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**ARE EXPERIENCE AND SCHOOLING COMPLEMENTARY?
EVIDENCE FROM MIGRANTS' ASSIMILATION IN THE
BANGKOK LABOR MARKET**

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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 and dynamics of matching are modeled and empirically assessed, using panel data of wages from the Bangkok labor market in Thailand. The analysis incorporates (1) the heterogeneity of technologies and products, characteristic of urban labor markets, (2) imperfect information on migrants' types and skill demanded in the markets, and (3) migrants' optimal learning over time. Returns to destination experience emerge endogenously. Estimation results, which control migrants' selectivity by first-differencing procedures, show that (1) schooling returns are lower for migrants than for natives, (2) the accumulation of destination experience raises wages for migrants, (3) the experience effect is greater for more-educated agents, i.e., education and experience are complementary, and (4) 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. Simulations show that, due to the complementarity, wages for different levels of upon-arrival human capital diverge in the migrants' assimilation process.

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Key words: 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 post-green revolution availability and diffusion of new 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 their productivity there, which leads their earnings to converge toward natives' earnings.^{1,2} As Theodore 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).

¹See, for example, Borjas (1989), Borjas, Bronars, and Trejo (1992), Chiswick (1978), and LaLonde and Topel (1992).

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

Diverse technologies require a variety of skills not typically demanded of those who work in agricultural production.³ 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 do 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 populations (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

³ Even in rural areas, nonagricultural industries demand a variety of skills. However, I would argue that technologies and products, therefore skills demanded are more heterogeneous than those required in rural areas.

it matters—in migrants’ localization process has not been properly answered, partly due to lack of appropriate data.⁴

I address two closely related questions. The first question is general: why are schooling and experience complementary? The second question is specific to migrants: why is this so when migrants assimilate to the local market? To answer the first question, human capital theory provides a first-hand answer to the complementarity between schooling and experience. Suppose that firms train more educated and capable workers.⁵ Then, specific human capital accumulates more among them. Since the specificity of human capital, on the other hand, 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, since 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 migrant status—why schooling and experience are complementary for migrants. Therefore, this explanation does not seem to offer a right direction.

⁴ Stylized facts in the literature, mostly from developed countries, are (1) migrants’ income converges toward natives’ income over time; (2) 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); (3) 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 the lack of longitudinal data. See the review of literature by Lucas (1997).

In developing countries, 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 are the uneducated (Williamson 1988; Yap 1977). These observations are also consistent with the above-mentioned 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.

⁵ 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 largely sensitive to estimation methods, and seem to need further investigation 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 firms train more capable workers. However, this might have reflected some characteristics of the sample period, 1998 to 2001, immediately after the Thai financial crisis.

In this paper, I rather focus on heterogeneous worker-firm matching in a simple framework. There are two types of imperfect information facing workers and firms. First, both workers and firms do not know workers' potential (types) that will be realized in urban labor markets. Since migrants are less familiar with the destination than urban natives, this imperfect information is particularly strong among migrants. Second, workers may also not know the skill needs demanded in urban labor markets. Since 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 the urban setting, these two types of imperfect information described above makes worker-firm matching important for migrants in urban labor markets. Due to the imperfect information on migrants' types and skill needs, worker-firm matching cannot be perfect.

The key insight is simple. If the quality of matching between workers and firms (occupations, industries) is better among educated than uneducated migrants, educated migrants are, on average, likely to accumulate more experience in the 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, the initial-stage subjective uncertainty on workers' types and skill needs is smaller for educated than uneducated workers. That is, education helps migrants make a better guess upon their arrival.

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 types, which could not be revealed perfectly while they were in their regions of origin, and they must also learn about the skill needs demanded in destination markets. Firms also need to learn about workers' types. If their matching is not perfect, at least at the initial stage, workers can change firms; firms can also relocate workers to more suitable positions inside firms or change workers. It is possible that 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 on imperfect information regarding workers' types that both workers and firms face. For brevity, I will omit imperfect information on skill demand and the possibility that workers change their skill-types to better match with skill demand. In this sense, the framework does not have any human capital investments. The cost of this modeling strategy is not large. First, we can also derive similar implications building upon a symmetric framework (see Appendix 1). Second, since urban labor markets support heterogeneous technologies and products, which encompass so many heterogeneous economic activities in the markets that a variety of skills are demanded in urban areas. A high density of heterogeneous activities concentrated in urban markets also reduces search costs, so workers can easily learn of the occupations and industries available in urban markets. In urban markets, therefore, imperfect information on skill needs is considered to be less important than that on migrants' potential types.⁶

