ELSEVIER

Journal of Development Economics 74 (2004) 489–513

JOURNAL OF Development ECONOMICS

www.elsevier.com/locate/econbase

Are experience and schooling complementary? Evidence from migrants' assimilation in the Bangkok labor market

Futoshi Yamauchi

International Food Policy Research Institute, 2033 K Street, NW, Washington, DC 20006, USA
National Graduate Institute for Policy Studies, Tokyo, Japan
Foundation for Advanced Studies on International Development, Tokyo Japan

Received 1 July 2001; accepted 1 June 2003

Abstract

This paper models the assimilation process of migrants and shows evidence of the complementarity between their destination experience and upon-arrival human capital. Bayesian learning is assessed, using panel data of wages from Bangkok, Thailand. It is found that (i) schooling returns are lower for migrants than for natives, (ii) the accumulation of destination experience raises wages for migrants, (iii) the experience effect is greater for more educated agents and (iv) the complementarity increases as destination experience accumulates. The results imply that more educated migrants have higher learning efficiency and can perform tasks of greater complexity, ultimately yielding higher wage growth in the destination market.

JEL classification: O15; J31; J61; D83
Keywords: Learning by doing; Schooling; Migrants; Urban labor markets; Wage dynamics

1. Introduction

In response to changes in environment, agents adjust their behavior to better adapt to the altered environment. For example, farmers in less developed countries changed farming methods in response to postgreen revolution availability and diffusion of new

E-mail addresses: f.yamauchi@cgiar.org, f.yamauchi@grips.ac.jp (F. Yamauchi).

doi:10.1016/j.jdeveco.2003.06.007

technologies such as imported high-yielding varieties (e.g., Foster and Rosenzweig, 1995). The burst of information technology in the United States during the 1980s and a regime switch to market economies in former communist countries are good examples of structural change to a new environment. Migration, too, is an example, although migrants' relocation reflects their own endogenous choice. Migrants' assimilation is a process in which migrants localize themselves in the destination environment. Once migrants move to a destination, they must acquire information from neighbors, master a new language, adopt a job search strategy suitable to their destination, and learn the work practices of a new workplace. If migrants learn from their experience in the new locale, the accumulation of destination experience raises migrants' productivity there, which leads their earnings to converge toward natives' earnings.[1,2] As Schultz (1975) argued, if those most able to deal with disequilibrium in a new environment—the destination—are likely to achieve the most productive outcome, the distribution of these abilities within a population of migrants is crucial to the transitional dynamics of the earnings of that population. This paper aims to empirically identify migrants' assimilation process, by examining migrants' wage dynamics in an urban labor market of a developing country: Bangkok, Thailand.

In contrast to their rural counterparts, urban labor markets in developing countries are characterized by heterogeneous technologies and products (Rosenzweig, 1988). Diverse technologies require a variety of skills not typically demanded of those who work in agricultural production. The heterogeneity of technologies and products, however, cannot be simply described in a traditional framework of formal–informal sectors as in Todaro (1969) and Harris and Todaro (1970). It is more reasonable to assume that urban labor markets encompass a variety of technologies, or sectors that require skills ranging from very simple to very complex. For instance, production workers in the hard disk drive industry of an urban labor market need different skills, including different levels of schooling, than workers in the food processing industry in the same market. Although prior studies on migration highlight the effects of schooling on the decision to move and the resulting selectivity of migrants' population (e.g., Lanzona, 1998; Dahl, 2002; Williamson, 1988), the role of schooling in migrants' assimilation process has not been carefully examined in the context of urban labor markets, except a few recent studies.

For example, Eckstein and Weiss (1999) show in the case of mass immigration of Russian Jews to Israel that wages of the more skilled (and therefore more educated) immigrants increased faster than wages of the less skilled. In the same context, Friedberg (2000) provides some evidence that schooling acquired before and after migration are complementary in their effect on immigrants' earnings. Schooling and new experience appear to be complementary in destination urban markets. In developing countries, migrants' assimilation process also seems to be fast (see, e.g., Yap, 1977; Williamson, 1988 for survey). However, the question of whether schooling matters—and, if so, how it

[1] See, e.g., Borjas (1989), Borjas and Trejo (1992), Chiswick (1978), and LaLonde and Topel (1992).

[2] Flinn (1986) analyzes job mobility of young workers, using the National Longitudinal Survey of Youth. The implications of agents' learning and matching in this paper are similar to those of job mobility.

matters—in migrants' localization process has not been properly answered, partly due to lack of appropriate data.[3]

I address two closely related questions. The first question is general: why can schooling and experience be complements? The second question is specific to migrants: why so, when migrants assimilate to local market? To answer the first question, the theory of specific human capital provides a first-hand answer to the complementarity between schooling and experience. Suppose that firms train more educated and capable workers.[4] Then, specific human capital accumulates more among them. On the other hand, because the specificity of human capital implies more attachment of workers to firms (Becker, 1962), it increases experience.

In the context of this study, however, this explanation has two pitfalls. First, the accumulation of firm-specific human capital is based on the length of tenure (i.e., firm-specific experience), not labor market experience. Second, because the theory of specific human capital cannot shed light on the location-specific nature of migrants' destination labor market experience, it cannot identify the role of schooling in migrants' assimilation—why schooling and experience are complementary for migrants. Therefore, this explanation does not seem to offer a right direction.

In this paper, I rather focus on heterogeneous worker–firm matching in a simple framework. In general, there are two types of imperfect information facing workers and firms. First, both workers and firms do not know workers' types that will be realized in urban labor markets. Because migrants are less familiar with destination than urban natives, this imperfect information is particularly strong in migrants' population. Second, workers also may not know skill needs demanded in urban labor markets. Because production technologies and organizations are likely different from those of rural industries (e.g., agriculture), this imperfect information is also stronger among migrants than urban natives. In urban setting, these two types of imperfect information make

[3] Stylized facts in the literature mostly from developed countries are (i) migrants' income converges toward natives' over time; (ii) returns to schooling for migrants are smaller than for natives, but the return increases over time (ability, correlated with schooling, is not rewarded at the initial stage, but price for unobservable abilities increases gradually); and (iii) highly skilled migrants are likely to experience a large income increase. For developing countries, the literature includes no analysis on migrants' adjustment to destination markets, mainly due to lack of longitudinal data. See the review of literature by Lucas (1997). On developing countries, however, there seem to be well-documented observations that educated migrants, whether on the job or unemployed, experience a longer period of job search and are more likely to find jobs in formal sectors than the uneducated (Williamson, 1988; Yap, 1977). These observations are also consistent with the abovementioned stylized facts from developed countries, if formal sectors offer higher wages than informal sectors. Migrants' transition from casual and informal jobs to more formal jobs appears to be more important in developing countries than in developed countries.

[4] Recent empirical findings on training and education in selected Thai manufacturing industries show that education and training investments can be complements in general, but seem to be substitutes for technicians and engineers (Ariga and Brunello, 2003; Yamauchi and Poapongsakorn, 2003; Poapongsakorn et al., 1992). However, these conclusions are sensitive to estimation methods and need further investigations on their robustness. On the other hand, it is also shown that unobserved endowment (ability) is substitutable to training investments (Yamauchi and Poapongsakorn, 2003). This finding is not consistent with the proposition that firm train more capable workers. However, this finding might have reflected some characteristics of the sample period, 1998–2001, immediately after Thai financial crisis.

worker–firm matching important for migrants in urban labor markets. Due to the imperfect information on migrants' types and skill needs in the markets, worker–firm matching cannot be perfect.

On the role of education, the key insight is quite simple. If the quality of matching between workers and firms (occupations and industries) is better among educated than uneducated migrants, educated migrants are on average likely to accumulate more experience in destination market. There are two kinds of informational advantage that education may facilitate. First, education can help workers achieve better matching at the initial stage in urban markets. In other words, at the initial stage, subjective uncertainty on workers' types and skill needs is smaller for educated than for uneducated workers. That is, education helps migrants make a better guess upon their arrival in destination.

Second, education may also help workers improve their matches with firms over time and therefore achieve higher earnings growth. Upon their arrival, migrants must learn about their own types, which would not be revealed perfectly while they were in their origins, and they must also learn about skill needs demanded in destination markets. Firms also need to learn about workers' types. If their matching is not perfect at the initial stage, workers will change firms and firms will also relocate workers to more suitable positions inside firms or change workers too. Educated migrants can learn about their types and skill needs better than uneducated migrants.

