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Is Learning by Migrating in Megalopolis Really Important?*

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Abstract

This paper examines learning by migrating effects on the productivity of migrants who move to the "megalopolis" from rural areas utilizing the Thailand Labor Force Survey Data. The main contribution of this paper is to develop a simple framework to empirically test for self-selection on the migration decision and learning by migrating. The role of the characteristics of the urban labour market is also examined. In conclusion, we find self-selection effects test (1) positive among new migrants from rural area (i.e. "new entrants" to the urban labour market); and (2) negative among new migrants who move to rural areas (i.e. "new exits" from the urban labour market). These results suggest a natural selection (survival of the fittest) mechanism exists in the urban labour market.

Keywords : Self-selection; Learning by migrating; Survival of the fittest; Natural Experiment
JEL Classification Numbers : D83, J61, R23

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1 Introduction

The aim of this paper is to examine learning by migrating effects on the productivity of migrants who move to the "megalopolis" from rural areas utilizing the Thailand Labor Force Survey Data, 1994 to 1996. The main contributions of this paper are: (1) providing a simple empirical framework to identify between self-selection effects in migration decision and learning by migrating effects; (2) discussing the role of the urban labour market (i.e. natural selection or location of human capital accumulation). This study is one contribution of understanding about the unobserved characteristics of migrants in concentrated area empirically. Policy makers, economists, and researchers of other fields like sociology and anthropology have been interested in sorting through urban immigration and unobserved heterogeneity of urban workers. Especially policy makers, macroeconomists, and labour economists are interested in the role of such a concentrated area to provide job matching and its aggregate properties. Due to the causal effects of migration decisions and individual characteristics, it has been difficult to identify the true impact of concentrated area on migrant 's wages and job matching. Thanks to exogenous sources of variation (or natural experiments) in our available empirical data, the impact of migration on wages is consistently estimated. Based on these estimates, we can start to discuss the role of the urban labour market, active labour market policies, and its macroeconomic implications.

Trying to identify self-selection effects and learning effects is growing field. This became seriously concerned using repeated cross-section data and panel data. Using panel-data, Clerides et al. (1998) studies similar question on the export market using panel-data. No empirical evidence about learning effects (i.e. improving productivity) by exporting are observed from their analysis. Self-selection in the domestic market is the main explanation for becoming exporters. Glaeser and Maré (2001) finds learning by migrating effects in cities after moving from small cities to big cities. On the other hand, studying inside learning by migrating effects is also growing field: Yamauchi (2003) finds the complementarities of schooling and experience is reinforced as migrant's experience increases in the destination market (Bangkok Metropolitan Area) using Thailand Labor Force Survey, 1994 to 1996. Using same data with Yamauchi (2003), Yamauchi and Tanabe (2003) concludes that the employment probability of recent migrants is negatively affected by a large population size of previous migrants originating from the same region and positively affected if the previous migrants are successful in getting work. Kimura (2004) examines the main explanations for urban wage premium: learning skills and learning job opportunities in urban labour market using household-block-level data in Thailand Labor Force Survey. Munshi (2003) focuses on employment at the destination among Mexican migrants in the U.S. labour market. He uses rainfall in the origin (Mexico) as instrumental variable to identify origin-communities network effects on employment opportunities at the destination.

The two unique characteristics in the available data are useful for our analysis, "the reason for migration" and "duration of stay" for migrants. The variable "the reason for migration" includes two types of migrants; job-seekers and migrants who move with the household head. The location choice for job-seekers is self-selective on their observed and unobserved characteristics. On the other hand, the location choice for migrants who move with the household head seems to be independent of their characteristics. Location choice is exogenous for these household migrants. We can observe that there is true location specific returns to migrants who move with the household head. To see the degree of self-selection bias for job-seekers, this paper compares the returns to location between job-seekers and household relations migrants. Clear results are drawn from our identification strategy. Our approach is similar to Gibbons and Katz (1991) and Gibbons and Katz (1992), this paper is the first attempt to identify self-selection and learning effects related to migration using exogenous sources of variation. On the other hand, the variable "duration of stay" for migrants suggests the possibility of examining learning effects of migration. There is a large wage difference between short-staying and long-staying migrants in each location. This pattern is quite different for migration streams; rural-rural, urban-rural, rural-urban, and urban-urban. Cohort difference provides the evidence of improving average productivity. The cohort difference between the reasons for migration (i.e. difference in differences) also provides the solution of the difference of learning by migrating effects between two types of migrants.

The innovation of this work is that we utilize the experimental evidences from empirical data to identify the self-selection of unobserved characteristics and examine the effects of learning by migrating in urban and rural area respectively. The main results are: first, positive self-selection among new migrants in the urban from rural areas (i.e. new entrants to the urban labour market); secondly, negative self-selection among new migrants in rural areas (i.e. "new exits" from the urban labour market). These results suggest a natural selection (survival of the fittest) mechanism exists in the urban labour market. Thirdly, a gap converges between job-seekers and household relations for new migrants in urban area from rural area. Fourthly, a gap converges between job-seekers and household relations for new migrants in rural area from the urban labour market. "New exits" from the urban area seem to be portable of their acquired skill potentially. These results show learning by migrating effects in urban area over time.

This paper proceeds as follows. Section 2 describes a simple model to understand some empirical hypotheses. Section 3 shows the structure of the dataset Thailand Labor Force Survey. Section 4 contains a simple identification framework to study self-selection effects on unobserved abilities and learning by migrating effects. Section 5 while is about the estimation of self-selection bias on individual characteristics, section 6 focuses on learning by migrating effects. In the final section, we conclude this paper and discuss the remaining issues.

2 A Model of Mobility and Job Matching in Cities

This section shows a simple model of migration, mobility among occupations, and job matching. The model is an extension of Neal (1999) with two-sided learning as in Jovanovic (1979) and Gibbons and Katz (1992).[1] The model provides a new approach to understanding the relationship between migration, endogenous mobility, and quality of matching.[2] The model provides (1) new results of job mobility with two-sided learning and (2) simple framework to study an empirical analysis. The sketch of the framework is the following. A young worker in the rural area decides to stay or move to the urban area depending on job matching (i.e. wage) conditions. Upon finding a good match in the urban area, the young worker stays in the urban area. If otherwise, either the young worker continues to search for a new job, or returns to the rural.

2.1 Production Technology and Information Structures

Let us consider model settings similar to Neal (1999) with two-sided learning and migration aspects. We assume that a young worker lives infinitely and derives utility from two types of matches: location θ and job ξ depicted by distribution, assumed to be known to the worker as $K(\theta)$ and $G(\xi)$ respectively. To incorporate two-sided learning into the model, we assume that there is endowment for each worker, individual ability ϕ with vertical qualities from the distribution $Q(\phi)$. The firm however, cannot observe individual ability ex-ante but has information on a vector of observed individual characteristics $\boldsymbol{X}$ (i.e. gender, age, education) before hiring. The true value of the job match is assumed to be revealed to both the firm and worker only after hiring or while on the job. The worker decides to keep or to change her job match depending on $K(\theta)$ and $G(\xi)$. On the other hand, the firm fires the worker when productivity ϕ is below offer ξ. Individual will stay at her job match $\xi(\phi)$ as long as individual ability ϕ is over an offer ξ. We define this process as two-sided learning. We can summarize the decision rule for keeping current job-matching here.

$$\begin{cases} Stay & \text{if } \ \xi < \phi \\ Exit & \text{otherwise} \end{cases}$$

2.2 Migration and Job Mobility Decisions

The worker's utility in period t is defined by $v_t \equiv \theta_t + \xi_t$ where each match is drawn at the beginning of period t. The worker is assumed to maximize the expected value of v infinitely

[1] Literature on two-sided learning spreads across many issues: see Jovanovic (1982), Hopenhayn (1992), Gibbons and Katz (1992), Topel and Ward (1993), and Farber and Gibbons (1996).

[2] Incorporating two-sided learning between firms and workers is also suggested by Neal (1999).

with discount factor δ. The choice alternatives are restricted to three types in detail: she keep pair of location and job matching (θ, ϕ) if and only if $\xi < \phi$; change her job if and only if $\xi > \phi$; change her both matches if and only if $\xi > \phi$ and depends on value of θ. For a given unobserved ability by firm ϕ and observed characteristics $\boldsymbol{X}$, the workers' decision problem also can be characterized by the following Bellman equation using the value of $V(\theta, \xi)$ like Neal (1999).

$$V(\theta, \xi; \phi, \boldsymbol{X}) \quad = \quad \theta + \xi + \delta \max \Big[\ V_0, \ EV(G), \ EV(K, G) \Big| \ \boldsymbol{X} \ \Big]$$

where

$$\begin{aligned} V_0 &\equiv V(\theta + \xi(\phi)) \\ EV(G) &\equiv \int V(\theta, \xi'(\phi)) \ dG(\xi'(\phi)) \\ EV(K, G) &\equiv \iint V(\theta', \xi') \ dK(\theta') \ dG(\xi'(\phi)) \end{aligned}$$

V_0 means value of match which worker keeps, $EV(G)$ means value of match that she leaves her current job and draws a new job, and $EV(K, G)$ means that she leaves her current job-location and introduces another round of draws.