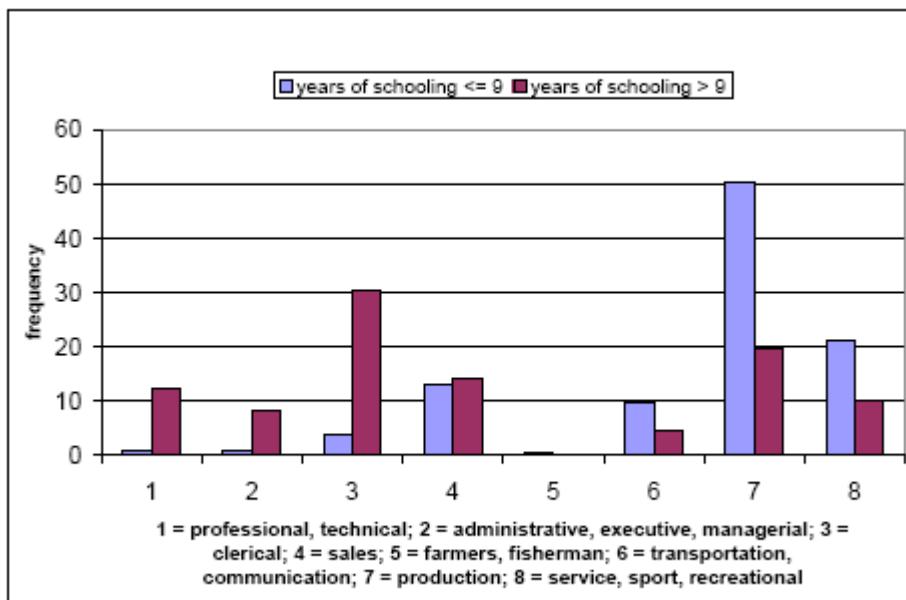
In this paper, it is hypothesized in a unified framework that (1) schooling may improve the initial-stage matching quality by increasing the subjective precision of workers' types upon arrival to destination, and (2) schooling may help workers learn their types efficiently and adjust their occupations, improving matching quality. Our framework also incorporates (3) the complexity of skills demanded in urban labor

⁶ Of course, the nature of urban life differs from that of rural life. The way of living dominant in urban areas can be quite new to many migrants, and migrants must learn about the optimal behavior in urban areas. However, this differs from skill investments in the ordinary sense.

markets.⁷ 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 decisionmaking abilities.

To provide a sense of the heterogeneity in urban labor markets, Figure 1 depicts occupational distributions of Bangkok migrants with different levels of education. It

Figure 1—Occupation distribution of migrants in Bangkok



⁷ In his analysis of potential sources of schooling-experience complementarity in the use of high-yielding varieties in Indian agriculture, Rosenzweig (1995) provides an 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 an initial informational advantage. He did not consider the complexity of tasks. Jovanovic and Nyarko (1995) examine the effect of task complexity on the learning curve, and show that as a task becomes more complex, the learning curve becomes more convex. If we take a similar approach to the problem at hand, we can obtain similar implications that educated agents may (1) learn efficiently through trial and error about an optimal action in the destination, (2) have smaller subjective uncertainty of the optimal action at the initial stage, and (3) 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 Rozensweig (1995) examine. Even in a mathematically similar setting, this paper examines market wage dynamics, not production efficiency.

shows that more-educated migrants (more than nine 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 nine years of schooling) are likely to work as production workers. Since those who work in the former group of occupations are considered to require a diverse set of skills and decisionmaking abilities, the Bangkok market displays assortative matching between schooling and task complexity. Table 1 compares wage growth rates (over six 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 that of Bangkok's natives. Schooling, complexity of tasks, and wage growth are positively correlated in migrants' population. The model in Section 2 provides some implications consistent with the above observations.