In the model of Section 2, I simplify the framework focusing only on imperfect information regarding workers' types, that face both workers and firms. For brevity, I will omit imperfect information on skill demand and the possibility that workers dynamically change their own skills—types—to better match with skill demands. In this sense, the model does not have any human capital investments. The cost of this modeling strategy is not large. First, we can also derive similar implications in an alternative framework in which uncertainty on skill demand plays a major role (see Appendix A). Second, because urban labor markets support heterogeneous technologies and products, which encompass so heterogeneous economic activities in the markets, that a variety of skills are demanded in urban areas. High density of heterogeneous activities concentrated in urban markets also helps reduce search costs, so workers can easily know available occupations and industries in the markets. In urban markets, therefore, I consider that imperfect information on skill needs is less important than that on migrants' potential types.[5]

In this paper, it is hypothesized in a unified framework that (i) schooling may improve the initial-stage matching quality by increasing the subjective precision of workers' types upon arrival to destination, and (ii) schooling may help workers learn their types efficiently and adjust their occupations, improving matching quality. Our framework also incorporates (iii) the complexity of skills demanded in urban labor

[5] The nature of urban life differs from that of rural life. The way of living dominant in urban areas can be quite new to the majority of migrants, and migrants must learn about the optimal behavior in urban areas. However, this type of adjustment differs from skill investments in the ordinary sense.

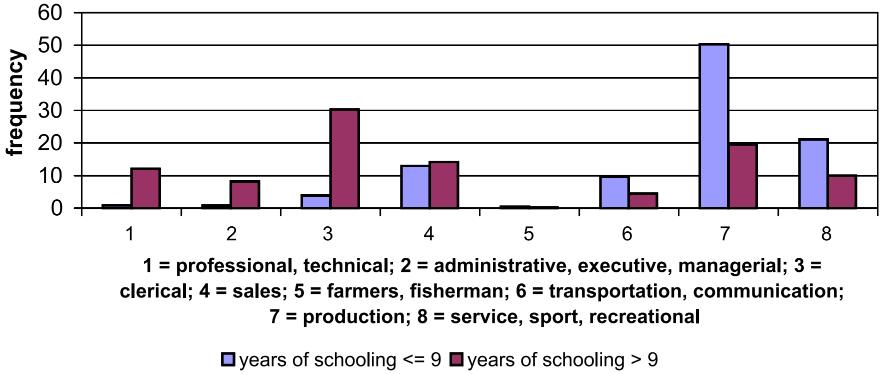

Fig. 1. Occupation distribution of migrants in Bangkok.

markets.[6] The last point is unique to urban environments because, in contrast to the simple technology characteristic of agriculture, urban labor markets demand diverse skills and decision-making abilities.

To provide a sense of the heterogeneity in urban labor markets, Fig. 1 depicts occupational distributions of Bangkok migrants with different levels of education. It shows that more educated migrants (more than 9 years of schooling) are likely to work in professional, technical, administrative, executive, managerial, and clerical occupations (codes 1, 2, and 3), whereas less educated migrants (less than 9 years of schooling) are likely to work as production workers. Because those who work in the former group of occupations are considered to require a diverse set of skills and decision-making abilities, the Bangkok market displays assortative matching between schooling and task complexity. Table 1 compares wage growth rates (over 6 months) across occupation types and between migrants and natives. It demonstrates that in the former group of occupations (codes 1, 2, and 3), migrants' wage growth is higher than natives'. Schooling, complexity of tasks, and wage growth are positively correlated in migrants' population in Bangkok. The model in Section 2 provides some implications consistent with the above observations.

Before going into analysis, I must state a possible limitation of this study. Informational learning and matching is not the only possibility that explains convergence of migrants' earnings with natives'. The selection process of agents in destination markets also

[6] In his analysis of potential sources of schooling–experience complementarity in the use of high-yielding varieties in Indian agriculture, Rosenzweig (1995) provides interesting insight. He shows some evidence that educated farmers (with primary schooling) in a new HYV technology regime learn the optimal use of inputs from new experience more efficiently than less educated farmers but do not have initial informational advantage. He did not consider the complexity of tasks. Jovanovic and Nyarko (1995) examines the effect of task complexity on the learning curve, and shows that as task gets complex, the learning curve becomes more convex. If we take a similar approach to the problem at our hand, we can obtain similar implications that educated agents may (i) learn efficiently through trial and error about an optimal action in the destination, (ii) have smaller subjective uncertainty of the optimal action at the initial stage, and (iii) be able to accomplish more complex tasks in urban labor markets. However, the problem in this paper differs from those in agricultural settings that Rosenzweig (1995) and Foster and Rosenzweig (1995) examine. Even in a mathematically similar setting, this paper examines market wage dynamics, not production efficiency.

Table 1
Average wage growth by occupation type

Occupation type	1	2	3	4	5	6	7	8
Migrants	0.1686	0.0428	0.1395	0.0489	N/A	0.0177	0.0358	0.0330
Natives	0.0431	0.0160	0.0272	0.0631	0.0056	0.0499	0.0739	0.0540

Occupation types: 1=professional, technical, and related workers; 2=administrative, executive, and managerial workers; 3=clerical workers; 4=sales workers; 5=farmers, fishermen, hunters, loggers, and related workers; 6=workers in transport and communication occupations; 7=craftsmen, production process workers, and laborers; 8=service, sports, and recreation workers. Wage growth rates are computed from wage panels of rounds 1 and 3 (see Section 4). The average of the wage growth rates taken over three years—1994, 1995 and 1996—is shown. Migrants and natives are defined as those who stayed in Bangkok less than 9 years, and more than 9 years, respectively.

generates a similar phenomenon.[7] Consider two scenarios. First, if migrants' ability is positively correlated to schooling (Spence, 1973), and more able migrants are more likely to survive in the markets, it appears that more educated migrants achieve higher growth of earnings, which enables a faster convergence toward earnings of natives. Second, suppose that migrants face liquidity constraints and some income risks. If migrants experience a negative shock to income, they can return to their rural origins in order to smooth their consumption path.[8] In both examples, observations of low wages are likely to drop from the sample. If the inference is based on cross-sectional observations of wage from different experience groups, a positive correlation between experience and earnings can easily, but erroneously be inferred from the data. To identify informational learning against the above cases, longitudinal information is necessary. Particularly to avoid the first problem, I chose to take a first differencing of wages over a 6-month interval to erase unobserved endowments that can be correlated with survival probability. However, the second problem can be only mitigated, but not entirely resolved by this approach. This issue will be discussed in Section 3.

Section 2 sets out a theoretical framework for this study. The role of schooling in migrants' matching with firms and learning from destination experience is defined from (i) initial informational advantage, (ii) learning efficiency, and (iii) complexity of tasks. In Section 3, empirical specification and identification issues are discussed. Section 4 describes the Labor Force Survey (LFS) conducted by the National Statistic Office in Thailand. The survey data enable the construction of panels of wages within a year and provide information on individual characteristics. In Section 5, empirical findings show that schooling and experience are complementary and that the complementarity increases as educated young migrants gain more experience. The results imply that more educated migrants have higher learning efficiency—adjustment speed—and can perform tasks of greater complexity, ultimately yielding higher wage growth in the destination market. In

[7] Jovanovic (1979) examines the endogenous turnover in a worker–firm matching model.

[8] Lucas and Stark (1985) and Rosenzweig and Stark (1989) show the role of kinship networks in smoothing consumption path. The former studies remittance between urban migrants and rural origin family, while the latter studies marriage-related migration and remittance in rural areas. If insurance-motivated remittance works as a substitute for credit borrowing, the probability that migrants return to rural origins will be smaller.

Section 6, some simulations illustrate the dynamic behavior of migrants' wages and of wage distributions. Concluding remarks are made in the final section.

2. Model: matching and migrants' adjustment

This section characterizes the roles of schooling and experience in migrants' assimilation process, based on matching between firms (skill needs) and workers (type) in urban labor markets. I assume (i) no transaction costs in job choice, workers' turnover and firms' recruitment, (ii) no human capital investments, and (iii) imperfect information on workers' type in destination market—both migrants and firms do not know it ex ante. Alternative interpretations of this model are provided in Appendix A.

In this study, n represents the dimension of skills needed in certain occupation and industry in destination market as well as the dimension of workers' types. Because technologies are so diverse in urban labor market, the extent of knowledge and skills required to master the technologies varies. Let $\theta_j(s_j)=[\theta_j^1(s_j),\theta_j^2(s_j),\ldots,\theta_j^n(s_j)]'$ denote worker j's type where s_j is j's schooling. Assume also that $n(s_1)\geq n(s_2)$ if and only if $s_1\geq s_2$. In other words, schooling augments the complexity of tasks the agent can potentially perform.[9] Worker's type $\theta_j(s_j)$ measures the content of education that he/she has received in their origins, including a variety of technical skills that he/she can potentially command such as language skill useful in destination, unobserved ability (i.e., endowment), and etc. I assume that all these elements depend on schooling s_j but contain idiosyncratic fixed factors that are unobservable before migrants move to urban areas. In other words, it is uncertain whether or not each component of types is actually effective in destination. For instance, there are substantial heterogeneities in school quality across regions, which affect workers' potential in urban areas. Similarly, the heterogeneity of individual ability affects workers' skills.