Optimal policy can be derived from the above dynamic programming. Derivations follow two processes: First, the condition of staying and keeping $(\theta, \xi(\phi))$ is examined. Secondly, we get the condition of only changing her job $(\theta, \xi'(\phi))$. By our definition, location change includes job change. The first condition is that the value of staying put weakly dominates the other two alternatives.

$$\frac{\theta + \xi(\phi)}{1 - \delta} \geq \max [\ EV(G), \ EV(K, G) \ ]$$

Now we are able to solve for the job ξ to satisfy the above equation for a given location θ. $\xi^*(\phi; \ \theta)$ is defined as a critical value; she stays as long as $\xi \geq \xi^*(\phi; \ \theta)$.

The second condition is also that the value of only changing jobs weakly dominates the value of changing both location and jobs given our first condition.

$$EV(G) \geq EV(K, G)$$

We can also solve for location θ to satisfy the above equation. θ^* is defined as her threshold of location choice. This critical value plays an important role on the policy to continue migrating or moving as long as $\theta < \theta^*$ with $\xi \geq \xi^*(\phi; \ \theta)$.

Finally, the optimal policies for workers with endowment of abilities ϕ are summarized by the decision below. The term *Stay* means that a young worker who keeps current location and job matches (θ, ϕ). The term *Draw* ξ' is defined as a young worker who changes jobs within current location: rural to rural migrants and urban to urban migrants. The term *Draw* (θ', ξ') is also defined as a young worker who changes jobs and location: rural to urban migrants and urban to rural migrants.

$$\begin{cases} \textit{Stay} & \text{if } \xi(\phi) \geq \xi^*(\phi;\theta),\ \xi < \phi \\ \textit{Draw}\ \ \xi' & \text{if } \theta > \theta^*,\ \xi(\phi) < \xi^*(\phi;\theta),\ \xi > \phi \\ \textit{Draw}\ \ (\theta', \xi') & \text{if } \theta < \theta^*,\ \xi(\phi) < \xi^*(\phi;\theta),\ \xi > \phi \end{cases}$$

These decision rules lead us to a second point: empirical analysis to location choice and wages. Before we look into the relationship between location choice and wages, samples must be clarified by location indicator $K \in \{R, U\}$ and migration indicator $M \in \{0, 1\}$. Location indicator confines itself to rural (R) and urban (U) simply. Migration indicator also confines itself to staying $(M = 0)$ and moving $(M = 1)$. For migrants, they have a new location indicator $K' \in \{R, U\}$. Migration streams for migrants are constituted by these two location indicators K and K'. Whole population branches out into the subgroups of stayers: rural stayers D_0^R, urban stayers D_0^U and migrants by migration streams: rural to rural migrants D_1^{RR}, urban to rural migrants D_1^{UR}, rural to urban migrants D_1^{RU}, and urban to urban migrants D_1^{UU}.

$$D_0^R = \begin{cases} 1 & \text{if } \xi_R(\phi) \geq \xi^*(\phi;\theta_R), \qquad \xi_R < \phi \\ 0 & \text{otherwise} \end{cases}$$

$$D_0^U = \begin{cases} 1 & \text{if } \xi_U(\phi) \geq \xi^*(\phi;\theta_U), \qquad \xi_U < \phi \\ 0 & \text{otherwise} \end{cases}$$

$$D_1^{RR} = \begin{cases} 1 & \text{if } \theta_R > \theta_R^*, \qquad \xi(\phi)_R < \xi^*(\phi;\theta_R), \qquad \xi_R > \phi \\ 0 & \text{otherwise} \end{cases}$$

$$D_1^{UR} = \begin{cases} 1 & \text{if } \theta_U < \theta_U^*, \qquad \xi(\phi)_U < \xi^*(\phi;\theta_U), \qquad \xi_U > \phi \\ 0 & \text{otherwise} \end{cases}$$

$$D_1^{RU} = \begin{cases} 1 & \text{if } \theta_R < \theta_R^*, \qquad \xi(\phi)_R < \xi^*(\phi;\theta_R), \qquad \xi_R > \phi \\ 0 & \text{otherwise} \end{cases}$$

$$D_1^{UU} = \begin{cases} 1 \quad \text{if} \quad \theta_U > \theta_U^*, & \xi(\phi)_U < \xi^*(\phi; \theta_U), \qquad \xi_U > \phi \\ 0 & \text{otherwise} \end{cases}$$

2.3 Testable Hypotheses

We can summarize our simple model to describe some testable hypotheses here. The dynamic program for a young worker gives us the following theoretical implications. First, if the individual ability is higher than current requirement of firm ξ and the wage is also higher than other value of location change and job change, she will stay in current pair of matches (location, job). Secondly, if ability is lower than current requirement of firm ξ and wage is also lower than other value due to job change, then she will move to find another job within her current location. Thirdly, if ability is lower than current requirement of firm ξ and wage is also lower than other value due to location change and job change, then she will move to another area to find another job. It is time now to put the empirical questions or some testable hypotheses regarding the rural and urban labour markets: do individuals become more productive after moving to the megalopolis?

Definition 1 *Self-selection of abilities on migration:*

Both observed characteristics $\boldsymbol{X}$ and unobserved abilities ϕ affect the migration decision M and choice of location K' considerably. The outcome of migration (θ, ξ') or (θ', ξ') are positively affected by ex-ante characteristics and abilities.

Definition 2 *Learning by migrating:*

Location changes K' through the migration decision M affect the individual unobserved abilities ϕ. The outcome of migration (θ, ξ') or (θ', ξ') is a function of ex-post characteristics and abilities.

Definition 3 *Sorting effects of reallocation:*

Aggregate productivity $q(\phi, \xi; \theta)$ for each group is affected by the reallocation effects in the local labour market K irrespective of improved abilities due to migration.

The three testable hypotheses are drawn here simply. The first hypothesis supports self-selection in the migration decision: relatively efficient individuals become migrants and these individuals also have a good job-match in the new location. We test it for each migration streams. The second hypothesis supports the improvement of average productivity over time: the average performance of long-experienced migrants is better than short-experienced migrants due to sorting or learning by migrating.

Hypothesis 1 *There is positive self-selection on individual abilities for "new entrants" to the urban labour market. There is negative self-selection on individual abilities for "new exits" from the urban labour market.*

This hypothesis suggests that (1) a young worker who has high abilities moves from the rural to the urban labour market and (2) a young worker who has low abilities moves from the urban to the rural labour market. This implies a natural selection mechanism exists in the urban labour market.

Hypothesis 2 *Average productivity for a long staying is higher than a short staying in the rural or the urban labour market through the two-sided learning process between firm and worker (i.e. selection mechanism over time) or learning by migrating.*

This hypothesis offers that (1) sorting matters among the local labour market and (2) learning by migrating exists in the local labour market.

Hypothesis 3 *A young worker who had drawn bad matches since migrating to the urban area does not stay long and tends to come back to the rural area.*

This additional hypothesis supports the prediction of Rothschild's two articles.[3] This hypothesis is formulated by the Rothschild's prediction that the rural wage distribution is known but the urban wage distribution is unknown to the rural worker. The migrants from the rural area "experiment" in the urban labour market observing rural wages in the rural labour market.

3 Data on Migrants

In this section, we examine "the reason for migration" and "duration of migration" provide statistical evidence based on the wages of migrants, utilizing data from Thailand Labor Force Survey, 1994 to 1996. The data set presents three issues related to (1) geography; (2) the unique characteristics of "the reason for migration" and "duration of migration"; (3) the evidence on wages. In fact, the proper treatment of these issues provides the key to understanding the self-selection mechanism and learning by migrating effects for migrants.

3.1 Why Do We Focus on Thailand?

Let us start with focusing on the geography of Thailand. Table 1 exhibits the patterns of urbanization of Thailand. We can observe a unique position of Thailand in the world from three indices of urbanization patterns. Urban area is defined as place with over a hundred thousand.

[3]Rothschild (1974a) and Rothschild (1974b) studies micro-foundation of search strategy when the price distribution is unknown for new market.