Table 1—Average wage growth, by occupation type

		Occupation type							
		Professional, technical, and related workers	Administrative, executive, and managerial workers	Clerical workers	Sales workers	Farmers, fishermen, hunters, loggers, and related workers	Workers in transport and communication occupations	Craftsmen, production-process workers, and laborers	Service, sports, and recreation workers
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

Notes: 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 1993—is shown. Migrants and natives are defined as those who stayed in Bangkok fewer than nine years, and more than nine years, respectively.

Before going into the 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 those of natives. The selection process of agents in destination markets also generates a similar phenomenon.⁸ Consider two scenarios. First, if migrants' ability is positively correlated to schooling (Spence 1973), and more-educated migrants are more likely to survive in the markets, it appears that more-educated

⁸ Jovanovic (1979) examines the endogenous turnover in a worker-firm matching model. This paper, however, does not incorporate the return migration from urban markets in the framework.

migrants achieve a 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.⁹ In both examples, observations of low wages are likely to drop from the sample. If the inference is based on cross-sectional observations of wages 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 six-month interval to erase unobserved endowments that can be correlated with survival probability. However, the second problem can be only mitigated, 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 (1) initial informational advantage, (2) learning efficiency, and (3) complexity of tasks. In Section 3, empirical specification and identification issues are discussed. Section 4 describes the Labor Force Survey 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 Section 6, some simulations illustrate the dynamic behavior of migrants' wages and of wage distributions. Concluding remarks are made in the final section.

⁹ Lucas and Stark (1985) and Rosenzweig and Stark (1989) show the role of kinship networks in smoothing the consumption path. The former studies remittances from urban migrants to the rural origin family, while the latter studies marriage-related migration and remittances in rural areas. If insurance-motivated remittances substitute for credit borrowing, the probability that migrants will return to rural origins is smaller.

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 (1) no transaction costs in job choice, workers' turnover, and firms' recruitment; (2) no human capital investments; and (3) 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 1.

In this study, n represents the dimension of skills needed in a certain occupation and industry in the destination market as well as the dimension of workers' types. Since technologies are so diverse in urban labor markets, the extent of knowledge and skills required to master the technologies varies. Let

$$\theta_j(s_j) = [\theta_j^1(s_j), \theta_j^2(s_j), \dots, \theta_j^n(s_j)]'$$

denote workers' type. 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.¹⁰ 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), etc. I assume that all of 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

¹⁰ The dimension of skills varies across occupations. Compare, for example, the abilities required of a vocational school graduate, A , who works as a production-line leader, and of a 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.

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 θ_j is not perfectly known to migrant 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 that they feel best suit their types. Let

$$z_{jt}(h, n) = [z_{jt}^1(h), z_{jt}^2(h), \dots, z_{jt}^n(h)]'$$

denote skill needs in dimension n for job h when migrant j chooses job h at time t . Skills required vary across occupations, industries, and firms, though the above notation does not distinguish various units of production. For example, we may suppose that a firm contains a range of jobs. Here, firms and jobs can be used interchangeably. Assume also that jobs are continuously distributed, i.e., workers can choose any skill demanded without transaction costs. If a certain skill, say q -th, is not required in job h , it can be any value. For convenience, assume

$$z_{jt}^q(h) = \theta_j^q(s_j) \text{ for } j.$$

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 the job type (skill needs) matches the 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. $N(0, \sigma_v^2(s))$, where t is time spent since arrival in destination market.

Idiosyncratic shock variance is a function of schooling and does not depend on skill demand characteristics. Therefore, I hereafter ignore the 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, for example, 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 an urban labor markets. 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 agents have rational expectations at the initial stage. Under this assumption, their initial prior is identical to the population distribution.