I assume that the vector of type $\theta_j(s_j)$ is not perfectly known to j before he/she moves to destination, while I assume that natives know $\theta_j(s_j)$ perfectly. In other words, urban natives know their capability in the local market and firms also know natives' types perfectly. For migrants, however, the value of $\theta_j(s_j)$ can be deciphered only gradually from realized matching quality through the process of learning in destination market.

The sequence of matching is as follows. First, migrants choose jobs at the initial stage. In other words, migrants choose the occupation and industry which they feel best suit their types. Let $z_{jt}(h,n)=[z_{jt}^1(h),z_{jt}^2(h),\ldots,z_{jt}^n(h)]'$ denote skill needs in dimension n for

[9] The dimension of skills varies across occupations. Compare, e.g., the abilities required of a vocational school graduate, A, who works as a production line leader, and of primary school graduate, B, who works as a line worker in an automobile assembly plant. Worker B needs to learn how to assemble auto parts efficiently, while worker A is required to learn what the best design of a production line is, how to train unskilled workers, and, of course, how to work in the line efficiently. In this example, the skill requirement is obviously greater for worker A than for worker B. The dimension of θ also varies across industries. For example, a plant worker in the food processing industry needs to master a smaller range of skills than does a worker in the hard disk drive industry. Similarly, θ can measure workers' mastery of the local language, and their abilities to acquire and process information, including computer skills, human relation skills, and knowledge of and skills required by technologies and products.

job h when migrant j chooses job h at time t. Skills required vary across occupations, industries and firms, although the above notation does not distinguish various units of production. For example, we can suppose that a firm contains a range of jobs. Here, firms and jobs can be used interchangeably. Assume also that jobs are continuously distributed, so that workers can choose any skill demand without transaction costs. If a certain skill, say qth, is not required in job h, it can be any value; for convenience, assume $z_{jt}^{q}(h)=\theta_j^{q}(s_j)$ for j.

Matching quality is measured as a distance in type space between worker j and job h, $d_{hjt}\equiv\theta_j(s_j)-z_{jt}(h,n)$. The best quality is achieved when job type (skill needs) is equal to workers' type, given the constraint $n(s_j)\geq n$. Assume also that matching quality is affected by some idiosyncratic shocks, and therefore is not perfectly observed. Workers and firms only observe the quality with shock v_{hjt}. Therefore, the observed (realized) matching quality is $d_{hjt}+v_{hjt}$. For simplicity, assume that v_{hjt}^{k} is distributed with i.i.d. $N(0,\sigma_v^2(s))$. Idiosyncratic shock variance is a function of schooling and does not depend on skill demand characteristics. Therefore, I hereafter ignore job index h for v_{jt}.

At the second stage, both firms and workers learn about workers' type and make adjustments in $z_{jt}(h,n)$. After workers choose firms at the initial stage, both workers and firms can adjust skill needs $z_{jt}(h,n)$, learning about $\theta_j(s_j)$ from $\theta_j(s_j)+v_{jt}$, without any transaction costs. For simplicity, assume that workers move freely from one firm to another. Firms can also change skill needs within a possible range, e.g., introducing new technology (job) h, and assign more suitable tasks to workers inside the firms. I do not assume any specific mechanism on this adjustment process. Without transaction costs in turnover and recruitment, the adjustment is smooth in urban labor market. A large adjustment of $z_{jt}(h,n)$ often involves turnover.

I assume that agents are Bayesian. Agents' type is distributed as $N(\mu_\theta^k(s),\sigma_\theta^2(s))$ for $\theta_j^k(s_j)$, where the mean and variance are functions of schooling. Assume that their initial prior is identical to the population distribution.

Consider the case that $\sigma_\theta^{2\prime}(s_j)<0$ and $\sigma_v^{2\prime}(s_j)<0$. Why so? Educated migrants may know more about their types which will be realized in destination market, and may also have smaller uncertainty in the job–worker match in new workplaces. Educated migrants may make efforts to compensate for lack of prior knowledge, and local networks of previous migrants can decrease the initial subjective uncertainty.[10]

Assume that workers' capability in the kth skill dimension is measured by $f_k(\theta,z)=\lambda_k-(d_{hjt}^k+v_{jt}^k)^2$. Here, I ignore subscripts and superscripts with θ and z for $f(\theta,z)$ unless necessary. The interpretation of λ_k is the maximum work capability attainable if matching is perfect. Assume that worker's productivity is determined by $\prod_{k=1}^{n(sj)} f_k(\theta,z)$ where capabilities in different dimensions are mutually complementary.[11,12] For sim-

[10] See Yamauchi and Tanabe (2002) for some recent evidence on nonmarket interactions among migrants, using Thai Labor Force Survey (see Section 3). Although in this model I focus on the effect of schooling on migrants' prior knowledge, the current setting does not exclude the possibilities mentioned in the text but needs to accommodate them as additional complexities in the model.

[11] Mathematically, this construction leads to similar specifications of Bayesian learning used in Foster and Rosenzweig (1995) and Jovanovic and Nyarko (1995).

[12] The maximum labor productivity is $\prod_{k\text{-}1}^{n(s)}\lambda_k$.

plicity, assume that $\lambda_k=\lambda$ for all k. Given the above environment, the decision problem is defined as

$$\max_{\{z_{jt}^k \mid n(s_j)\}_k} E\left[\prod_{k=1}^{n(s_j)} f_k(\theta,z) \mid \ s_j, \Omega_{jt}\right]$$

in each period. Given the information available in each period, the optimal choice of $z(h,n)$ is made. In this problem, migrants minimize the subjective variance of the matching loss function, because $E\left[(d_{hjt}^k+v_{jt}^k)^2 \mid \ s_j, \Omega_{jt}\right] = E\left[d_{hjt}^{k2} \mid s_j, \Omega_{jt}\right] + E\left[v_{jt}^{k2} \mid s_j, \Omega_{jt}\right]$. Therefore, it is optimal to set $z_{j0}^k(h,n)=\mu_\theta^k(s_j)$ at the initial stage. Again, I do not ask whether workers or firms make the adjustment. Following the standard Mincerian wage specification, I assume that migrants' expected log wage is given as

$$\begin{aligned}\max_{\{z_{jt}^k \mid n(s_j)\}_k} E\left[\ln\, w_{jt}^m \mid s_j, \Omega_{jt}\right] &= \max_{\{z_{jt}^k \mid n(s_j)\}_k} E\left[\prod_{k=1}^{n(s_j)} f_k(\theta,z) \mid \ s_j, \Omega_{jt}\right] + \boldsymbol{X}_{jt}\beta + \phi_j \\ &= \left[\lambda - \sigma_{\theta \mid t}^2(s_j) - \sigma_v^2(s_j)\right]^{n(s_j)} + \boldsymbol{X}_{jt}\beta + \phi_j \\ &= \left[\lambda - (\rho_\theta(s_j) + t\rho_v(s_j))^{-1} - \sigma_v^2(s_j)\right]^{n(s_j)} + \boldsymbol{X}_{jt}\beta + \phi_j \end{aligned} \tag{2.1}$$

where ϕ_j is unobserved ability, $\boldsymbol{X}_{jt}$ is the vector of observable attributes including level of schooling, precision is given as $\rho_\theta(s_j)=\sigma_\theta^2(s_j)^{-1}$ and $\rho_v(s_j)=\sigma_v^2(s_j)^{-1}$ and $\sigma_\theta^2(s_j)$ is identical to the variance of $\theta_j^k(s_j)$ at the initial time.[13] In Bayesian updating, as their experience increases, $\sigma_{\theta|t}^2(s_j)$ decreases for all migrants and $\mu_{\theta j|t}^k(s_j)$ approaches $\theta_j(s_j)$. The variance of $\mu_{\theta j|t}^k(s_j)$ (i.e., firm and occupation choice) increases as migrants experience more in destination. Ex post adjustment by workers and firms and resulting learning raise the expected matching quality in urban market, thus increasing migrants' earnings. Moreover, the extent of earnings growth varies by levels of schooling.[14]

Natives, on the other hand, have no subjective uncertainty about their types being specific to urban market, i.e., $\sigma_{\theta|t}^2(s_j)=0$, and schooling effects do not interact with experience. Given all other conditions set equal, migrants' wage converges to natives' wage. From Eq. (2.1), I obtain some interesting predictions:

---

[13] Suppose that labor earnings have returns to skills, $\Sigma_k\beta^k\theta_j^k(s_j)$. In this case, income depends not only on the quality of matching between type and job but also on workers' skills and market returns to skills. Though the expected quality of matching converges for all workers, the expected value of returns to skills diverges over time. Therefore, we can model return migration such that migrants return to the place of origin if $\Sigma_k\beta^kE[\theta_j^k(s_j)|s_j,\Omega jt]$ becomes lower than some cutoff point. To focus on worker–firm matching, however, I do not incorporate returns to skills, except observed level of schooling in wage equation.