This criteria is lower bound of the definition of urban area.[4] *Primacy* means the level of urban primacy: ratio of urban population residing in Bangkok to second largest city. Urban primacy of Thailand (about 25) is the highest value of the world. *Megalopolitan* means the ratio of Bangkok to whole city in Thailand. Almost 77% of urban residents concentrates in Bangkok. These two indices show agglomeration of economic activity in Bangkok and also represent that there is only one megalopolis in Thailand. Finally, *Urbanization* means the ratio of the number of urban residents to whole domestic population. Only 15% of the whole population is located in urban areas (i.e. almost 85% of population is located in rural areas.). These indices eloquently show a clear contrast between urban and rural areas in Thailand.

These indices of economic geography in Thailand can simplify our empirical analysis. But it is difficult to see above clear contrast utilizing USA data, for example, recent literatures on labour migration in USA: Glaeser and Maré (2001), Borjas et al. (1992), Wheeler (2001), Dahl (2002), Moretti (2003a), Moretti (2003b). Many big cities seem to distribute discretely in USA. If we utilize USA data, then we have to set up multiple discrete choice models. We refer to the Greater Bangkok Area as the urban area. We assume that workers can commute to center of Bangkok as long as they locate in GBA. GBA seems a kind of basin of attraction. We also define all rural areas as non-GBA.

3.2 Overview of the Thailand Labor Force Survey

We shall examine our pooled sample of the Thailand Labor Force Survey (We call LFS hereafter). LFS is random sampling of all households in Thailand taken during two survey rounds. It is two rounds (February and August) every year. This paper pools annual sample of LFS, 1994 to 1996. We do not add our sample to the LFS, from 1997 to present. But the impacts were uneven for each occupation and industry. The number of pooled observations adds up to approximately one million. This paper leaves out of agricultural and self-employed workers, housewives, and students. The results are a sample of 250,000 wages workers in which 56.634 are migrant workers. We concentrate on this sample in this paper. We do not examine about 200,000 staying (i.e. non migrants) among sample of wages workers here. The main contents of LFS are following: gender, age, years of education, weekly wage, bonus, occupation, industry, firm size, unemployment spells, the reason for migration, and length of stay when the survey was taken.

For the moment let us look at our key variables for empirical analysis closely. Variables such

[4] We should notice that this criteria is correlated with domestic population. For example, USA seems to easy to satisfy this criteria because USA has a population of about two hundred million of population. On the other hand, Thailand (0.6 hundred millions of population $\approx 3/10$ of USA) is not easy to satisfy this.

as "the reason for migration" and "length of stay when the survey was taken" (or duration, exposure to destination) have unique characteristics. Variable "the reason for migration" can be grouped into seven categories: (1) Job search; (2) Job transfer; (3) Education/Training; (4) Medical treatment; (5) Move with household head; (6) Back to former place of residence; and (7) Other reasons. These reasons are automatically recorded for migrants who have 0 to 4 years of experience in each destination. Next, duration or exposure to each destination is recorded for migrants who also have 0 to 4 years of experience in each destination.[5] We tabulate the relationship between the reason for migration and duration of destination in Table 2. The main groups are job-hunting, job transfer, and move with household head. Migration attributed to study purpose also constitutes about 10% of all migrants. First, the tension of exit rises to the peak at within the first year of the move and after 3 years for migrants due to looking for jobs. On the other hand, the tension of exit also rises to a peak after 3 years for migrants due to job transfer and for migrants who move with the household head.

3.3 Evidence on Wages by Migration Status

Based on the length of stay in migrant primacy destination, we shall classify migrants into two main groups: (A) Job search, job transfer, and other reason; (B) Move with the household head. We call the former group "Job related" simply. This distinct classification is useful for our identification and estimation in the next section. Secondly, migration streams are also divided into four types: (*1*) from rural to rural migrants; (*2*) from urban to rural migrants; (*3*) from rural to urban migrants; (*4*) from urban to urban migrants. Thirdly, the duration of migrant status is divided into two categories: short (0-2 years) and long (3-4 years) duration. All migrants are classified by reason of migration, migration streams, and length of stay.

We are now ready to see the evidence of wages on each migration status. We assume two labour markets: rural and urban; First, we see the sample of new entrants to the rural labour market from rural areas. Secondly, we also see the sample of new entrants to the rural labour market from the urban area. Mean, standard deviations, and the number of observation are shown in each cell by migration status. The descriptive statistics for new entrants to the rural labour market is shown in Table 3, using whole sample, and the two subsample for job search, and move with household head respectively. Comparing the wage differentials in the sample of rural-rural migrants, there is a gradual growth (from 6.771 to 6.993) in the long-staying migrants looking for jobs. There is also a gradual growth (from 6.763 to 6.801) in the long staying migrants due to household reasons. Next, we shall discuss the difference between the

[5] Migrants who have 5 to 9 years of experience are also recorded. But these migrants do not have any record of original area, unable us to specify their migration streams from original area to destination area. Thus, we do not include these migrants who have 5 to 9 years of experience in our empirical analysis.

reasons for migration. The level of wages is higher for migrants looking for jobs than migrants moving with household head. This difference seems to be represented by gender. The ratio of females to new migrants due to household related reasons is almost 60%.

We also see that there is a rapid growth (from 6.81 to 7.058 for new entrants of looking for job and from 6.707 to 6.88 for new entrants of move with household head) in the members of the long cohort group in the urban to rural sample. And we also see wage differentials between the reasons for migration. Over 60% are females in the new migrants due to household related reasons in this sample. Finally, we compare the wage differentials between migration streams: from rural to rural and from urban to rural. The level of wage is higher for migrants from urban areas except for the subsample of migrants due to household related reasons. This fact seems to be represented by age differentials between two migration streams.

The descriptive statistics for new entrants to the urban labour market is shown in Table 4. After we compare the wage differentials between the short and long-staying migrants from rural to urban areas, there is a rapidly increasing (from 6.721 to 6.878) number of a long-staying migrants looking for jobs. We shall consider the difference between the reasons for migration next. The level of wages is higher for migrants due to household related reasons than migrants looking for jobs. This difference maybe attributed to the age and gender characteristics of this subsample. Our sample is restricted to wage workers. Reservation wage is high for females who comprise the majority of migrants due to household related subgroup. The difference of mean age between migrants looking for job and migrants who move with the household head is approximately 5 years.

Looking at the urban-urban category, we also see that there is a rapid growth (from 7.074 to 7.252) in the number of long-staying migrants looking for jobs. There is likewise a sharp growth (from 7.058 to 7.271) in the number of long-experienced for migrants who move with the household head. Finally, wage differentials between migration streams: from rural to urban and from urban to urban. As expected, the level of wage is quite higher for new entrants from urban areas than new entrants from rural areas. This is most likely due to differentials with respect to age, urban experience (i.e. benefit from search within urban area or improving productivity), and sectors (i.e. formal and informal) between the migration streams. This paper does not mention about the dataset on occupation, industry, and firm sizes in LFS.

4 Identification

This section provides a simple framework to empirically test to our hypotheses. We assume that a young worker has all the information to evaluate his or her own ability as well as the returns to this ability. It is easy for us to imagine correlation among own ability, migration decision, and returns to ability. If there is a self-selection bias in the migration decision, then we cannot evaluate the true learning effects in urban area. This paper proposes a new method to evaluate self-selection and learning by migrating effects utilizing the unique characteristics of Thailand Labor Force Survey: "the reason for migration" and "length of stay" for migrants. Our identification approach is quite different from Clerides et al. (1998) which studies learning by exporting effects among new establishments using panel-data. And our approach also quite different from Glaeser and Maré (2001) which examines learning effects in cities using panel-data.

4.1 Identification strategy

First, every worker has to choose migration decision every period: stay in current labour market or move to another area. We call this decision variable $M \in \{0, 1\}$. Staying is captured by $M = 0$ and mover is also captured by $M = 1$. This paper restricts our analysis for movers (i.e. $M = 1$). Secondly, every worker chooses their labour market every period: rural or urban labour market. We also call this location choice variable $K \in \{R, U\}$. Rural worker is captured by $K = R$ and urban worker is also captured by $K = U$. Thirdly, we define the variable $Z \in \{0, 1\}$ which is "the reason for migration" for movers. The reasons of migration for movers are (1) Looking for job (i.e. job search), (2) Job transfer; (3) Education/Training; (4) Medical treatment; (5) Move with household head; (6) Back to former residence, and (7) Others. With respect to household related reasons of migration, we assume that the member moving with the household head is captured by $Z = 1$ and the member of actively seeking employment or another reason is captured by $Z = 0$. These bring us to the second point: description of decision and state space for each individual.