Consider the case that $\sigma_\theta^2(s_j) < 0$ and $\sigma_v^2(s_j) < 0$. Why? Educated migrants may know more about their types that will be realized in the destination market; they may also have less uncertainty in the job-worker match in new workplaces. Educated migrants may make efforts to compensate for the lack of prior knowledge, and local networks of previous migrants can decrease the initial subjective uncertainty.¹¹

Assume that workers' capability in the k -th skill dimension is measured by

¹¹ See Yamauchi and Tanabe (2003) for some recent evidence on nonmarket interactions among migrants, using the 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.

$$f_k(\theta, z) = \lambda_k - (d_{hjt}^k + v_{jt}^k)^2.$$

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

$$\prod_{k=1}^{n(s_j)} f_k(\theta, z),$$

where capabilities in different dimensions are mutually complementary.^{12,13} For simplicity, assume that $\lambda_k = \lambda$ for all k . Given the above environment, the decision problem is defined as

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

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, since

$$E \left[(d_{hjt}^k + v_{jt}^k)^2 \mid s_j, \Omega_{jt} \right] = E \left[d_{hjt}^{k2} \mid s_j, \Omega_{jt} \right] + E \left[v_{jt}^{k2} \mid s_j, \Omega_{jt} \right].$$

Therefore, it is optimal to set

$$z_{j0}^k(h, n) = \mu_\theta^k(s_j)$$

¹² Mathematically, this construction leads to similar specifications of Bayesian learning used in Foster and Rosenzweig (1995) and Jovanovic and Nyarko (1995).

¹³ The maximum labor productivity is $\prod_{k=1}^{n(s)} \lambda_k$.

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 that log wage is given as

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

where ϕ_j is unobserved ability, 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.¹⁴ 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 to $\theta_j(s_j)$. 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.¹⁵

¹⁴ Suppose that labor earnings have returns to skills, $\sum_k \beta^k \theta_j^k(s_j)$. 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 $\sum_k \beta^k E[\theta_j^k(s_j) | s_j, \Omega_{jt}]$ 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.

¹⁵ This implication is different from that of a simple job-search model. In search theoretic framework, transition from unemployment (or underemployment) 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 do so at individual levels.

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 that all other conditions are set equal, migrants' wage converges to natives' wage. From equation (1), I obtain some interesting predictions.

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 2.

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.¹⁶

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-

¹⁶ Yamauchi (2001) analyzes the emergence of labor earnings 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.

experience complementarity from reduced-form parameter estimates in the wage growth equation.

Specification, Identification, and Estimation

Given the earnings function with matching quality (equation 1), I use a reduced form equation for the empirical analysis.

$$\ln w_{jt}^m = \alpha_t + \beta_{1t}s_j + \beta_{2t}t_j + \beta_{3t}s_jt_j + \beta_{4t}age_j + \phi_j + \varepsilon_{jt}, \quad (2)$$

where s_j is schooling, t_j is experience, and ϕ_j is earnings endowment. A well-known self-selection problem exists in this wage equation. If workers who are better endowed are likely to move to Bangkok and migrants who have a larger endowment will survive over time, the expected value of ε_{jt} conditional on migration and/or survival in the destination is not equal to zero, and therefore 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, which defines the degree of self-selection in migration and duration decisionmaking.

To characterize implications of the wage function (equation 2), I begin with the simplest case. In the case of $n = 1$ (the simplest task), schooling effect is shown as

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

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

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

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 experience¹⁷:

$$\begin{aligned}\beta_{3t} \big|_{n=1} &= \frac{\partial^2 E_t \ln w_{jt}}{\partial s_j \partial t_j} \big|_{n=1} \\ &= \frac{-2\rho_\theta' \rho_v + \rho_v'(\rho_\theta - \rho_v t_j)}{(\rho_\theta + \rho_v t)^3} > 0.\end{aligned}\tag{3}$$

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

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

¹⁷ Using an input-target model, Rosenzweig (1995) considers the case that $\rho_\theta'(s) > 0$, $\rho_v'(s) > 0$ 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 , though Rosenzweig also incorporates learning from neighbors.

Now 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

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

for small t . Schooling-experience complementarity increases as experience increases. In complex technologies, not only does efficient learning by educated agents raise gains from experience accumulation, but the effect also increases as experience increases up to a certain stage. Focusing on changes in schooling-experience complementarity, summarized by $\beta_3(t)$, makes it possible to identify the degree of assortative matching between more-educated agents and more-complex tasks. To check the above points, I discuss empirical specifications in the next section.