[14] This implication is different from that of a simple job search model. In search theoretic framework, transition from unemployment (or underemployement) to employment is the focus. Although reservation wage is predicted to decrease over time under reasonable assumptions, the transition implies a discrete change in income. As this transition proceeds, the average income of migrants is predicted to increase over time but it does not necessarily so at individual levels.

Theoretical predictions

(i) Experience in the destination market raises the expected value of log wage.
(ii) If $\rho_v'(s)>0$ and $\rho_\theta'(s)$ is small enough (and $n(s)=n$ for all s), the initial human capital and experience are complementary. ($\partial^2 E[\ln w_{jt}^m|\Omega_t]/\partial s \partial t>0$).
(iii) If $n(s_1)>n(s_2)$ (assuming $s_1>s_2$) and $\rho_v'(s)=\rho_\theta'(s)=0$, the initial human capital and experience are complementary.
(iv) In this case, experience–schooling complementarity is increasing in t for small t.

Proof. See Appendix B. □

The proposition states that if educated migrants learn about their types faster than uneducated migrants do, improving matching quality faster, then schooling and experience can be complementary. Moreover, in more complex jobs to which educated migrants are likely to attach, the complementarity between schooling and experience will be reinforced. This result also implies that income inequality between the educated and uneducated widens over time.[15]

3. Empirical strategy

In this section, empirical specifications and identification issues are discussed. In particular, the section explores whether it is possible to identify sources of schooling experience complementarity from reduced form parameter estimates in the wage growth equation.

3.1. Specification, identification and estimation

Given the earning function with matching quality Eq. (2.1), I use a reduced form equation for the empirical analysis.

$$\ln w_{jt}^m = \alpha_t + \beta_{1t}s_j + \beta_{2t}t_j + \beta_{3t}s_jt_j + \beta_{4t}\mathrm{age}_j + \phi_j + \varepsilon_{jt} \tag{3.1}$$

where s_j is schooling, t_j is experience, ϕ_j is earnings endowment and $E[s_j\phi_j]\neq 0$. A well-known self-selection problem exists in this wage equation. If workers who are well endowed are likely to move to Bangkok and migrants whose unobserved ability is high will survive in the destination market, the expected value of ε_{jt} conditional on migration and/or survival is not equal to zero. It is possible that the errors are correlated with observable individual characteristics in the equation. In this sense, ϕ_j contains not only endowment but also the inverse Mill's ratio that defines the degree of self-selection in migration decision making.

[15] Yamauchi (2001) analyzes the emergence of labor earning inequality in a similar framework, by endogenizing workers' effort decision and provides possible interpretations of observations from Japan, Germany, the United Kingdom and the United States.

To characterize implications of the wage function Eq. (3.1), let's begin with the simplest case. In the case of $n=1$ (the simplest task), schooling effect is shown as

$$\beta_{1t}|_{n=1} = \frac{\partial E_t \ln w_{jt}}{\partial s_j}|_{n=1} = \frac{\rho'_\theta(s_j) + t_j\rho'_v(s_j)}{[\rho_\theta(s_j) + t_j\rho_v(s_j)]^2} + b_s^m > 0$$

Both terms are positive, given a positive conventional rate of return to schooling b_s^m. Similarly, a positive experience effect is obtained:

$$\beta_{2t}|_{n=1} = \frac{\partial E_t \ln w_{jt}}{\partial t_j}|_{n=1} = \frac{\rho_v(s_j)}{[\rho_\theta(s_j) + t_j\rho_v(s_j)]^2} > 0.$$

Notice that $\beta_2(t)|_{n=1}$ decreases as t increases. This prediction is consistent with stylized facts; returns to experience decrease as destination experience accumulates, which generates a concave assimilation curve. Schooling–experience complementarity is measured by the cross-derivative with respect to schooling and experience: [16]

$$\beta_{3t}|_{n=1} = \frac{\partial^2 E_t \ln w_{jt}}{\partial s_j \partial t_j}|_{n=1} = \frac{-2\rho'_\theta\,\rho_v + \rho'_v\,(\rho_\theta - \rho_v t_j)}{(\rho_\theta + \rho_v t)^3} > 0 \tag{3.2}$$

$\beta_3(t)$ is positive if $\rho'_v(s)$ is large enough. In other words, if schooling strongly improves learning efficiency, schooling–experience complementarity arises. The dynamic change of this schooling–experience complementarity depends on experience. In the case of the simplest task, the complementarity decreases as experience increases.

$$\frac{\partial \beta_{3t}}{\partial t_j}|_{n=1} < 0 \text{ since } \rho'_v(s_j) > 0.$$

Now let's consider a more complex task. Schooling and experience returns are also both positive in this case. As with the simplest task, returns to experience decrease as experience accumulates. For simplicity, assume two levels of education, with $h>l$. Given a weakly positive assortative matching, $n(h)>n(l)$. Then,

$$\frac{\partial \beta_{3t}}{\partial t_j}|_{n(h)>n(l)} > 0$$

for small t. Schooling–experience complementarity increases as experience increases. In complex technologies, not only does efficient learning by educated agents raise gains from

[16] Using an input-target model, Rosenzweig (1995) considers the case that $\rho'_\theta(s)\geq 0$, $\rho'_v(s)\geq 0$ in the context of agricultural production. He obtains that

$$\frac{\partial^2 \pi}{\partial s \partial t} > 0 \text{ if } \rho'_v(s) > 0 \text{ and } \rho'_\theta(s) \approx 0$$

where π is farm profit. However, in his case $\frac{\partial^2\pi}{\partial s\partial t} = \frac{-2\rho'_\theta\,\rho_v + \rho'_v\,(\rho_\theta - \rho_v t)}{(\rho_\theta + \rho_v t)^3}$ is decreasing as t increases. It is assumed that agents learn only from their own experience, measured by t, although Rosenzweig also incorporates learning from neighbors.

experience accumulation, but the effect also increases as experience increases up to a certain stage. Focusing on changes in schooling–experience complementarity, summarized by $\beta_3(t)$, enables us to identify the degree of assortative matching between more educated agents and more complex tasks.

Suppose now that, differencing wages over t and t+1, log wage difference is regressed on predetermined period t variables:

$$\Delta ln\ w^m_{j(t,t+1)} = (\Delta\alpha + \beta_{2t+1} + \beta_{4t+1}) + (\Delta\beta_1 + \beta_{3t+1})s_j + \Delta\beta_2 t_j + \Delta\beta_3 s_j t_j + \Delta\beta_4 \text{age}_j + \Delta\varepsilon_j$$

Therefore, (α,β) is expressed in terms of γ below:

$$\Delta ln\ w^m_{j(t,t+1)} = \gamma_{0t} + \gamma_{1t}s_j + \gamma_2 t_j + \gamma_3 s_j t_j + \gamma_4 \text{age}_j + \Delta\varepsilon_j \tag{3.3}$$

Signs of estimated γ, therefore, imply intertemporal changes in (α,β). Thus, I derive the results that follow.

Empirical predictions

Correspondence between reduced form parameters and time-variant returns to schooling and experience is summarized as:

(i) schooling effect: $\gamma_{1t}<0$ implies $\Delta\beta_1<0$
(ii) experience effect: $\gamma_2 \gtreqless 0$ if and only if $\Delta\beta_2 \gtreqless 0$
(iii) schooling–experience complementarity: $\gamma_3 \gtreqless 0$ if and only if $\Delta\beta_3 \gtreqless 0$
(iv) age effect: $\gamma_4 \gtreqless 0$ if and only if $\Delta\beta_4 \gtreqless 0$

Two points deserve special attention. First, in the case of the simplest task (n=1), $\beta_3(t)|n=1$ decreases as t increases (i.e., $\gamma_3<0$). However, if $n(s)$ increases in s, $\beta_3(t)$ increases as t increases, and therefore $\gamma_3>0$. Hence, the sign of γ_3 identifies the relationship of task complexity n and schooling s, which is a source of schooling–experience complementarity. Second, because schooling requires time, a higher level of education completed before migration means a higher age at the time of migration. Therefore, $\gamma_1+\gamma_4$ can be interpreted as the total schooling effect, including a correlated age effect. Even if $\gamma_1<0$, the total schooling effect on wage growth can be positive (i.e., $\gamma_1+\gamma_4>0$).

3.2. Selectivity and ability bias

Two types of selectivity problems emerge in this type of study. The first one is the self-selection problem associated with migration decisions. Because agents endogenously make decisions on whether to move to urban labor markets, migrants' population does not make up a random sample of origin population in the destination market. A subpopulation of migrants with certain characteristics is highly likely to be selected from the origin population. For example, educated agents who can expect a higher wage in the destination market are likely to move first. If earnings endowment ϕ_j is correlated to the probability of migration, self-selection generates correlations between ϕ_j and migrants' characteristics, including schooling $E[\phi_j X_{jt}]\neq 0$, $E[\phi_j s_j]\neq 0$. In this case, well-known sample selection bias occurs (Heckman, 1979; Borjas, 1987). In the above methodology that uses differenced wage equations, the problem of migration selectivity disappears.

