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Abstract

In this paper I examine whether change occurred in migration decision of workers. Observation from Thai data shows that migration to Bangkok is mostly pursued by young workers despite uncertainty attributed to urban wages. The urban wage uncertainty is related to signals for unobserved ability of potential migrant. Empirical results from Thai data show that learning about own ability worked as a motive for relocation to Bangkok in the pre-crisis but not in the post-crisis period. I also show

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that the component of such structural change in the relocation behavior is mostly attributable to an increase in the noise variance of urban wage signals after the crisis.

1 Introduction

Various issues regarding the human capital investment aspects of labor migration have often been discussed. Rural to urban migration is inevitably accompanied with occupation change from agriculture to various kinds of urban jobs. People move to cities to gain information about job opportunities, or acquire skills. The question I address in this paper is whether rural-to-urban migration in developing countries are motivated by learning about own ability. Relocation and experience in urban jobs make the workers' perception on their own ability more accurate, and increases the workers' lifetime income through job choice later in life.

Human capital aspects of migration arise primarily from skill acquisition. This is often discussed in job turnover literature, e.g., Jovanovic and Nyarko (1997), Miller (1984). Skill acquisition raises the lifetime income of workers and so motivates them to move earlier in life. Although learning skills have important implication to migration in developing countries, this feature of migration in is not the main concern here.

Human capital aspects of labor mobility arise also from gaining information on job opportunity in urban areas [see, e.g., Jovanovic (1978), Flinn (1986)]. Participating in urban labor market simply inform the worker better about job opportunity, which is scarce information in their origin districts. More importantly, workers also have more chances to find out about suitability between his/her innate attributes or abilities, and different kinds of jobs. Since returns to own ability in the urban labor market are only vaguely known to workers ex-ante, they gradually learn from experience and become more sure about it. Such aspect of labor mobility is called 'job as experience good by Nelson(1970) in the context of occupational change. It is equally important in inter-regional mobility in developing countries. Because most occupations are concentrated in urban areas, relocation is the only way for workers to gain job experience.

Mobility is particularly intensive among young workers. This coincides with stylized facts reported in turnover literature [Topel and Ward (1992), Light and McGarry (1998), Kean and Wolpin (1997)]. Most frequent mobility among the young is consistent with the human capital nature of migration. Learning is pursued using wage signals that workers receive from urban jobs. They update their subjective perception of their own ability in Bayes' fashion, and accumulation of knowledge is captured by the decrease in the variance of initial perception. The wage signals consist of two factors: one is the portion that depends on the workers' ability, and the other is the job specific factors, or noise. As the wages become more dependent on ability, such signals enable more efficient learning. Wages become more uncertain at the same time, reflecting heterogeneity among workers. This is consistent with our observation from Thai data. Among migrant workers to Bangkok, wages are more diverse for young workers given other observable attributes.

I show first that the accuracy of urban wage signals positively explain the migration decision. Then I test the hypothesis using individual migration data from Thailand. I explain the intensive mobility of young workers on the basis of learning about their own ability. I have shown in Kimura (2001) that migrant wages in Bangkok reflect unobserved attributes more accurately for younger migrants, and that the accuracy of wage signals on unobserved ability positively explains the relocation decision from non-Bangkok regions. In the same line of analysis, this paper is aimed at examining the structural change migration caused by the financial crisis in 1997. I use two subsets of individual relocation data from Thailand around the financial crisis, 1994 to 1996 and 1998 to 2000.

2 Data and Facts on Migrants' Wage

2.1 Data Description

We exploit the Labor Force Survey (LFS), NSO, Thailand, 1994-96 and 1998-2000. From 1984-97, the survey was conducted in February, May, August, and also in November since 1998. The scope of the survey is over 180 thousand people or around 50 thousand wageworkers across the whole country. From those surveys, we exploit round 1 and round 3 of the survey, which contain relatively abandoned information. Further, we use two subset of the data from periods around the financial crisis, 1994 to 1996 and 1998 to 2000.

The survey data provides worker's wage by type (daily, weekly, monthly), number of work-days per week, occupation, industry, and sector in which the worker's job is affiliated, worker's attributes such as sex, age, education, marital status, and so on. Concerning migration, it provides previous place of residence down to the village level, persistence of residence or working experience in the current place.

2.2 Ages at Migration and Urban Wage Distributions

Migrant laborers that move into the Bangkok Metropolis from non-Bangkok are generally young. From the Labor Force Survey, it is observed that migrants are the youngest among the labor force at the origin. Figure 1 and 2 illustrate this point for both pre-crisis and post-crisis periods.