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

$$\begin{aligned} \Delta \ln w_{j(t,t+1)}^m = & (\Delta \alpha + \beta_{2t+1} + \beta_{4t+1}) + (\Delta \beta_1 + \beta_{3t+1}) s_j \\ & + \Delta \beta_2 t_j + \Delta \beta_3 s_j t_j + \Delta \beta_4 age_j + \Delta \varepsilon_j \end{aligned}$$

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

$$\Delta \ln w_{j(t,t+1)}^m = \gamma_{0t} + \gamma_{1t} s_j + \gamma_{2t} t_j + \gamma_{3t} s_j t_j + \gamma_{4t} age_j + \Delta \varepsilon_j. \quad (4)$$

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.

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

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, since 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 growth can be positive (i.e., $\gamma_1 + \gamma_4 > 0$).

Selectivity and Ability Bias

Selectivity problems should be resolved in estimation. Two types of selectivity problems emerge in this type of study. The first is the self-selection problem associated with migration decisions. Since agents endogenously make decisions on whether to move to urban labor markets, the migrant population is not 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, therefore, is a consequence of endogenous decisions. If higher earnings 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 a selectivity problem of this sort.

However, if there exists a 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 leave 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 upward 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, since the data I use do not encompass three periods of observation of individual wages, twice differencing is not possible. However, as discussed below, since 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 the 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 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 (1) $E[\Delta \ln w_j^m | \ln w_{jt}^m > q]$ or (2) $E[\Delta \ln w_j^m | \varepsilon_{jt} > r]$ for some q and r . The former case assumes that unless the wage is above some level, migrants leave. 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

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

where $f(\cdot)$ and $F(\cdot)$ 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 into 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 the answer as follows. First, since 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.¹⁸

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 equation (3).

4. Data

The data 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, 1995, and 1996. In recent years, the survey has been 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.

¹⁸ 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, since 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 difference form.

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. Since samples are totally replaced from year to year, I focus on wage changes between the dry and monsoon seasons within a year. Because the focus of this paper is on the Bangkok urban labor market, seasonality is not important. 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.¹⁹

The sample used in this study comes from metropolitan Bangkok. Though the use of municipalities in the whole kingdom of Thailand is one approach, the analysis concentrates on the Bangkok urban labor market, since it is the largest urban cluster 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 important, the share of migrants in the whole population of Bangkok is large. Strikingly, the average shares computed from the

¹⁹ Observations with inconsistent ages and gender between the two rounds, either due to migration and replacement or to survey errors, are dropped. Preliminary yet detailed examinations show that nearly 30 percent of wage observations are dropped in the Bangkok region and that nearly 92 percent of the matched individuals are from households whose size did not change between the two rounds. About 8 percent are from households who experienced death, birth, or in- and/or out-migration 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).

first rounds are 21.23 percent and 13.11 percent for those who stayed fewer than nine years and five 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 nine years. Therefore, this definition of experience is different from labor-market experience in general. It is experience specific to the destination labor market—Bangkok in this study. Migrants are defined as those who have stayed in Bangkok fewer than nine years. For natives, I assume the length of stay is uniformly 10 years. This assumption means that migrants' learning through the localization process ends after 10 years in the destination market. This assumption is necessary to identify migrants' learning process. Since destination-specific experience does not include labor market 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 fewer than five years. Since the analysis uses origin-fixed effects, migrants' population is restricted to migrants of fewer than five years in all estimations. 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 fewer than nine years—are quite stable in this period. This observation supports stationarity of migrants' population in the Bangkok labor market from 1994 through 1996. This condition is necessary for the analysis of migrants' learning through the localization process.²⁰

²⁰ Yamauchi (2002) shows some evidence that migrants' learning process and returns to destination experience have changed during the 1997 financial crisis. Returns to destination experience have decreased, while returns to schooling remained robust, i.e., constant, in the face of crisis.

Table 2—Summary statistics migrants sample (experience: length of stay less than nine years)