The second selectivity problem relates to the endogenous determination of migrants' length of stay in a destination market. Upon arrival in the destination market, migrants face a decision in each period about whether to remain or leave (e.g., return to their origin). The observed duration of stay is, therefore, a consequence of endogenous decisions. If higher earning endowment leads to a higher probability of staying in the destination market, the problem of endogenously determined duration causes a correlation between ϕ_j and observed duration t_j: $E[t_j \phi_j]>0$. Differencing also erases this problem.

However, if there exists fixed effect on wage growth, first differencing does not solve the above problems. In particular, the problem of endogenously determined duration is more serious than the problem of self-selection in migration decisions. In this case, the unobserved individual-specific component is written as $\phi_i+\varphi_i t$. First differencing does not erase φ_i, which can be correlated with schooling and experience. To the extent that the variation of φ_i is large and positively correlates with schooling and experience, there will still be upwards bias in return estimates in wage growth equations (i.e., γ_1, γ_2, and γ_3). For example, if firms train more capable (and educated) workers, wage growth becomes higher for those workers. In this case, wage growth equations should contain unobserved fixed effects, which may correlate to both years of schooling and destination experience. Therefore, while upward bias is expected to be smaller in the first differencing than cross-sections, the bias may still remain even after first differencing. As discussed in the next section, because the data I use do not encompass three periods of observation of individual wages, twice differencing is not possible in this study. However, as discussed below, because I also include origin-fixed effects even in first-differenced specifications, potential bias that comes from unobserved heterogeneity in migrants' attributes specific to the place of origin are controlled. Origin-specific heterogeneities contain the two types of selectivity problems mentioned above.

Besides fixed effects discussed above, wage shocks can be correlated with endogenously determined duration. In particular, ε_{jt-1} can be correlated to the attrition rate at t, and therefore to the observed duration of stay. For example, a negative wage shock makes migrants who face liquidity constraints experience a drop in their consumption level, which triggers return migration to their rural place of origin. Therefore, such migrants in the period t sample are likely to drop from the period t+1 sample. This group of migrants will not be observed in subsequent periods, and options to handle this problem are quite limited. Moreover, the existence of bias depends on whether the focus is on (i) $E[\Delta \ln w_j^m | \ln w_{jt}^m > q]$or (ii) $E[\Delta \ln w_j^m | \varepsilon_{jt} > r]$ for some q and r. The former case assumes that as long as the wage is above some level, migrants stay. The latter case assumes that unless negative shock is sufficiently large, migrants stay. In the first case, under normal distribution assumption on error term, the conditional expectation of $\Delta\varepsilon_j$ is written as

$$\frac{-\sigma_\varepsilon f((q - E[\Delta ln\ w_j \,|\, \Omega_t])/\sigma_\varepsilon)}{1 - F((q - E[\Delta ln\ w_j \,|\, \Omega_t])/\sigma_\varepsilon)}$$

where $f(.)$ and $F(.)$ are standard normal p.d.f. and c.d.f. respectively. In the second case, the conditional expectation is

$$\frac{-\sigma_\varepsilon f(r/\sigma_\varepsilon)}{1 - F(r/\sigma_\varepsilon)}$$

It is evident from these expressions that in the first case individual characteristics (s_j, t_j, age_j) enter the conditional expectation of differenced errors but that they do not enter in the second case. Therefore, in the first case, there exists some bias in estimates. Although which case is plausible is an empirical question, I conjecture as follows. First, because migrants' wages grow in transition, converging to natives', the expression in the first case needs a time-varying threshold q_t that increases over time. If q_t increases proportionally to $E[\ln w_{jt}^m|\Omega_t]$, the first case will be hardly distinguishable from the second case because in both cases a deviation of $\ln w_{jt}^m$ from $E[\ln w_{jt}^m|\Omega_t]$—wage shock—triggers migrants' attrition. I therefore assume, for simplicity, the second case hereinafter—those migrants whose wage shocks are small enough will be unobserved in the next period. The conditional expectation of differenced error is technically captured by a constant term in first differencing estimation.[17]

Finally, it is well known as screening hypothesis that ability or earnings endowment ϕ_j is positively correlated with schooling s_j; $E[s_j\phi_j]>0$. It causes a well-known ability bias in the estimation of schooling returns. Strikingly, most literature on migration does not deal with this problem. To eliminate the correlation to ϕ_j, I difference reduced form wage equations and estimate Eq. (3.2).

4. Data

The data I use in empirical analysis come from the Labor Force Survey (LFS), Thailand, collected by the National Statistical Office. The survey covers a wide range of information on labor, such as wages and payments, work practices, unemployment, migration status, and more. The information used here is from the first and third rounds of the survey in 1994,

[17] In the first case, bias direction depends on autocorrelations of wage shocks. If agents try to make up for the drop in earnings in a previous period by continuing to work in the next period, bias direction would be opposite to that predicted in the liquidity constraint case. In both cases, because residual estimates from cross-sections cannot be distinguished from endowments and are possibly biased due to correlations of schooling and endowments, it is impossible to identify the effects of past wage shocks on attrition from the sample. Estimation of differenced form parameters assumes observability of two consecutive wage observations, and only provides estimates of differenced wage shocks. Therefore, estimated returns to experience and their interaction with schooling could still be subject to biases in the differenced form.

1995, and 1996. In recent years, the survey is conducted in four rounds. The first round is surveyed in February and the third in August. The second and fourth are surveyed in May and November, respectively.

One unique characteristic of the LFS is that, in principle, an identical set of households is visited in the first and third rounds, and another identical set is visited in the second and fourth rounds. It is therefore possible to constitute panel data of individual wages from February and August, and from May and November within the same year. The following analysis constructs and uses panel data from February to August. Thailand in February is in the midst of the dry season and August is in the monsoon (agricultural) season. Because samples are totally replaced from year to year, I focus on wage changes between the dry and monsoon seasons within a year. In the Bangkok urban labor market, seasonality is less important than rural counterparts. However, the matching of the first- and third-round observations is not straightforward, due to migration of individuals and households. In the LFS, individuals are identified by block, household, and household member IDs. The procedure followed in this paper matches individual wage observations by these IDs and then excludes individuals (and households) who moved in or out before the third round.[18]

The sample used in this study comes from metropolitan Bangkok. Although the use of municipalities in the whole kingdom of Thailand is one approach, the analysis concentrates on the Bangkok urban labor market because Bangkok is the largest among Thai urban clusters in terms of population and population density, size of labor force, and domestic product. The use of the Bangkok sample also avoids heterogeneities in the labor demand structure of different destination markets. Seasonal fluctuations in agricultural productivity are also of minor importance in Bangkok. Most importantly, the share of migrants in the whole population in Bangkok is quite large. Strikingly, the average shares computed from the first rounds are 21.23% and 13.11% for those who stayed less than 9 and 5 years, respectively.

In the empirical analysis below, experience is defined as the duration of stay in Bangkok since migration. The LFS identifies the duration of stay up to 9 years. Therefore, this definition of experience is different from labor market experience in general. It is experience specific to the destination labor market, which is Bangkok in this study. Migrants are defined to be those who have stayed in Bangkok less than 9 years. For natives, I assume the length of stay is uniformly 10 years. This assumption regarding natives means that migrants' learning through the localization process ends after 10 years of stay in the destination market. This assumption is necessary to identify a process of migrants' learning. Because destination-specific experience does not include labor market

[18] Observations with inconsistent ages and gender between the two rounds, either due to migration and replacement or due to survey errors, are dropped. It is found in preliminary yet detailed examinations that nearly 30% of wage observations are dropped in the Bangkok region. Close examination shows that nearly 92% of the matched individuals are from households whose size did not change between the two rounds. About 8% are from households who experienced death, birth, or in and/or outmigration of members. It is also found that this attrition propensity from the first to third rounds actually differs across regions and the attrition rate through this matching procedure is lowest in the Bangkok region. For seasonal migration in Thailand, see Sussangkarn (1987).

experience in migrants' original provinces, age will capture returns to experience specific to their original labor markets. Similarly, for natives, age captures returns to general labor-market experience.

Migrants are sorted by provinces of origin. In the LFS, information on migrants' previous province is available only for migrants who have stayed less than 5 years. Because the analysis uses origin-fixed effects, migrants' population is restricted to migrants of less than 5 years in all estimation. The benchmark case is Bangkok natives. In the LFS, 76 provinces are coded as domestic origin regions. I treat foreign countries as one group.

Table 2 shows descriptive statistics in the Bangkok migrants' sample, by rounds and years. Comparison of the variables shown in the table across different rounds shows that characteristics of migrants—those who have stayed less than 9 years—are quite stable in this period. This observation supports stationarity of migrants' population in the Bangkok labor market 1994 through 1996. This condition is necessary for the analysis of migrants' learning through the localization process.