[Figure 1. Age profiles of workers by migration status, 1994-1996]

[Figure 2. Age profiles of workers by migration status, 1998-2000]

The figures show the age distributions of workers by migration status. Mig_status=1,2,3 represents Bangkok migrant (length of stay up to eight years), Bangkok native workers (more than eight years), and non-Bangkok workers respectively. The sample covers wage workers, self-employed in both sexes, with wage or profit entries. Ages are in terms of age-at-migration for mig_status=1, current ages for 2 and 3. It can be seen from the figures that migrant labor force consists of considerably young cohorts compared to the other groups. For both periods, ages at migration of Bangkok migrant workers hits the peak at ages around

17 and rapidly decreases towards age 40, while peak ages are around 30 for Bangkok native workers and non-Bangkok workers. Migrant age distributions suggest that they tend to move slightly after finishing from certain level of schooling, such as fourth or sixth grade of elementary school, lower high school, and high school. The frequency was the highest for fourth graders followed by sixth graders. Accordingly, they are most likely to relocate at ages slightly over 10,12,15 and 18.

Non-Bangkok workers in those age cohorts are most likely potential migrants also when compared with other cohorts in the origin. Figure 3 and 4 show the rate of migration to Bangkok by ages, from the rest of the country, for pre-crisis and post-crisis period respectively. The migration rate is taken as the ratio between number of workers relocated in the past four years by ages at the move and number of workers by current age. Peak ages of mobility are around 18 and the same for both pre-crisis and post-crisis periods. Difference between the two periods is while the rate is 5.2 per cent among the workers at the origin, at the peak age in the pre-crisis, it declines to 0.75 per cent in the post-crisis period, reflecting deterred migration. The relocation decreases with workers age and almost ceases at age 40 in the both periods.

[Figure 3. Rate of out-migration by age, 1994-1996]

[Figure 4. Rate of out-migration by age, 1998-2000]

An important restriction in the following figures is that our data being cross-sectional, the migration age distribution doesn't necessarily mean first time mover. Even though we cannot distinguish between first-time and more experienced migrants, the distribution exclusively for first-time migrants would be even younger than shown in the figures.

The wage prospects of young migrants pose a puzzle. While mean wages at the destination are higher for elder migrants at ages of relocation, uncertainty of wages measured by diversity are greater for the young. This is illustrated in the next regression which shows the relation between those within-group mean and diversity of wages, and ages at migration for both the pre-crisis and the post-crisis periods. The attribute groups of migrants, h's are defined by sex, ages at migration, years of schooling[1]. For the pre-crisis period,

$$\begin{aligned}
E^h[\ln w_i^{ar}] &= .18 * sex + .0076 * migage_i + .033 * yr_sch + .018 * exprnce_i \\
&\quad (.0076) \quad (.00069) \qquad\quad (.0024) \qquad\quad (.002) \\
adj.R^2 &= 0.64
\end{aligned}$$

$$\begin{aligned}
sd^h[\ln w_i^{ar}] &= .008 * sex - .0011 * migage_i - .0017 * yr_sch + .0021 * exprnce_i \\
&\quad (.0058) \quad (.00042) \qquad\quad (.0013) \qquad\quad (.0025) \\
adj.R^2 &= 0.067
\end{aligned}$$

[1] Year/round dummies, origin district dummies are included in the estimation, but parameters are suppressed. Standard errors are reported in parenthesis. Heteroschedastisity by individual and cluster effect by origin district are allowed in calculation of standard errors.

For the post-crisis period,

$$E^h[\ln w_i^{ar}] = .17 * sex + .018 * migage_i + .066 * yr\_sch + .0065 * exprnce_i$$

$$(.0113) \quad (.004) \quad (.000075) \quad (.0040)$$

$$adj.R^2 = 0.72$$

$$sd^h[\ln w_i^{ar}] = -.030 * sex - .0012 * migage_i + .0053 * yr\_sch + .0062 * exprnce_i$$

$$(.0056) \quad (.00037) \quad (.00085) \quad (.0039)$$

$$adj.R^2 = 0.071$$

Wages are in therms of weekly log wage conditional on working experience in Bangkok, so that those represent estimated wages on arrival. For both the pre-crisis and the post-crisis periods, mean wages are higher for migrants at higher ages, and within-group diversity of wages are higher for those at younger ages.

Decreasing wage uncertainty in the destination could also be viewed as natural outcome of workers' behavior. Rural workers are reported to repeatedly relocate to Bangkok while holding jobs at home. Especially agricultural workers called 'circular migrants' or 'seasonal labor' often relocate temporally during the agricultural slack season. They acquire information on job opportunities in Bangkok through those repeated relocation experiences, and aged workers are more certain about their prospect at the destination. From the young workers' point of view, a benefit from relocating is to find out about their future prospect at the destination. Accordingly, our scope is on relatively long term migrants. the number of Bangkok migrants by persistence of stay is distributed as shown in Figure 5.