Assumption 1 *(A decision space).*
Let a decision space D is constituted by below three elements: migration decision M; location choice K; reason of migration Z. Let these choices are mapped from the elements in a real finite dimensional set $\boldsymbol{X}, \boldsymbol{\Phi}, \boldsymbol{\Theta}, \boldsymbol{\Xi}$: the individual characteristics $x \in \boldsymbol{X}$, the individual specific abilities $\phi \in \boldsymbol{\Phi}$, the location specific returns $\theta \in \boldsymbol{\Theta}$, the job specific returns $\xi \in \boldsymbol{\Xi}$ such that

$$F_D : (x,\ \phi,\ \theta,\ \xi) \longrightarrow D = M \times K \times Z$$

Assumption 2 *(A state space).*
Let a state space Y for each individual is also constituted by the individual characteristics,

the individual specific abilities, the location specific returns, the job specific returns, and the individual decision space as

$$F_Y : (x,\ \phi,\ \theta,\ \xi,\ D) \longrightarrow Y$$

These assumptions of decision and state space will lead us further into a empirical investigation. We assume that the household head decides whether his family migration or not. Therefore we use the heterogeneity in the reason for migration as exogenous sources of variation in endogenous variables. This paper constructs the *household related* dummy variables D_{1H}. If a young worker follows the household head to move, then econometrician will treat the member of $D_{1H} = 1$. If the job-seekers move, $D_{1H} = 0$. The indicator variable D_{1H}^K is generated as follows:

$$D_{1H}^K = \begin{cases} 1 & \text{if } Z = 1,\ K \text{ for } M = 1 \\ 0 & \text{if } Z = 0,\ K \text{ for } M = 1 \end{cases}$$

The outcome variables for individual worker i in location K and at survey week s is defined Y_{is}^K. The cross-section outcome function is formalized as an additive separable form.

$$Y_{is}^K = f(X_{is}) + \Gamma \cdot D_{1H}^K + g\left(\phi_{is},\ \xi_{is}\right)$$

where $f(X)$ is a function of a vector of observed individual characterisitics, D_{1H}^K is a dummy variable equal to one if individual i follows the household head to move to location K, and $g\left(\phi_{is},\ \xi_{is}\right)$ is a function of unobserved characteristics for an individual worker and firm: ϕ_{is} is an error term for unobserved abilities for individual i at survey week s, and unobserved firm specific characteristics ξ_{is}.

The choice of location K correlates to pecuniary returns to individual characteristics: observed component X_i and component of unobserved ability ϕ_i. The high frequency of moving to urban area for young and more educated is a known and observed first. Young and highly educated workers know the urban area to be a thick labour market (varieties in occupation, industry, and technology). The returns to schooling is also higher in urban areas. Recent literature Borjas et al. (1992), Wheeler (2001), Dahl (2002), Moretti (2003a), and Moretti (2003b) show this using USA data. This is the logic of self-selection. The location choice K of the migrant in the household related subgroup ($Z = 1$) is assumed to be orthogonal to her ability ϕ and the location choice K of the migrant job-related subgroup ($Z = 0$) is assumed to be non-orthogonal to her ability ϕ by definition.

$$\begin{aligned} \phi_i &\ \propto\ D_{1H}^R = 0,\ D_{1H}^U = 0 \\ \phi_i &\ \perp\ D_{1H}^R = 1,\ D_{1H}^U = 1 \end{aligned}$$

Undoubtedly, a worker in the local labour market K have a location specific premium, however, the econometrician cannot distinguish between the true premiums in location and the self-selection bias in the migration decision. Our identification method suggests that move with household head is exogenous on migration decision. And we can call the member of $D_{1H} = 1$ treatment group. We can examine the true effects of moving to local labour market K on individual outcome to see the coefficient Γ. The coefficient Γ means the premium differentials between household related ($D_{1H} = 1$) and of job related ($D_{1H} = 0$) subgroup in location K. This paper develops a new and a simple identification method to distinguish between the true premium in K and the impact of self-selection bias in the migration decision to K.

Next, this paper tries to identify learning by migrating effects (i.e. productivity increasing on migration) in location K. For example, learning by migrating effects in urban areas include formal training, learning by doing, knowledge spillovers by communication, reduction in mismatch by turnover, and R&D investments by firms. We assume that firms can offer a wage after removing the returns to investment in technology. If this assumption is valid, then we will be able to exclude the latest possibility of learning by migrating effects: investment in technology by firm. Now we may restrict our discussion on learning effects due to individual efforts (i.e. learning and job turnover) and spillovers.

We use the variable τ for duration of stay after migration τ and relate this to experience in K to study learning effects. The data "length of migrant stay" $\tau \in \{0, 1, 2, 3, 4\}$ years is useful in identification of learning by migrating effects. This paper divides years $T \in \{S, L\}$ according to the duration of stay τ. The short-staying migrant worker is captured by $T = S$. The longer-staying migrant worker is captured by $T = L$. We define (1) short experience as $S \in \{0, 1, 2\}$ years and (2) long experience as $L \in \{3, 4\}$ years of moving to current location K based on the survey week. We are also now able to expand individual decision space from D to D_T with duration of stay.

Assumption 3 *(A decision space with duration).*
Let a decision space D_T is constituted by below four elements: migration decision; location choice; reason of migration; length of stay. Let these choices are mapped from the elements in a real finite dimensional set $\boldsymbol{X}, \boldsymbol{\Phi}, \boldsymbol{\Theta}, \boldsymbol{\Xi}$: the individual characteristics $x \in \boldsymbol{X}$, the individual specific abilities $\phi \in \boldsymbol{\Phi}$, the location specific returns $\theta \in \boldsymbol{\Theta}$, the job specific returns $\xi \in \boldsymbol{\Xi}$ such that

$$F_{D_T} : (x,\ \phi,\ \theta,\ \xi\ ) \longrightarrow D_T = M \times K \times Z \times T$$

Assumption 4 *(A state space with duration).*
Let a state space Y_T is expanded by duration of stay. Individual state also can be mapped from

the observed characteristics, the individual specific abilities, the location specific returns, the job specific returns, and individual decision space with the dimension of length of stay as

$$F_{Y_T} : (x,\ \phi,\ \theta,\ \xi,\ D_T) \longrightarrow Y_T$$

These assumptions lead to empirical study on the learning by migration. We construct the dummy variable $D_{1H}^K(S) = 1$ if individual i moved to K due to household related reasons and had spent short years until the time the survey was taken. The indicator variable for short cohort is written as:

$$D_{1H}^K(S) = \begin{cases} 1 & \text{if } Z = 1,\ K \text{ for } M = 1 \cap\ T = S, \\ 0 & \text{if } Z = 0,\ K \text{ for } M = 1 \cap\ T = S. \end{cases}$$

We also construct the dummy variable $D_{1H}^K(L) = 1$ if individual i moved due to household related reasons to K and stayed long years after migration. The indicator variable for long cohort is also written as

$$D_{1H}^K(L) = \begin{cases} 1 & \text{if } Z = 1,\ K \text{ for } M = 1 \cap\ T = L, \\ 0 & \text{if } Z = 0,\ K \text{ for } M = 1 \cap\ T = L. \end{cases}$$

These indicator variables suggest the time differentials of self-selection between the members of the *short* and *long* cohort groups. That is, the differentials between coefficients of dummy variables $D_{1H}^K(S)$ and $D_{1H}^K(L)$ can show the time differentials of learning effects between the two types of migrants. The outcome variables for individual worker i in location K is defined by Y_{is}^K. The cross-section outcome function is also formalized in the equation.

$$Y_{is}^K = f(X_{is}) + \Gamma(S) \cdot D_{1H}^K(S) + \Gamma(L) \cdot D_{1H}^K(L) + g\left(\phi_{is},\ \xi_{is}\right)$$

where $f(X)$ is a function of vector of observed individual characterisitics, D_{1H}^K is a dummy variable equal to one if individual i moves due to household related reasons to K, and $g\left(\phi_{is},\ \xi_{is}\right)$ is a function of unobserved characteristics: ϕ_{is} is an error term for unobserved abilities, and ξ_{is} is unobserved firm-specific characteristics for employee i.

5 Testing for Self-selection on Migration

5.1 Specification and Estimation of Self-selection on Migration

First, we test one of our hypotheses: there is a self-selection bias on ability when a young worker moves to location K. Outcome variable is the level of wage. Wage represents self-selection about employment and productivity. To test for self-selection in observed characteristics and unobserved abilities, we estimate **reason differentials** from the cross-section wage function like Gibbons and Katz (1991) and Gibbons and Katz (1992) by following their linear regression formulations:

$$\log W_{is}^K = X_{is}\beta + \Gamma \cdot D_{1H}^K + \phi_{is} + \xi_{is}^K \tag{1}$$

where the dependent variable $\log W_{is}^K$ is log weekly earnings for individual i at survey week s in location K, X is a vector of observed individual characteristics (gender, age, education, square of years of education, and marital status), the dummy variable $D_{1H}^K = 1$ if individual i moves to location K due to household related reasons, and otherwise if individual i moves to location K to actively seek employment. ϕ_{is} is unobserved abilities for individual i, ξ_{is}^K is unobserved firm technology if individual i is employed in this firm. Finally, u_{is}^K is a mixed error component of ϕ_{is} and ξ_{is}^K.

