paper, we used data from a survey Thai and Filipino employees to show that the relationship between education and training depends on the type of training. Although specific survey formula employed in our research project produced unique data and information not readily available in other types of the survey, the limitation imposed upon by the specificity is strong. Ideally, the future research effort should be directed toward more comprehensive employer-employee matched data in order to take full account of complex interaction among training, technical change and education.

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APPENDIX: A Brief Description of Survey 2001

The survey was conducted during July - September of 2001, jointly with the Thailand Development Research Institute (TDRI), Society for the Advancement of Technology Management in the Philippines (SATMP). The survey consists of the following parts: (1) personal information, (2) job history, (3) current job, (4) job transfer and promotion, (5) wage, (6) training, (7) education, and (8) family background. In (2), (4), (5) and (6) we asked retrospective questions for the period between 1998 and 2001 in order to have panel data on training history and wages.

Interviews were face to face, and took place in facilities provided by participating firms. We used regular work hour time (rather than lunch break or off hours). Firms allowed sampled workers to leave the work temporarily for the interview. We paid 100 bahts [100 pesos in Philippines] (which corresponds to roughly 1% of average monthly wage of sample production workers) to each participant. Although the survey consisted of more than 100 questions and typically lasted 40 minutes, sample employees were quite cooperative and happy to participate in the survey under these arrangements.

We hired roughly 15 people to interview sampled employees. On the first day of the survey, we gave them a 2 hour instruction session together with a manual on how to conduct the interviews. The interviewers were supervised by two to three researchers from TDRI in Thailand and SATMP in Philippines.