Table 2
Summary statistics migrants sample (experience: length of stay <9 years)

	94/Rd1	94/Rd3	95/Rd1	95/Rd3	96/Rd1	96/Rd3
Difference ln$w$		0.0240		0.0714		0.0435
		(0.2494)		(0.2524)		(0.3090)
		[215]		[320]		[224]
Age	26.488	26.582	27.421	27.148	27.665	27.735
	(8.738)	(9.548)	(10.055)	(10.413)	(10.092)	(9.004)
	[1113]	[1044]	[1458]	[1282]	[1271]	[1123]
Sex	0.4938	0.4539	0.5295	0.5256	0.5052	0.4960
	(0.500)	(0.500)	(0.499)	(0.500)	(0.500)	(0.500)
	[1113]	[1044]	[1458]	[1282]	[1271]	[1123]
No. of household members	3.0638	3.3529	3.5046	3.0735	3.4257	3.0311
	(1.557)	(1.956)	(1.810)	(1.417)	(2.591)	(1.819)
	[1113]	[1044]	[1458]	[1282]	[1271]	[1123]
Years of schooling	7.3645	7.7894	7.4597	7.5273	7.3446	7.2655
	(3.871)	(4.135)	(3.970)	(3.953)	(3.816)	(3.982)
	[1110]	[1042]	[1450]	[1279]	[1268]	[1121]
Weekly wage	1031.93	1168.43	1074.06	1448.55	1404.51	1285.80
	(893.59)	(928.43)	(821.76)	(1832.50)	(1833.88)	(758.80)
	[699]	[640]	[887]	[750]	[848]	[666]
ln weekly wage	6.7890	6.9063	6.8405	7.0437	7.0334	7.0446
	(0.5289)	(0.5510)	(0.5134)	(0.5617)	(0.5217)	(0.4778)
	[699]	[640]	[887]	[750]	[848]	[666]
Duration of stay (years)	4.0717	3.8059	3.9958	3.9472	3.8525	4.0191
	(2.3386)	(2.356)	(2.444)	(2.398)	(2.455)	(2.315)
	[1113]	[1044]	[1458]	[1282]	[1271]	[1123]

Numbers in parentheses and brackets are standard deviations and numbers of observations, respectively. Duration of stay in Bangkok (years) is defined to be the median year, computed from interval index, (e.g., 0.5 is assigned if length of living is less than a year). Weekly wage is estimated from types of wage payment (daily, weekly, monthly, etc.) and amount of payment closest to the survey week. Difference in log weekly wage is ln wage (round 3) minus ln wage (round 1), and the number of observations is reduced mostly because sample observations are excluded if ages are not matched between the two rounds of 6-month intervals.

5. Empirical results

This section summarizes empirical results. Log wage equations of Mincerian type and then differenced log wage equations are estimated. Table 3 shows cross-section estimates of Mincerian log wage equations in the Bangkok population of age less than 40. Since the LFS identifies origin provinces only for migrants who have stayed in Bangkok less than 5 years, the sample uses migrants of less than 5 years and natives (those who stayed 9 years or more). As discussed, I assume 10 years of duration for natives, as learning in the destination market is probably completed within 10 years. In the table, both returns to experience and schooling are positive and significant in columns 1 and 2. The inclusion of schooling–experience interaction reduces the significance of the experience effect in column 3. The schooling returns also decrease from 0.0717 to 0.0357. In this sense, experience and upon-arrival schooling are complementary in wage adjustment in the Bangkok labor market. In column 4, the complementarity is robust against a squared term of experience. However, these cross-section estimates are likely biased due to the selectivity problems and endogenous schooling choices discussed in the previous section.

To confirm differentiated schooling returns for natives and migrants, column 5 includes the interaction of schooling years and a migrant dummy. Consistent with the previous

Table 3
Wage equations

Cross-section					
Dependent variable: log weekly wage					
Sample: Age<40					
Years of schooling	0.0716	0.0717	0.0358	0.0357	0.0743
	(25.40)	(25.40)	(5.07)	(5.04)	(24.42)
Years of schooling×migrants					−0.0280
					(4.72)
Years of schooling×experience			0.0039	0.0039	
			(4.80)	(4.80)	
Experience		0.0375	0.0144	−0.0070	
		(3.34)	(1.25)	(0.18)	
Experience squared				0.0042	
				(0.58)	
Age	0.0569	0.0505	0.0479	0.0480	0.0550
	(3.85)	(3.37)	(3.21)	(3.22)	(3.74)
Age squared	−0.00049	−0.00039	−0.00035	−0.00035	−0.00046
	(1.85)	(1.44)	(1.30)	(1.31)	(1.76)
Male	0.1439	0.1429	0.1469	0.1469	0.1483
	(6.06)	(6.02)	(6.22)	(6.22)	(6.27)
No. of observations	5370	5370	5370	5370	5370
Adjusted R^2	0.5493	0.5508	0.5543	0.5544	0.5527

Absolute t values are in parentheses. Standard errors are robust estimates with individual-level heteroskedasticity. Origin-fixed effects are included in all specifications. Migrants in this estimation are those who have stayed in Bangkok for less than 5 years, and natives are those who have stayed in Bangkok for more than 9 years. For the native sample, the length of stay (experience) is set at 10.

literature (e.g., Eckstein and Weiss, 1999) and columns 3 and 4, schooling returns are higher for natives than for migrants. Because natives are defined as those who stayed in Bangkok more than 9 years, they are more experienced and experience augments schooling returns.

Table 4 shows estimates of nonlinear approximations of log wage difference equations in Eq. (3.3). The specification is robust to selectivity problems from endogenous migration and duration choice, under the assumption that fixed effect is additive to learning effect and differenced out in wage growth equations. As discussed in the previous section, if there exists a fixed effect in wage growth, it makes the returns estimated here biased. To control fixed factors specific to origin provinces, I include origin-fixed effects.

First, the growth effect of destination experience is all negative. Wage growth decreases as experience increases, although significance levels are generally low. Therefore, β_2 decreases as experience increases. Second, the schooling effect is also negative and

Table 4
Wage growth (1)

Dependent variable: difference in log weekly wage						
Sample: Age<40						Natives Only
Experience	0.0187	0.0069	−0.0078	−0.0110	−0.0089	
	(1.69)	(0.65)	(0.19)	(0.26)	(0.20)	
Experience squared			0.0028	0.0029	0.0026	
			(0.37)	(0.37)	(0.31)	
Experience×schooling		0.0017	0.0017	0.0032	0.0021	
		(2.16)	(2.18)	(1.87)	(2.38)	
Experience×schooling×age				−0.00005		
				(0.72)		
Experience×schooling×sex				−0.0002		
				(0.33)		
Years of schooling	−0.00051	−0.0167	−0.0169	−0.0286	−0.0192	0.0069
	(0.28)	(2.21)	(2.23)	(1.42)	(2.39)	(0.60)
Schooling×age				0.0003		−0.00020
				(0.41)		(0.53)
Schooling×sex				0.0072		
				(0.93)		
Age	−0.0238	−0.0250	−0.0251	−0.0280	−0.0281	−0.0326
	(1.98)	(2.08)	(2.09)	(1.94)	(2.37)	(1.75)
Age squared	0.00039	000041	0.00041	0.00049	0.00047	0.00057
	(1.90)	(1.99)	(2.00)	(1.91)	(2.32)	(1.79)
Male	0.0180	0.0196	0.0195	−0.0369	0.0076	0.0210
	(1.16)	(1.26)	(1.25)	(0.87)	(0.46)	(1.19)
Occupation dummies					yes	
Industry dummies					yes	
No. of observations	1953	1953	1953	1953	1704	1556
Adjusted R^2	0.0633	0.0663	0.0664	0.0689	0.0829	0.0077

Absolute t values are in parentheses. Standard errors used here are robust estimates with individual-level heteroskedasticity. Origin-fixed effects are included in all specifications. For migrants, schooling is that of upon arrival. Migrants in this estimation are those who stayed in Bangkok less than 5 years, and natives are those who stayed in the city more than 9 years. For natives, the length of stay (experience) is set at 10.

significant. Wage growth is lower for educated agents than for uneducated agents. In terms of wage-level equation, β_1 decreases as experience increases. Third, most interestingly, experience and schooling are complementary even in wage growth. The schooling–experience interaction (complementarity) is positive and significant. Therefore, β_3 increases as experience increases, but a previous finding that $\Delta\beta_1+\beta_{3t+1}<0$ implies that β_3 is bounded above (i.e., $\beta_3<-\Delta\beta_1$), which is satisfied in the results. The results confirm that the complementarity between migrants' schooling and destination experience becomes stronger as migrants accumulate their experience in the destination market.