5.2 Empirical Results of Self-selection on Migration

The expected sign of the estimates on self-selection are as follows. First, the coefficient Γ of urban-rural migrant is positive (i.e. migrants of job-seekers receive lower rural premium than migrants of the household relations because of the negative self-selection on exit decision from the urban labour market).

$$\begin{aligned} H_0 &: \Gamma^{UR} < 0 \\ H_1 &: \Gamma^{UR} > 0 \quad \text{(negative self-selection for job-seekers)} \end{aligned}$$

Secondly, the coefficient Γ of rural-urban migrant is negative (i.e. migrants of job-seekers receive higher urban premium than the migrants of the household relations because of the positive self-selection on entry decision to the urban labour market).

$$\begin{aligned} H_0 &: \Gamma^{RU} \geq 0 \\ H_1 &: \Gamma^{RU} < 0 \quad \text{(positive self-selection for job-seekers)} \end{aligned}$$

The estimates for the four subsamples urban (rural) migrants to urban (rural) areas in Table 5 provide evidence that there are highly significant on self-selection effects on unobserved abilities: (1) there is positive self-selection for new entries to both the urban and rural labour markets from rural areas; (2) there is negative self-selection for newly exits from urban labour market and movers within urban area. The estimates show that the household related subgroup has approximately 4.5% lower wages migrants in the job related subgroup in the rural to rural subsample. Alternatively, the estimates show that job-seeking migrants earn 4.5% higher wages than migrants in the household related subgroup. Job turnovers established residences in the rural area have positive self-selection effects. For the urban to rural subsample, results show that there is a negative and highly significant self-selection bias on unobserved abilities for job-seeking migrants who have 5.1% lower wages than movers with household head.

On average, job-seeking migrants in the urban-rural subsample have 5.1% lower level of rural true premium than migrants in the household related subgroup. Namely, if job-seeking subgroup sample have same level of ability as the household related subgroup, the job search sample will have true rural premium. Therefore, "low ability" of job search sample reduce their own rural premium from true rural premium to lower level. Almost urban to rural movers were migrants to urban area from rural area.

For the rural-urban and urban-urban subgroups, migrants with household related reasons have true urban premium independent of self-selection effects with respect to location choice and ability by our identification strategy in the previous section. The coefficient of this dummy variable means the differential of unobserved ability from urban premium. Estimates for rural-urban subsample appears that positive and highly significant self-selection bias on unobserved abilities for job-seekers who have 8.8% higher wages than the household related control group. Estimates for the job-seeking migrants in the rural-urban subsample indicate positive self-selection effects on abilities. Estimates for the urban-urban subsample also show that negative and significant self-selection effects on unobserved ability for migrant job-seekers who have 5.1% lower wages than those in the household related control group. Turnovers of a job and established a residence in the urban area do not seem to have positive self-selection effects.

We are now ready to say that there is positive and quite significant (1% level) self-selection effects on unobserved abilities for migrants from rural areas: rural to rural and rural to urban subsamples. But on average, there is a significant negative self-selection bias on unobserved abilities for migrants from urban areas: urban to rural and urban to urban subsamples.[6] In conclusion, young migrants from rural areas show clearly their high ability reflected on wages in rural and urban areas on the average. Our model predicts that a migrant with high ability can keep a job as long as she obtains a job requiring skill/training/know-how early in the migration process.

[6] These results support the "lemon" effects for migrants from urban area. On the other hand, these results also support the no lemon effect for migrants from rural area.

Migrants who find jobs choose to stay. But migrants who cannot find a job will return to their place of origin or move to another location to seek jobs. Both of rural movers from urban area and urban movers from urban area seem to have bad match in urban area. But results using the urban to rural and urban to urban subsamples (see Table 5) show that there are less learning effects in urban area for job-seeking subgroup than the household related subgroup. If there are positive spillovers in the urban area, the certain gaps between the two types of migrants mean that there is heterogeneity in learning by migrating effects in urban areas.

6 Testing for Learning by Migrating

6.1 Specification and Estimation of Learning by Migrating

We test our next hypothesis on learning by migrating effects to improve productivity after a young worker moves to location K. Learning by migrating effects are mentioned by Glaeser and Maré (2001) using panel regressions. This is comprehensive work. But there are shortcomings about self-selection bias on migration decision.

Outcome variable is also wage level. We divide the explanatory variable D_{1H}^{K} into *short* $D_{1H}^{K}(S)$ and *long* $D_{1H}^{K}(L)$ cohort. Testing for learning by migrating effects means that we compare the coefficients $\Gamma(S)$ and $\Gamma(L)$ of the household related subgroup dummy variables. The coefficient $\Gamma(L)$ includes various sources of improving productivity due to individual efforts in location K (for example, formal training or learning by doing), due to knowledge spillovers in location K, and due to reallocation effects by sorting and two-sided learning between individuals and firms. Occurrence of reallocation represents self-selection on ability. Information of matching quality is accumulated by firm and individual after their production.

If we assume that ability does not change over time, we can say that reallocation effects are self-selective in innate (or natural) ability. If we assume that individual ability is changed over time through learning by migrating effects, we can say that reallocation effects are self-selective in acquired ability after migration. Even if any doubt remains about identification between learning by migrating effects (i.e. individual efforts and spillovers) and reallocation effects, it is clear that average productivity can be higher for a *long* cohort L than a *short* cohort S.[7] To see these effects, we also specify and estimate **cohort differentials** in estimates of reason differentials from the cross-section wage function by following linear regressions.

[7] Literature on TFP show in detail that higher level in productivity among long lived firms than short lived firms can be explained by exiting of non productive firms. This reallocation effects also can be drawn from literatures on exporting market and two-sided learning in the labour market. Our theoretical model also predicts the natural selection or survival of the fittest through job mobility.

$$\log W_{is}^K = X_{is}\beta + \Gamma(S) \cdot D_{1H}^K(S) + \Gamma(L) \cdot D_{1H}^K(L) + \phi_{is} + \xi_{is}^K \tag{2}$$

where $\log W_{is}^K$ is log weekly earnings for individual i in location K, X_{is} a vector of observable individual characteristics (gender, age, years of education, square of years of education, marital status), the dummy variables $D_{1H}^K(S)$ and $D_{1H}^K(L)$ equal to 1 if individual i moved with the household head to location K and has short (long, respectively) experience in location K, and u_{is}^K is an error term of individual unobserved abilities ϕ_i and firm's technology, ξ_{is}.

6.2 Empirical Results of Learning by Migrating

We also estimate the effects of dummy variables $D_{1H}^K(S)$ and $D_{1H}^K(L)$ in the four migration flow subsamples: (*1*) rural to rural; (*2*) urban to rural; (*3*) rural to urban; and (*4*) urban to urban. The coefficient of dummy variable Γ means the differentials of location specific premium between the two migrant subgroups of job-seekers and household relations in each location K. The coefficient $\Gamma(S)$ means the difference of location premium for short-staying in the two migrant groups. Same thing is true for the coefficient $\Gamma(L)$ for long-staying workers in the two groups. Therefore, the difference between $\Gamma(S)$ and $\Gamma(L)$ represents "difference in differences": the difference of learning by migrating effects between two types of migrants (looking for job versus household relations) in location K. This difference $G(T)$ is defined as follows:

$$G(T) \equiv \Gamma(L) - \Gamma(S)$$

where $G(T)$ also means the differences of improvement of average productitvity between two types of migrants.

The expected sign of the estimates on learning by migrating effects by migration are as follows. First, the difference between the coefficients $\Gamma(S)$ and $\Gamma(L)$ for urban-rural migrant is constant over time (i.e. the productivity differentials between job-seekers and the household relations is not changing because of learning by migrating effects by migration to the "new exit" from the urban labour market).

$$\begin{aligned} H_0 &: \Gamma^{UR}(L) = \Gamma^{UR}(S) \quad \text{(the uniform learning by migrating effects in rural area)} \\ H_1 &: \Gamma^{UR}(L) \neq \Gamma^{UR}(S) \end{aligned}$$

Secondly, the difference between the coefficients $\Gamma(S)$ and $\Gamma(L)$ for rural-urban migrant is constant over time (i.e. the productivity differentials between job-seekers and the household realations is not changing because of learning by migrating effects among "new entrants" to the urban labour market).

$$\begin{aligned} H_0 &: \Gamma^{RU}(L) = \Gamma^{RU}(S) \quad \text{(the uniform learning by migrating effects in urban area)} \\ H_1 &: \Gamma^{RU}(L) \neq \Gamma^{RU}(S) \end{aligned}$$

The estimates for each sample in Table 7 and Table 8 show that there is less reallocation effects in urban labour market and there are no learning effects in urban areas for "newly exits" from urban area: (1) the gap $G(T)$ increases between job-seekers and household relating migrants in the rural-rural subsample due to the sharp reallocation effects for job-seeking migrants of looking for job; (2) convergence of $G(T)$ between job seekers and household related migrants in the urban-rural subsample due to learning by migrating effects for household relations; (3) convergence of $G(T)$ between job seekers and household relations in the rural-urban subsample because of less reallocation effects for less able workers in the urban market; (4) higher $G(T)$ for job-seekers and household relation in the urban-urban subsample due to less reallocation effects for less able workers in the urban market.