	1994		1995		1996	
	Round 1	Round 3	Round 1	Round 3	Round 1	Round 3
diff 1nw		0.0240 (0.2494) [215]		0.0714 (0.2524) [320]		0.0435 (0.3090) [224]
age	26.488 (8.738) [1,113]	26.582 (9.548) [1,044]	27.421 (10.055) [1,458]	27.148 (10.413) [1,282]	27.665 (10.092) [1,271]	27.735 (9.004) [1,123]
sex	0.4938 (0.500) [1,113]	0.4539 (0.500) [1,044]	0.5295 (0.499) [1,458]	0.5256 (0.500) [1,282]	0.5052 (0.500) [1,271]	0.4960 (0.500) [1,123]
#hh members	3.0638 (1.557) [1,113]	3.3529 (1.956) [1,044]	3.5046 (1.810) [1,458]	3.0735 (1.417) [1,282]	3.4257 (2.591) [1,271]	3.0311 (1.819) [1,123]
yr sch	7.3645 (3.871) [1,110]	7.7894 (4.135) [1,042]	7.4597 (3.970) [1,450]	7.5273 (3.953) [1,279]	7.3446 (3.816) [1,268]	7.2655 (3.982) [1,121]
weekly wage	1,031.93 (893.59) [699]	1,168.43 (928.43) [640]	1,074.06 (821.76) [887]	1,448.55 (1,832.50) [750]	1,404.51 (1,833.88) [848]	1,285.80 (758.80) [666]
ln weekly wage	6.7890 (0.5289) [669]	6.9063 (0.5510) [640]	6.8405 (0.5134) [887]	7.0437 (0.5617) [750]	7.0334 (0.5217) [848]	7.0446 (0.4778) [666]
duration of stay (yrs)	4.0717 (2.3386) [1,113]	3.8059 (2.356) [1,044]	3.9958 (2.444) [1,458]	3.9472 (2.398) [1,282]	3.8525 (2.455) [1,271]	4.0191 (2.315) [1,123]

Notes: 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 six-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 under age 40. Since the LFS identifies origin provinces only for migrants who have stayed in Bangkok fewer than five years, the sample uses migrants of fewer than five years and natives (those who stayed nine years or more). As discussed, I assume 10 years of duration for

natives, as learning in the destination market probably is 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 0.07166 to 0.03576. 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.

Table 3—Wage equations

Cross-section					
Dependent variable: log weekly wage					
Sample: Age < 40					
yrs of schooling	0.0716 (25.40)	0.0717 (25.40)	0.0358 (5.07)	0.0357 (5.04)	0.0743 (24.42)
yrs of sch*mig					-0.0280 (4.72)
yrs of sch*expr.			0.0039 (4.80)	0.0039 (4.80)	
experience	0.0375 (3.34)	0.0144 (1.25)	-0.0070 (0.18)		
expr. squared				0.0042 (0.58)	
age	0.0569 (3.85)	0.0505 (3.37)	0.0479 (3.21)	0.0480 (3.22)	0.0550 (3.74)
age squared	-0.00049 (1.85)	-0.00039 (1.44)	-0.00035 (1.30)	-0.00035 (1.31)	-0.00046 (1.76)
sex	0.1439 (6.06)	0.1429 (6.02)	0.1469 (6.22)	0.1469 (6.22)	0.1483 (6.27)
number of observations	5,370	5,370	5,370	5,370	5,370
Adjusted-R squared	0.5493	0.5508	0.5543	0.5544	0.5527

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

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

Table 4 shows estimates of nonlinear approximations of log wage difference equations in equation (4). The specification is robust against selectivity problems from endogenous migration and duration choice, under the assumption that fixed effect is

Table 4—Wage growth equations 1

Dependent variable: Difference in log weekly wage						Natives only
Sample: Age < 40						
experience	0.0187 (1.69)	0.0069 (0.65)	-0.0078 (0.19)	-0.0110 (0.26)	-0.0089 (0.20)	
exp squared			0.0028 (0.37)	0.0029 (0.37)	0.0026 (0.31)	
exp*sch		0.0017 (2.16)	0.0017 (2.18)	0.0032 (1.87)	0.0021 (2.38)	
exp*sch*age				-0.00005 (0.72)		
exp*sch*sex				-0.0002 (0.33)		
yrs of sch.	-0.00051 (0.28)	-0.0167 (2.21)	-0.0169 (2.23)	-0.0286 (1.42)	-0.0192 (2.39)	0.0069 (0.60)
sch*age				0.0003 (0.41)		-0.00020 (0.53)
sch*sex				0.0072 (0.93)		
age	-0.0238 (1.98)	-0.0250 (2.08)	-0.0251 (2.09)	-0.0280 (1.94)	-0.0281 (2.37)	-0.0326 (1.75)
age squared	0.00039 (1.90)	0.0041 (1.99)	0.0041 (2.00)	0.00049 (1.91)	0.00047 (2.32)	0.00057 (1.79)
sex	0.0180 (1.16)	0.0196 (1.26)	0.0195 (1.25)	-0.0369 (0.87)	0.0076 (0.46)	0.0210 (1.19)
occupation dummies					yes	
industry dummies					yes	
Number of observations	1,953	1,953	1,953	1,953	1,704	1,556
adj-R sq	0.0633	0.0663	0.0664	0.0689	0.0829	0.0077