In columns 4 and 5, I check the robustness of the schooling–experience complementarity in two ways. First, in column 4, the interaction of schooling and experience is once again interacted with age and male dummy. Similarly, years of schooling are also interacted with age and male dummy. These interactions are all insignificant. The schooling–experience complementarity is found to remain marginally significant, with a p-value of 0.062. Next, in column 5, occupation dummies (10 categories, as in Fig. 1)

Table 5
Wage growth (2)

Dependent variable: Difference in log weekly wage					
Sample: Age<40					
Experience	0.0182	−0.0038	−0.0165	−0.0224	−0.0216
	(1.64)	(0.29)	(0.34)	(0.45)	(0.42)
Experience squared			0.0024	0.0030	0.0033
			(0.27)	(0.32)	(0.35)
Experience×schooling		0.0032	0.0032	0.0047	0.0033
		(2.09)	(2.11)	(1.46)	(2.01)
Experience×schooling×age				−0.00006	
				(0.41)	
Experience×schooling×sex				−0.0003	
				(0.28)	
Years of schooling	−0.00071	−0.0191	−0.0193	−0.0195	−0.0214
	(0.41)	(2.21)	(2.22)	(0.90)	(2.39)
Schooling×age				0.00002	
				(0.02)	
Schooling×sex				0.0003	
				(0.03)	
Age	−0.0236	−0.0246	−0.0247	−0.0263	−0.0285
	(2.04)	(2.12)	(2.13)	(1.95)	(2.47)
Age squared	0.00040	000041	0.00042	0.00049	0.00049
	(1.99)	(2.07)	(2.08)	(2.06)	(2.48)
Male	0.0272	0.0284	0.0284	0.0061	0.0224
	(1.81)	(1.90)	(1.89)	(0.16)	(1.30)
Occupation dummies					yes
Industry dummies					yes
No. of observations	2210	2210	2210	2210	1953
Adjusted R^2	0.0565	0.0586	0.0586	0.0598	0.0741

Absolute t values are in parentheses. Standard errors used here are robust estimates with individual-level heteroskedasticity. Origin-fixed effects are included in all specifications. For migrants, schooling is that of upon arrival. Migrants in this estimation are those who stayed in Bangkok less than 5 years, and natives are those who stayed in the city more than 5 years. For natives, the length of stay (experience) is set at 6.

and industry dummies are added to control heterogeneity of wage growth and occupation—industry specific factors which may drive the complementarity of schooling and destination experience. Even by controlling the heterogeneity specific to occupations and industries (all estimates are not shown in the table), the schooling–experience complementarity remains robust. The result suggests that the reinforced schooling–experience complementarity is not fully captured by assortative occupational and industry choice.

For the purpose of comparison, I also estimated a wage growth equation for natives only—those who have stayed more than 9 years in Bangkok (column 6). For this group, because the duration of stay is normalized to be 10 years, returns to destination experience cannot be estimated. As discussed in the previous section, age captures general labor market experience, and its interaction with years of schooling measures complementarity of schooling and general labor market experience. The results show that experience in general is not complementary with schooling in the sample of natives, who by definition are not in an assimilation process. In contrast to previous results, wage growth does not vary with years of schooling, age, and gender too.

Finally, in Table 5, I use a different definition on the distinction between migrants and natives—migrants: less than 5 years of stay and natives: more than 5 years—to check the robustness of the previous findings. To normalize the returns to migrants' destination experience and the learning process, I set the length of experience as 6 years for those who have stayed more than 5 years. The results are quite similar to those in Table 4. This proves that key results of schooling–experience complementarity does not rely on the definition of natives (comparison group in this study).

6. Simulations

In this section, dynamic wage paths are simulated for migrants with different levels of schooling upon their arrival in the destination market. The main purpose of this exercise is to quantitatively clarify implications on migrants' adjustment process, based on the estimates of the schooling–experience complementarity. The specification used here comes from column 4 in Table 4. Wage paths are simulated for male migrants with different levels of schooling: primary (6 years), junior high (9 years), high school (12 years), and 4-year college (16 years). Fig. 2 displays wage paths of migrants with levels of education higher than primary school, relative to primary school graduates' wage paths. Because actual wage paths are sensitive to the assumption on mean wage growth, Fig. 2 shows distance in wage from benchmark primary school graduates.

Insignificant parameters are set as zeros (those with p-values larger than 0.010). Initial log wages are equal to averages for corresponding groups. In the simulations below, parameter estimates are doubled to adjust the time frame between wage differences in 6-month term and explanatory variables in annual term. The initial age at which destination experience starts is set at 17 for all the groups to normalize age effects. Top, middle and bottom curves correspond to wage paths for university, high school and junior high school graduates, respectively. The figure shows that convexity in wage path is strengthened as schooling increases. Highly educated migrants experience a more

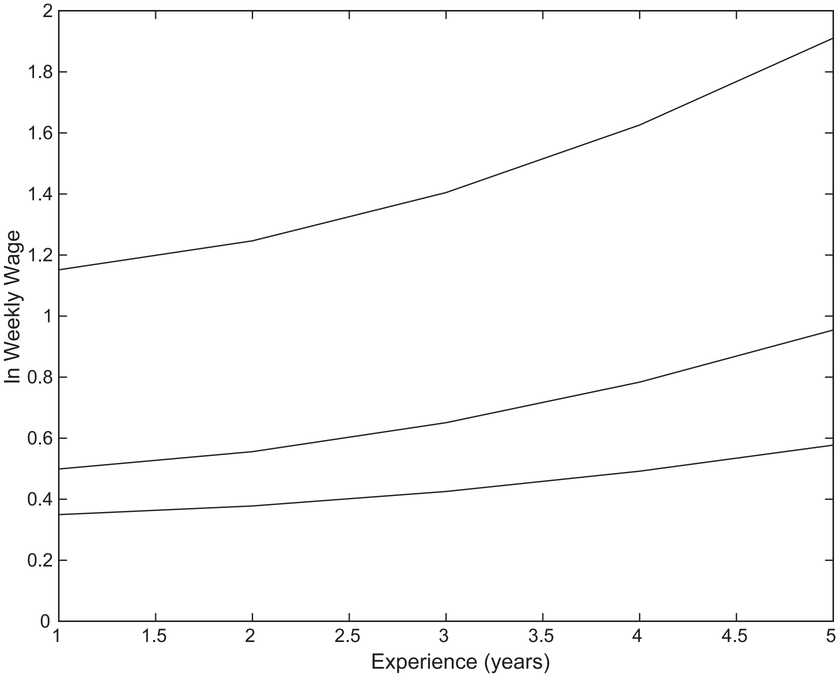

Fig. 2. Wage dynamics and schooling–experience complementarity.

rapid rate of learning in their assimilation process. The gap in log wage between graduates of primary school (6 years of education) and college (16 years of education) is gradually widening over time. The complementarity of schooling and experience makes labor earnings more divergent between more and less educated migrants in the new environment.

7. Conclusion

This paper shows evidence that schooling and destination experience are complementary in migrants' wage adjustment in urban labor markets of developing countries. Schooling enhances migrants' learning from their experience in the destination labor market. Moreover, the complementarity of schooling and experience is reinforced as migrants' experience increases in the destination market. This empirical finding is consistent with assortative matching in urban labor markets by which educated migrants are likely to work in occupations that require diverse and complex skills.

Concentration of economic activities in cities, which create heterogeneity in technologies and products, attracts migrants from rural areas in developing countries. This urbanization process also causes income differentials within urban areas as well as between rural and urban areas. The findings of this paper suggest that schooling investments in migrants can reduce income differentials between migrant and native populations inside cities. Because schooling facilitates migrants' assimilation process and matching quality, the convergence of migrants' earnings toward natives' earnings is faster for educated migrants than for uneducated migrants. However, if education increases the probability of migration to urban areas significantly, large-scale inflows of migrants into urban labor markets may worsen the income distribution in urban areas at least in the short run. The formal–informal sector framework, initially proposed by Todaro (1969) and Harris and Todaro (1970) and influential in recent literature (e.g., Bencivenga and Smith, 1997), ignores the transitional dynamics of urban migrants' earnings and the heterogeneity of technologies and skills that this paper highlights.

This paper also provides a new insight into returns to schooling in developing countries. Prior studies support that schooling facilitates learning speed when farmers face an opportunity to use a new technology, such as high-yielding varieties (Foster and Rosenzweig, 1995). Recent evidence from the United States also supports a similar phenomenon; the burst of information technology in the 1980s might have increased returns to schooling and unobserved skills (e.g., Murphy and Welch, 1992). In the context of rural-to-urban migration, this paper shows that even after controlling migration selectivity (in a differencing procedure), schooling significantly contributes to migrants' learning through assimilation process in urban labor markets. While schooling is often found to increase the probability of migration, the role of schooling in migrants' assimilation process in urban labor markets has not been carefully identified in the literature.