It is useful to interpretate between the share of short and the share of long duration in each migration streams. Table 6 represents some interesting facts of similarity and differentials between the reasons for migration. We shall now look more carefully into our empirical results. The estimate for rural to rural subsample with short-staying in rural area shows that job-seekers have experience of 3.5% higher wages than household related migrants. On the other hand, for long-staying migrants in rural after migration from another rural area, job-seekers have an experience of 6.4% higher wages than household related migrants. There is a steep rise from short to long between two types of migrants. It seems reasonable to suppose that there are learning by migrating effects in rural areas or reallocation effects gained from the sorting process through job matching.[8]

From Table 3, our reallocation hypothesis seems reasonable. Increased average productivity of job-seekers can be explained by the differences of the survival rate between the two types of migrants: 24.2% (= 7841/32388) of job-seekers versus 33.6% (= 3124/9285) of household relations migrants. The migrant who can not find a good job match seems to change her location at an early stage, before the second years (i.e. our definition is *short* cohort). But the

[8]A possible explanation is: if learning by migrating effects exist, then the 2.9% gap (= 6.4% − 3.5%) between short and long cohort can be explained by the difference of the learning speeds between the two types of migrants. Another explanation is: if reallocation effects are the main reason, then approximately 3% gap between two cohorts can be explained by the difference of exit speeds from rural labour market between job-seekers and household relations migrants.

migrant who can have a good match will stay in rural area and to enter a *long* cohort. It is likely that improvement in average productivity for long cohort of job-seekers can be explained by survival of the fittest in the rural to rural subsample.

The estimate for urban to rural subsample with short-staying in Table 7 shows that migrants looking for jobs have experience of 3.2% lower wages than migrants who move with the household head. On the other hand, for long staying migrants, migrants of looking for job has experience of 4.4% lower wages than migrants of move with the household head. We already build up two hypotheses: self-selection on abilities and learning by migrating effects in each location. At first, result of short cohort shows significant but small differences between two types of migrants. But result of long cohort represents growth of differences between two types of migrants. This 1.2% (= 4.4% − 3.2%) gap between short and long cohort among two types of migrants can be explained by the difference of innate ability or the difference of learning speeds in rural area.[9] Exit patterns of two types of migrants are similar: 20.4% (= 1175/5768) of looking for job versus 22.6% (= 241/1066) of move with the household head. We may say that the difference of exit patterns is not the main reasons.

Let us, for the moment, examine to urban migrants. The estimate for the rural to urban subsample with short-staying in urban area in Table 8 shows that job-seeking migrants experience 10.4% higher wages than household relations migrants. On the other hand, for long-staying migrants, job-seekers experience of 6.3% higher wages than household relations migrants. Gaps between two types of migrant decrease: due to convergence of abilities between the two migrant groups or due to staying in urban job-seeking. Exit patterns are also quite similar: 31.9% (= 1689/5292) for job-seekers versus 31.4% (= 152/484) for household relations migrants. If a young migrant has a bad match in urban area, then she will change her location to look for another job match, average productivity of migrants in urban area can be improved over time. We observe that this reallocation effect is common for our two types of migrants. We have two explanations: first, if declining the reallocation effects among job-seeking migrants is the main explanation, it is likely that less able workers stay in the urban area due to the thick market. This leads to our result of declining gap between two types of migrants. Secondly, if learning by migrating effects are the main explanation, we may say that household relations migrants catch up with job-seeking migrants: there is an observed convergence among urban migrants.

[9] We already discussed that there is negative self-selectivity in ability for urban to rural movers in former section. There is complement between ability and the learning speed. We cannot identify whether ability is main explanation or not here. Even if any complication remains about complement, it is clear that there is gap between two types of migrants from urban to rural area.

Results on urban migrants show that in the urban to urban subsample, short-staying job-seeking migrants experience 2.8% lower wages than household relations migrants. But this estimate is insignificant. We do not observe clear differentials between two types of migrants in the *short* cohort group. On the other hand, long-staying job-seeking migrants experience 10.2% lower wages than household relations migrants. We can also understand this 7.4% gap (10.2% − 2.8%) between two cohorts due to reallocation effects or due to learning by migrating effects in urban areas. We shall now look more carefully into both explanations. First, there is substantially a large difference between 22% (=335/1524) of looking for job versus 30% (=248/827) of moving with head. If reallocation effects can mainly explain the gap between two estimates, then we will have to observe that this gap decreases: there are strong reallocation effects among migrants looking for jobs and sorting effects force to improve their average productivity. But this hypothesis contradicts the gap of two estimates. Average productivity among migrants looking for jobs is decreasing. Secondly, we can refer possibility of learning by migrating effects in the urban area. It seems reasonable to say that the differentials in ability or differentials of learning speed for two types of migrants are quite significant on the average. The initial gap between migrants looking for jobs and migrants who move with the household head seems to be widening over time.

6.3 More on Learning by Migrating: the Reason for Migration

In earlier parts of the paper, we discussed the differences among learning by migrating effects due to various reasons for four migration streams. Next, we test for learning effects related to the length of stay of migrants. Two dummy variables are used to estimate the impacts of the length of stay on productivity for two types of migrants: job-seekers and the household relations. For job-seeking migrants (i.e. $Z = 0$), the dummy variable $D_S^K(0)$ is equal to 1 if individual i moved to location K and has short experience in location K.

$$D_S^K(0) = \begin{cases} 1 & \text{if } T = S,\, K \text{ for } M = 1 \cap\ Z = 0, \\ 0 & \text{if } T = L,\, K \text{ for } M = 1 \cap\ Z = 0. \end{cases}$$

For the migrants of the household relations (i.e. $Z = 1$), the dummy variable $D_S^K(1)$ is equal to 1 if individual i moved with the household head to location K and has also short experience in location K.

$$D_S^K(1) = \begin{cases} 1 & \text{if } T = S,\, K \text{ for } M = 1 \cap\ Z = 1, \\ 0 & \text{if } T = L,\, K \text{ for } M = 1 \cap\ Z = 1. \end{cases}$$

To see learning by migrating effects of the length of stay on productivity, we specify and estimate **reason differentials** based on cohort differentials from the cross-section wage function.

$$\log W_{is}^{K} = X_{is}\beta + \Gamma_S(0) \cdot D_S^K(0) + \Gamma_S(1) \cdot D_S^K(1) + \phi_{is} + \xi_{is}^{K} \tag{3}$$

where coefficient $\Gamma_S(0)$ captures the difference of productivity between *short* and *long* cohort for the migrants of job-seekers, on the other hand, coefficienct $\Gamma_S(1)$ also captures the difference of productivity between *short* and *long* cohort for the migrants of household relations.

These coefficients provide us the empirical understanding of the impact of duration on abilities. There is the issue of endogeneity: each individual chooses the length of stay in location K after migration, and the pitfall is related to comparing two coefficients due to sample truncation. But we can focus on the results of share of long-staying for two types of migrants because Table 6 suggests same patterns of sample-attrition for job-seekers and household relations among urban-rural migrants (i.e. 20.4% for job-seekers vs 22.6 % for household relations) and among rural-urban migrants (i.e. 31.9% for job-seekers vs 31.4% for household relations).