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

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, though significance levels are generally low. Therefore, β_2 decreases as experience increases. Second, the schooling effect is also negative and significant. Therefore, wage growth is lower for educated than for uneducated agents. In terms of wage-level equation, β_1 decreases as experience increases. Third, experience and schooling are complementary 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.

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 is 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 Figure 1) and industry dummies are added to control heterogeneity of wage growth and occupation- and industry-specific factors that may drive the complementarity of schooling and destination experience. Even by controlling the heterogeneity specific to occupations and industries (all estimates are not shown), 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 nine years in Bangkok (column 6). For this group, since 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, or gender.

Finally, in Table 5, I use a different definition of migration status—migrants fewer than five years of stay and natives more than five 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 six years for those who have stayed more than five years. The results are quite similar to those in Table 4. This proves that key results of schooling-experience complementarity do not rely on the definition of natives (the 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 four-year college (16 years). Figure 2 shows wage paths of migrants with levels of education higher than primary school, relative to primary-school graduates' wage paths. Since actual wage paths are sensitive to the assumption on mean wage growth, Figure 2 shows distance in wage from benchmark primary-school graduates.

Table 5—Wage growth equations 2

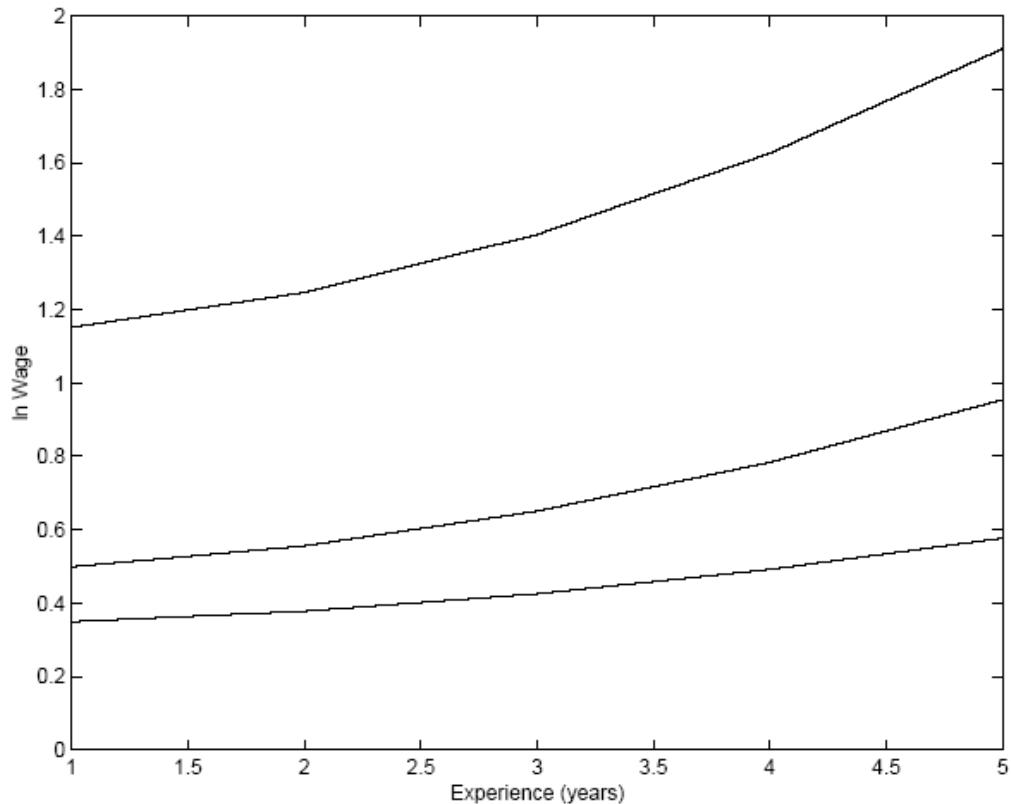
Dependent variable: Difference in log weekly wage					
Sample: Age < 40					
experience	0.0182 (1.64)	-0.0038 (0.29)	-0.0165 (0.34)	-0.0224 (0.45)	-0.0216 (0.42)
exp squared			0.0024 (0.27)	0.0030 (0.32)	0.0033 (0.35)
exp*sch		0.0032 (2.09)	0.0032 (2.11)	0.0047 (1.46)	0.0033 (2.01)
exp*sch*age				-0.00006 (0.41)	
exp*sch*sex				-0.0003 (0.28)	
yrs of sch.	-0.00071 (0.41)	-0.0191 (2.21)	-0.0193 (2.22)	-0.0195 (0.90)	-0.0214 (2.39)
sch*age				0.00002 (0.02)	
sch*sex				0.0003 (0.03)	
age	-0.0236 (2.04)	-0.0246 (2.12)	-0.0247 (2.13)	-0.0263 (1.95)	-0.0285 (2.47)
age squared	0.00040 (1.99)	0.00041 (2.07)	0.00042 (2.08)	0.00049 (2.06)	0.00049 (2.48)
sex	0.0272 (1.81)	0.0284 (1.90)	0.0284 (1.89)	0.0061 (0.16)	0.0224 (1.30)
occupation dummies					yes
industry dummies					yes
Number of observations	2,210	2,210	2,210	2,210	1,953
adj-R sq	0.0565	0.0586	0.0586	0.0598	0.0741