Acknowledgements

I thank Kulnaree Oomesri at the National Statistical Office, Thailand, for answering my questions, and Worawan Chandoevwit and Nipon Poapongsakorn of the Thailand Development Research Institute and two anonymous referees of the Journal for their valuable comments. I am grateful to Kei Kajisa, Keijiro Otsuka, Lire Ersado and seminar participants at the Foundation for Advanced Studies on International Development (FASID), Tokyo and the 2001 Far Eastern Meeting of the Econometric Society, Kobe, for their useful suggestions. Any remaining errors are, of course, mine.

Appendix A. Alternative interpretations

In the model of Section 2, workers' types are predetermined and firms' skill needs can be adjusted in order to improve matching quality. This is possible because workers can change firms if matching quality is not good, or because firms can relocate workers inside firms from one position to another or change workers, under the assumption that skill needs in urban markets are very heterogeneous. Similarly, we may model migrants' assimilation process such that skill need demanded in destination market is unique and predetermined, but unknown, and migrants adjust themselves so as to match well with skill needs gradually. In this setting, workers have signals on the skill needs: $y_{jt}=\theta+v_{jt}$ where θ is the identical target-level of skill needs for urban markets and v_{jt} is idiosyncratic shock (noise). Workers change their skills z_{jt} so as to minimize the expected value of the quadratic loss function. Under the same set of assumptions on noise and prior distributions as in Section 2, we obtain the same expected log wage equation. It can be hypothesized that education helps workers guess precisely about correct skill needs, i.e., $\sigma_\theta^{2\prime}(s)<0$, and also learn efficiently about the skill needs over time, i.e., $\sigma_v^{2\prime}(s)<0$. Although similar implications are obtainable from this setting, the interpretation based on worker–firm matching has some appealing features. First, it assumes heterogeneous technologies and products, therefore skill needs in urban labor markets. This is consistent with stylized facts from many countries. Second, it also incorporates assortative matching between skill needs (task complexity) and workers of different levels of education. As shown in Fig. 1, more schooled migrants are likely to find jobs in more complex nature, which demand a variety of skills. The second point cannot be captured by this alternative framework.

Appendix B. Proof of theoretical predictions

(i) and (ii) Come directly from differentiations. (iii) Suppose $n(h)>>n(l)$. Define

$$\Delta \equiv E_{jt}[\ln w_{jt}^m \mid n(h)] - E_{jt}[\ln w_{jt}^m \mid n(l)]$$

Let $X(t)$ denote $\lambda - (\frac{1}{\rho_\theta + t\rho_v} + \sigma_v^2)$. Differentiating Δ with respect to t,

$$\frac{\partial \Delta}{\partial t} = \frac{n(h)\rho_v}{(\rho_\theta + t\rho_v)^2} X(t)^{n(l)-1} \left\{ X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)} \right\} > 0$$

Under the assumption that $X(t)>1$,

$$X(t)^{n(h)-n(l)} > 1 > \frac{n(l)}{n(h)}$$

(iv) follows:

$$\frac{\partial^2 \Delta^2}{\partial t^2} = \frac{n(h)\rho_v^2}{(\rho_\theta + t\rho_v)^4} X(t)^{n(l)-2} \left[\begin{array}{c} (n(h)-1)\left[X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)} \left(\frac{n(l)-1}{n(h)-1} \right) \right] \\ -2X(t)(\rho_\theta + t\rho_v)\left[X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)} \right] \end{array} \right]$$

Rearranging,

$$\frac{\partial^2 \Delta^2}{\partial t^2} > 0$$

$$\Leftrightarrow$$

$$\frac{(n(h)+1)\left[X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)}\left(\frac{n(l)+1}{n(h)+1}\right)\right]}{2\left[X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)}\right]} > -\rho_v^{-1}(\rho_\theta + t\rho_v)$$

Because $n(h) >> n(l) \geq 1$, the condition holds if t is small enough. Q.E.D.

References

Ariga, K., Brunello, G., 2003. "Are the educated receiving more training?" Asian Development Bank Institute, Discussion Paper.

Becker, G., 1962. Investment in human capital: a theoretical analysis. Journal of Political Economy 70, 9–49.

Bencivenga, V.R., Smith, B.D., 1997. Unemployment, migration and growth. Journal of Political Economy 105, 582–608.

Borjas, G.J., 1987. Self-selection and the earnings of immigrants. American Economic Review 77, 531–553.

Borjas, G.J., 1989. Immigrant and emigrant earnings: a longitudinal study. Economic Inquiry 27, 21–37.

Borjas, G.J., Trejo, S., 1992. Assimilation and the earnings of young internal migrants. Review of Economics and Statistics 32, 159–185.

Chiswick, B.R., 1978. The effects of Americanization on the earnings of foreign born men. Journal of Political Economy 86, 897–921.

Dahl, G., 2002. Mobility and the return to education: testing a Roy model with multiple markets. Econometrica 70, 2367–2420.

Eckstein, Z., Weiss, Y., 1999. The Absorption of Highly Skilled Immigrants: Israel 1990–1995. Mimeo. Tel Aviv University, Tel Aviv, Israel.

Flinn, C., 1986. Wages and job mobility of young workers. Journal of Political Economy 94, S88–S110.

Foster, A.D., Rosenzweig, M.R., 1995. Learning by doing and learning from others: human capital and technical change in agriculture. Journal of Political Economy 103, 1176–1209.

Friedberg, R., 2000. You can't take it with you?: immigrant assimilation and the portability of human capital. Journal of Labor Economics 18, 221–251.

Harris, R., Todaro, M.P., 1970. Mining, unemployment and development: a two sector analysis. American Economic Review 60, 126–142.

Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.

Jovanovic, B., 1979. Job matching and the theory of turnover. Journal of Political Economy 87, 972–990.

Jovanovic, B., Nyarko, Y., 1995. A Bayesian learning model fitted to a variety of empirical learning curves. Brookings Papers: Microeconomics 1995, 247–299.

LaLonde, R., Topel, R., 1992. The assimilation of immigrants in the U.S. labor markets. In: Freedman, R.B., Borjas, G.J. (Eds.), Immigration and the Workforce: Economic Consequences for the United States and Source Areas. University of Chicago Press, Chicago, IL.

Lanzona, L.A., 1998. Migration, self-selection and earnings in Philippine rural communities. Journal of Development Economics 56, 27–50.

Lucas, R.E.B., 1997. Internal migration in developing countries. In: Rosenzweig, M.R., Stark, O. (Eds.), Handbook of Population and Family Economics, vol. 1B. Chap. 13, North Holland.

Lucas, R.E.B., Stark, O., 1985. Motivations to remit: evidence from Botswana. Journal of Political Economy 93, 901–918.

Murphy, K.M., Welch, F., 1992. The structure of wages. Quarterly Journal of Economics 107, 285–326.

National Statistical Office, Thailand, Report of the Labor Force Survey, various years.

Poapongsakorn, N., et al., 1992. Training in the Thai Manufacturing and Service Sectors, (in Thai) Thammasat University, Bangkok.

Rosenzweig, M.R., 1988. Labor markets in low-income countries. In: Chenery, H., Srinivasan, T.N. (Eds.), Handbook of Development Economics, vol. 1. Chap. 15, North Holland.

Rosenzweig, M.R., 1995. Why are there returns to schooling. American Economic Review. Papers and Proceedings 85, 153–158.

Rosenzweig, M.R., Stark, O., 1989. Consumption smoothing, migration and marriage: evidence from rural India. Journal of Political Economy 97, 905–926.

Schultz, T.W., 1975. The ability to deal with disequilibria. Journal of Economic Literature 13, 827–846.

Spence, M., 1973. Job market signaling. Quarterly Journal of Economics 87, 355–374.

Sussangkarn, C., 1987. The Thai Labour Market: A Study of Seasonality and Segmentation, mimeo., Thailand Development Research Institute.

Todaro, M.P., 1969. A model of labor, migration and urban unemployment in less developed countries. American Economic Review 59, 138–148.

Yamauchi, F., 2001. Does inequality of labor earnings emerge in young days or later? Labor earnings dynamics and learning about individual ability in heterogeneous society. Journal of Economic Behavior and Organization 44, 413–434.

Yamauchi, F., Poapongsakorn, N., 2003. "What determines the returns to training investments in developing countries: evidence from Thailand," Asian Development Bank Institute. Discussion Paper.

Yamauchi, F., Tanabe, S., 2002. Nonmarket Networks among Migrants: Evidence from Metropolitan Bangkok, Thailand, mimeo. International Food Policy Research Institute.

Yap, L., 1977. Attraction of cities: a review of the migration literature. Journal of Development Economics 4, 239–264.

Williamson, J.G., 1988. Migration and urbanization. In: Chenery, H., Srinivasan, T.N. (Eds.), Handbook of Development Economics, vol. 1, pp. 425–465. Chap.11, North-Holland.