Each expected sign of learning by migrating effects is as follows. First, the coefficient Γ_S of urban-rural migrant is negative (i.e. average productivity of migrants grows after entry into the rural labour market).

$$\begin{aligned} H_0 &: \Gamma_S^{UR}(0) \geq 0 \quad \cap \quad \Gamma_S^{UR}(1) \geq 0 \\ H_1 &: \Gamma_S^{UR}(0) < 0 \quad \cap \quad \Gamma_S^{UR}(1) < 0 \quad \text{(learning by migrating effects in rural area)} \end{aligned}$$

Secondly, the coefficient Γ_S for the rural-urban migrant is negative (i.e. average productivity of migrants grows after entry into the urban labour market).

$$\begin{aligned} H_0 &: \Gamma_S^{RU}(0) \geq 0 \quad \cap \quad \Gamma_S^{RU}(1) \geq 0 \\ H_1 &: \Gamma_S^{RU}(0) < 0 \quad \cap \quad \Gamma_S^{RU}(1) < 0 \quad \text{(learning by migrating effects in urban area)} \end{aligned}$$

Empirical results are shown in Table 9 for the rural labour market and Table 10 for the urban labour market. There is no empirical observation of the learning by migrating effects for job-seekers in the rural area: we have no results to show that coefficient is negatively significant at 1% level. On the other hand, we have the following observation of the learning by migrating effects for rural-rural migrants of household relations: the coefficient is negatively significant at 1% level. However, for the learning by migrating effects of urban-rural migrants of household relations, we obtained insignificant coefficients. In conclusion: (1) there is no advantage for *long* experienced job-seekers in the rural labour market and (2) there is advantage of *long* experienced migrants of household relations in the rural labour market. The main difference by the reason for migration seems to be derived from the difference of search intensity in the early stages after migration.

The empirical results in Table 10 suggest that the advantage of *long* experienced migrants exists. "New entrants" to the urban labour market has negative learning by migrating effects for both job-seekers and household related migrants: the coefficients are negatively significant at 1% level. There is advantage of staying because of thick market externalities in the urban area. Migrants of household relations benefit from staying in the urban labour market more than migrants of job-seekers because of the duration of the search activities. Job-seeking migrants within the urban labour market also benefit from their search activities. On the other hand, there is no advantage for household relation migrants to stay in the urban labour market: the coefficient is negative but insignificant. We therefore conclude that (1) *long* experienced job-seekers gain in the urban labour market and (2) *long* experienced household relations migrants to the urban area. These advantages for duration of stay come from the search activities in the urban labour market (i.e. thick market externalities).

7 Discussions and Conclusion

Some issues remain to discuss. First, the validity of our instrumental variable used in "the reason for migration". Both recent works by Rosenzweig and Wolpin (2000) and Angrist and Krueger (2001) argue the general shortcomings about the instrumental variables due to "natural experiment". Our identification strategy depends on whether moving with the household head to a new location is orthogonal to individual abilities: following the head is exogenous. We have to examine that the location choice for migrants who move with the household head seems to be independent of their characteristics. Location choice seems to be exogenous for these household relations migrants. But we can conjecture the co-location problems for husbands and wives like Costa and Kahn (2001). If there is strategic complementarities to co-location between wives and husbands, our identification strategy fails. Secondly, to study the self-selection effects on abilities and the learning by migrating, we used wage worker migrants. This leads to sample selection bias. We have to examine transitions from migrants to agricultural, self-employed, wage workers, and household workers such as housewives. Thirdly, we do not control for the categories of occupation, industry, and firm size. Self-selection effects on abilities and the learning by migrating effects can be quite different for these categories.

In this paper we develop a simple framework to identify the learning by migrating effects and self-selection effects on abilities with instrumental variable. This is the first attempt of the identification of learning by migrating effects from self-selection effects using exogenous sources of variation: the reason for migration. This paper is useful to know the role of the urban labour market: natural selection or the location of learning. Our empirical results for self-selection on migrating are summarized below:

- There is positive self-selection on abilities for rural-urban job-seekers significantly.
- There is negative self-selection on abilities for urban-rural job-seekers significantly.

In short, these rigorous inferences suggest the survival of the fittest in the urban labour market. Highly able job-seekers tend to move to the urban labour market from the rural area, while less skilled job-seekers tend to exit from the urban labour market to the rural labour market. The origin of migrants from the urban labour market to rural can be rural area. These migrants (i.e. returnees) moved from the rural to the urban labour market and then back to the rural area because of bad job-matching experience in the urban labour market. Our empirical results for learning by migrating effects are also summarized below:

- There is a convergence of productivity between rural-urban job-seeking migrants and rural-urban household relations migrants over time.
- There is a divergence of productivity between urban-rural job-seeking migrants and urban-rural household relations migrants over time.

It seems reasonable to say that better job-matching can be found by the rural-urban migrants of household relations after *learning where better job opportunities are located* in the urban thick market. It is due to the difference of a necessity for getting a job between job-seekers and household relations migrants. Household relations migrants have more search or waiting premiums than *impatient* job-seekers. The result for both rural-urban migrants can apply to the result for both urban-rural migrants and urban-urban migrants but not for rural-rural migrants. These results lead to the conclusion that there is a search option in the urban thick market.

References

Angrist, Joshua D. and Alan B. Krueger, "Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiment," *Journal of Economic Perspectives*, 2001, *15*, 69–85.

Borjas, George J., Stephen G. Bronars, and Stephen J. Trejo, "Self-Selection and Internal Migration in the United States," *Journal of Urban Economics*, 1992, *32*, 159–185.

Clerides, Sofronis, Saul Lach, and James R. Tybout, "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco," *Quarterly Journal of Economics*, 1998, *113*, 903–947.

Costa, Dora and Matthew E. Kahn, "Power Couples: Changes in the Locational Choice of the College Educated, 1940-1990," *Quarterly Journal of Economics*, 2001, *115*, 1287–1315.

Dahl, Gordon, "Mobility and the Return to Education: Testing a Roy Model with Multiple Markets," *Econometrica*, 2002, *70*, 2367–2420.

Farber, Henry S. and Robert Gibbons, "Learning and Wage Dynamics," *Quarterly Journal of Economics*, 1996, *111*, 1007–1047.

Gibbons, Robert and Lawrence F. Katz, "Layoffs and Lemons," *Journal of Labor Economics*, 1991, *9*, 351–380.

_ **and** _ , "Does Unmeasured Ability Explain Inter-Industry Wage Differentials?," *Review of Economic Studies*, 1992, *59*, 515–535.

Glaeser, Edward and David Maré, "Cities and Skills," *Journal of Labor Economics*, 2001, *19*, 316–342.

Hopenhayn, Hugo, "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 1992, *60*, 1127–1150.

Jovanovic, Boyan, "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 1979, *87*, 972–990.

_ , "Selection and the Evolution of Industry," *Econometrica*, 1982, *50*, 649–670.

Kimura, Yuichi, "The Role of Big Cities in Human Capital Accumulation: Evidences from Thailand," *Ph.D. Dissertation, Kyoto University*, 2004.

Moretti, Enrico, "Estimating the Social Return to Higher Education: Evidence From Longitudinal and Repeated Cross-Sectional Data," *forthcoming in Journal of Econometrics*, 2003.

_ , "Human Capital Externalities in Cities," in "Handbook of Regional and Urban Economics (forthcoming)," North Holland-Elsevier, 2003.

Munshi, Kaivan, "Networks in the Modern Economy: Mexican Migrants in the U.S. Labour Market," *Quarterly Journal of Economics*, 2003, *118*, 549–597.

Neal, Derek, "The Complexity of Job Mobility Among Young Men," *Journal of Labor Economics*, 1999, *17*, 237–261.

Rosenzweig, Mark R. and Kenneth I. Wolpin, "Natural "Natural Experiments" in Economics," *Journal of Economic Literature*, 2000, *38*, 827–874.

Rothschild, Michael, "Searching for the Lowest Price when the Distribution of Prices is Unknown," *Journal of Political economy*, 1974, *82*, 689–712.

_ , "A Two-Armed Bandit Theory of Market Pricing," *Journal of Economic Theory*, 1974, *9*, 185–202.

Topel, Robert and Michael Ward, "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 1993, *107*, 441–479.

Wheeler, Cristopher H., "Search, Sorting, and Urban Agglomeration," *Journal of Labor Economics*, 2001, *19*, 879–899.

Yamauchi, Futoshi, "Are Experience and Schooling Complementary? Evidence from Migrants' Assimilation in the Bangkok Labor Market," *Journal of Development Economics*, 2003, *74(2)*, 489–513.

_ **and Sekiko Tanabe**, "Nonmarket Networks Among Migrants: Evidence from Metropolitan Bangkok, Thailand," *IFPRI Discussion Paper*, 2003, *No. 169.*

Table 1: A Position of Urbanization Patterns for Thailand in the World

Rank	Country	Primacy	Country	Megalopolitan	Country	Urbanization
1	**Thailand**	24.994	Angola	0.857	UAE	0.997
2	Angola	15.520	Azerbaijan	0.846	South Korea	0.736
3	Chile	14.847	Ireland	0.841	Dominican	0.727
4	Peru	10.332	Paraguay	0.832	Lebanon	0.722
5	Lebanon	9.847	Sierra Leone	0.828	Japan	0.696
6	Sierra Leone	9.221	Lebanon	0.814	USA	0.689
7	Madagascar	9.078	Kyrgyzstan	0.785	Australia	0.659
8	Argentina	8.787	Tajikistan	0.7712	Venezuela	0.644
9	Hungary	8.707	**Thailand**	0.7706	Mexico	0.633
10	Mali	8.542	El Salvador	0.750	Chile	0.623
91	Ecuador	1.307	Venezuela	0.203	India	0.159
92	South Africa	1.282	South Africa	0.197	Mali	0.154
93	USA	1.267	Poland	0.173	**Thailand**	0.150
94	Vietnam	1.236	Germany	0.167	Tajikistan	0.147
95	China	1.194	Netherlands	0.159	Kenya	0.141
96	Cameroon	1.157	Ukraine	0.138	Madagascar	0.131
97	Australia	1.150	Russia	0.135	Sri Lanka	0.092
98	UAE	1.103	India	0.113	Niger	0.091
99	Syria	1.059	USA	0.085	Ethiopia	0.062
100	Netherlands	1.035	China	0.047	Nepal	0.056

Source: United Nations World Urban Prospects 2000.