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

Insignificant parameters are set as zeros (those with p-values larger than 10). 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 six-month terms and explanatory variables in annual terms. The initial age at which destination experience starts is set as 17 for all the groups so as 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 the wage path is strengthened as schooling increases. Highly educated migrants experience a more 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.

Figure 2—Wage paths of migrants



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. These empirical findings are 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 creates 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. Since schooling facilitates migrants' assimilation process and matching quality, the convergence of migrants' earnings toward those of natives' is faster for educated than for uneducated migrants. However, if education significantly increases the probability of migration to urban areas, 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 show 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-urban migration, 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. 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.

Appendix 1: Alternative Interpretations

In the model presented in Section 2, workers' types are predetermined but firms' skill needs can be adjusted to improve matching quality. This is possible because workers can change firms if the 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 heterogeneous. Similarly, we may model migrants' assimilation process such that skill needs demanded in the destination market are predetermined but unknown, and migrants adjust themselves so as to match with skill needs gradually. In this setting, workers receive signals on the skill needs, $y_{jt} = \theta + \nu_{jt}$, where θ is the identical target-level of skill needs for urban markets and ν_{jt} is idiosyncratic shock (noise). Workers change their skills z_{jt} so as to minimize the expected value of the quadratic loss function, as formulated in our matching technology, $\prod_{k=1}^n (y_{jt}^k - z_{jt}^k)^2$. 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., $\sigma_\theta^2(s) < 0$, and also learn efficiently about the skill needs over time, i.e., $\sigma_\nu^2(s) < 0$. 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 education levels. As shown in Figure 1, more schooled migrants are likely to find jobs in more complex nature that demand a variety of skills. The second point cannot be captured by this alternative framework.

Appendix 2: Proof of Theoretical Predictions

(i) and (ii) Come directly from differentiations.

(iii) Suppose $n(h) \gg n(l)$. Define

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

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

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

Since $X(t) > 1$,

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

(iv) follows:

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

Rearranging,

$$\begin{aligned} \frac{\partial^2 \Delta^2}{\partial t^2} &> 0 \\ \Leftrightarrow & \\ \frac{(n(h)+1) \left[X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)} \left(\frac{n(l)+1}{n(h)+1} \right) \right]}{2 \left[X(t)^{n(h)-n(l)} - \frac{n(l)}{n(h)} \right]} &> -\rho_v^{-1} (\rho_\theta + t\rho_v). \end{aligned}$$

Since $n(h) \gg n(l) \geq 1$, the condition holds if t is small enough.

Q.E.D.

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