Table 2: Reason of migration and duration of stay

Reason	0	1	2	3	4	Total
Job-seeking	7380	5642	4601	3541	2087	23251
Job transfer	3156	3077	2792	2135	1412	12572
Medical treatment	7	3	1	3	0	14
Household relations	2719	2567	2611	2267	1498	11662
Return to former residence	2384	1402	1077	741	440	6044
Others	1062	745	603	427	254	3091
Total	16708	13436	11685	9114	5691	56634

Note. Each column shows years of stay from time of migration until the survey week. By definition, we rule out students, self-employed, housewives, and farmers in the analysis. We focus on migrant wages worker only. Source: Thailand Labor Force Survey, 1994-1996

Table 3: Log weekly wage for new entrants to the rural labour market

Subsample		Mean	S.D	Obs.
Rural to rural migrants		6.814	.663	41673
	Short	6.770	.663	30708
	Long	6.939	.645	10965
Job-seeking		6.825	.670	32388
	Short	6.772	.674	24547
	Long	6.993	.630	7841
Household relations		6.776	.633	9285
	Short	6.763	.618	6161
	Long	6.801	.663	3124
Urban to rural migrants		6.861	.694	6834
	Short	6.810	.684	5418
	Long	7.058	.697	1416
Job-seeking		6.883	.700	5768
	Short	6.829	.690	4593
	Long	7.094	.699	1175
Household relations		6.745	.647	1066
	Short	6.706	.639	825
	Long	6.880	.659	241

Note. All new entrants to rural labour market are classified by the reason for migration, migration streams, and years of stay. All new entrants is restricted to wage workers age 40 or below. Source: Thailand Labor Force Survey, 1994-1996

Table 4: Log weekly wage for new entrants to the urban labour market

Subsample	Mean	S.D	Obs.
Rural to urban migrants	6.773	.478	5776
Short	6.727	.462	3935
Long	6.873	.496	1841
Job-seeking	6.771	.474	5292
Short	6.721	.461	3603
Long	6.878	.482	1689
Household relations	6.802	.512	484
Short	6.794	.465	332
Long	6.818	.626	152
Urban to urban migrants	7.116	.531	2351
Short	7.069	.512	1768
Long	7.260	.562	583
Job-seeking	7.113	.518	1524
Short	7.074	.496	1189
Long	7.252	.569	335
Household relations	7.122	.556	827
Short	7.058	.545	579
Long	7.271	.553	248

Note. All new entrants to the rural labour market are classified by the reason for migration, migration streams, and duration of stay. All new entrants are restricted to wage workers age 40 or below. Source: Thailand Labor Force Survey, 1994-1996

Table 5: Coefficients of household related subgroup dummy in wage equations

Subsample	Γ	Adjusted R^2	Obs.
Rural to rural	$-.045^{***}$	.436	41673
	(.005)		
Urban to rural	$.051^{***}$	.346	6834
	(.018)		
Rural to urban	$-.088^{***}$	.340	5776
	(.022)		
Urban to urban	$.051^{***}$	.445	2351
	(.019)		

Note. subsamples using rural (urban) migrants from rural (urban) areas. Dependent variable is log weekly wage. Explanatory variables are gender, age, years of education, squares of years of education, marital status, and household related subgroup dummy. All individual explanatory variables are highly significant at 0.1% level. This table focuses on each coefficient of exogenous variable on migration decision: household related subgroup dummy. Numbers in parentheses are standard errors. Source: Thailand Labor Force Survey, 1994-1996

*** significant at 1 % level.

Table 6: Relationship between the reason, migration streams, and duration

Subsample	*Short*	*Long*	Total	% of *Long*
Rural to rural	30708	10965	41673	26.3%
Job-seeking	24547	7841	32388	24.2%
Household relations	6161	3124	9285	33.6%
Urban to rural	5418	1416	6834	20.7%
Job-seeking	4593	1175	5768	20.4%
Household relations	825	241	1066	22.6%
Rural to urban	3935	1841	5776	31.87%
Job-seeking	3603	1689	5292	31.9%
Household relations	332	152	484	31.4%
Urban to urban	1768	583	2351	24.8%
Job-seeking	1189	335	1524	22.0%
Household relations	579	248	827	30.0%

Note. First column shows the migration streams and the reason for migration by its migration streams. Column two shows the number of observations in a short duration: 0, 1, and 2 years. Column three shows the number of observations in a long duration: 3 and 4 years. Column four also shows the number of whole observations. Share of long duration belongs to the last column. Source: from Thailand Labor Force Survey, 1994-1996

Table 7: Coefficients on household related subgroup dummies in wage equations of *short* and *long* cohort in the rural labour market

Subsample		Γ	Adjusted R^2	Obs.
Rural to rural			.436	41673
	Short	$-.035^{***}$		
		(.006)		
	Long	$-.064^{***}$		
		(.008)		
Urban to rural			.346	6834
	Short	$.032^{**}$		
		(.019)		
	Long	$.044^{***}$		
		(.040)		

Note. Dependent variable is log weekly wage. Explanatory variables are gender, age, years of education, square of years of education, marital status, and household relations migrants dummy. All individual explanatory variables are highly significant at 0.1% level. This table also focuses on each coefficient of exogenous variable on migration decision: household relations migrants dummy. Numbers in parentheses are standard errors. Source: Thailand Labor Force Survey, 1994-1996

*** significant at 1 % level.

** significant at 10 % level.

Table 8: Coefficients on household related subgroup dummies in wage equations of *short* and *long* cohort in the urban labour market

Subsample		Γ	Adjusted R^2	Obs.
Rural to urban			.340	5776
	Short	$-.104^{***}$		
		(.027)		
	Long	$-.063^{**}$		
		(.034)		
Urban to urban			.446	2351
	Short	.028		
		(.021)		
	Long	$.102^{***}$		
		(.028)		

Note. Dependent variable is log weekly wage. Explanatory variables are gender, age, years of education, square of years of education, marital status, and household relations migrants ' dummy. All individual explanatory variables are highly significant at 0.1% level. This table also focuses on each coefficient of exogenous variable on migration decision: household relations migrants ' dummy. Numbers in parentheses are standard errors. Source: Thailand Labor Force Survey, 1994-1996

*** significant at 1 % level.

** significant at 10 % level.

Table 9: Coefficients on *Short* dummies in wage equations by the reason for migration in the rural labour market

Subsample	Γ_S	Adjusted R^2	Obs.
Rural to rural		.435	41673
Job-seeking	.004		
	(.006)		
Household relations	$-.019^{***}$		
	(.007)		
Urban to rural		.346	6834
Job-seeking	$.085^{***}$		
	(.018)		
Household relations	$-.044$		
	(.040)		

Note. Dependent variable is log weekly wage. Explanatory variables are gender, age, years of education, square of years of education, marital status, and *Short* experience dummies. All individual explanatory variables are highly significant at 1% level. This table also focuses on each coefficient *Short* experience dummies. Numbers in parentheses are standard errors. Source: Thailand Labor Force Survey, 1994-1996

*** significant at 1 % level.

Table 10: Coefficients on *Short* dummies in wage equations by the reason for migration in the urban labour market

Subsample	Γ_S	Adjusted R^2	Obs.
Rural to urban		.353	5776
Job-seeking	$-.114^{***}$		
	(.011)		
Household relations	$-.165^{***}$		
	(.028)		
Urban to urban		.445	2351
Job-seeking	$-.062^{***}$		
	(.021)		
Household relations	$-.031$		
	(.024)		

Note. Dependent variable is log weekly wage. Explanatory variables are gender, age, years of education, square of years of education, marital status, and *Short* experience dummies. All individual explanatory variables are highly significant at 1% level. This table also focuses on each coefficient of *Short* experience dummies. Numbers in parentheses are standard errors. Source: Thailand Labor Force Survey, 1994-1996

*** significant at 1 % level.