[Figure 5. Length of stay profile of migrant workers]

Circular migrants whose length of stay is less than 1 year is not the majority. Although the number of workers decrease with the length of stay, most of them continue to stay through the course of the year and try to remain in Bangkok regardless of agricultural seasons.

3 Reference group, Information Set

We suppose potential migrants observe other migrants and their own past wage distribution on which they base their relocation decision. The decision to make is whether to move to Bangkok at their current age and their reference group, the source of wage information is past migrants who moved at similar ages as the decision maker. The standards that distinguish between reference groups are sex, ages at migration, and years of schooling. Pool of potential migrant in non-Bangkok are also grouped by those attributes, except that ages are in terms of current age. Our basic supposition is that non-Bangkok workers' information is the wage distribution of corresponding reference group.

Prior to relocation, non-Bangkok workers' information set includes their own attributes, sex, age and years of schooling, and their current place of residence. For information available to the workers, they will control from the past migrant wage they observe. Additionally, we suppose Bangkok migrants' years of working experience in the destination are also observable.

As mentioned earlier, one problem with our data is that it does not identify when migrants acquire information on a particular job. In case they only move after they have fixed or have obtained reliable information on a particular job opportunity, destination earnings distribution or uncertainty in the destination will no longer be relevant to the relocation decision. That corresponds to O'Connell's 'wait and see' migration. Banerjee(1983) reports for the case of India, around one half of rural-to-urban migrants have pre-fixed jobs at the destination before they actually move. With respect to the Thai labor market, it is widely recognized that they tend to obtain at least vague information on job opportunity before they move, from acquaintances in the destination. Sometimes it can be the case that they are informed of a particular post. Even so, we maintain the assumption that information available to a worker is the wage distribution they confront with, rather than a particular job. Our data set provides number of migrants by reasons of relocation. One evidence favouring our supposition is that among economic reasons for Bangkok migrants with earnings observation, the overwhelming majority, 88 per cent was 'job search', and simple job-related reasons without job turnover was less than 3 per cent. The answer 'job search', however, does not necessarily mean that they did not search in the origin. The most likely situation, when they can not avail of a particular post at the move, would be that they become dependent on some acquaintances or get assigned to a temporal job until they settle down. The destination wage distribution implies such situation in the period after the relocation.

4 Theoretical Framework

In this section, we demonstrate a framework to discuss relation between earnings uncertainty and worker's choice of regions, following Johnson(1978). The source of lifetime earnings uncertainty is generated from the fact that workers' innate ability is heterogenous, and that, ex-ante, they only know vaguely about their own. They can gradually become sure about own ability through learning from wage signal.

A potential migrant who is currently residing in rural areas, and has lifetime of two periods. The worker will choose his / her carrier path from the two groups of jobs, one in the urban area, and the other in rural. Each job group has no explicit correspondence with industries or occupations. Those job groups are, so to speak, 'Bangkok job', stretching over various industries and sectors, while 'rural job', which is supposed to be agricultural for the most part. Following the discussion in the preceding section, the wage signals are assumed to become observable only after the worker moved to the region and engaged in a job.

Those two groups of jobs have the same mean and different degrees of earnings uncertainty. The uncertainty comes from two factors: the heterogeneous return to migrants' attributes or ability of the worker (θ) and worker-job match specific productivity, or the worker's job-specific preferences or ability (u_j). u_j makes a noise in learning process.

Ability of a worker, in general, has multiple dimensions. I implicitly consider θ^k; k represents the dimensions of the workers' ability. Different dimensions of ability matter in different tasks; rewards and target parameters to be learned depend on the dimensions in question. In our context, engaging in non-Bangkok, agricultural jobs require relatively small number of certain ability dimension, such as physical toughness, knowledge about crops or weather. Bangkok jobs will require other, possibly greater number of ability dimensions[2]. In this paper, however, I keep the question of ability dimensions implicit for simplicity. Thereafter, reword to ability is just denoted θ.

Log of wage return from jobs in region j, $j = 1, 2$, is written as

$$\ln w_j = a + b_j\theta + u, \tag{1}$$

where $j = 1$ stands for Bangkok job, $j = 2$ for rural job. a represents the mean return which is common to both regions, b_j is attributes of the worker such as sex, age, education. a and b_j are known to the worker. On the other hand, uncertainty of return is generated from two unknown factors, θ and u_j, of which the worker considers as random variables with distribution $\theta\tilde{}N(0, \sigma_\theta^2), u_j\tilde{}(0, \sigma_{uj}^2)$. Thus, the distribution of earnings from jobs in region j, $g(\ln w_j)$ has a mean $E(\ln w_j) = a$, and variance $\sigma_j^2 = b_j\sigma_\theta^2 + \sigma_{uj}^2$. We suppose $\sigma_1^2 > \sigma_2^2$, that is, urban

[2]In a context of skill learning, Jovanovic and Nyarko(1995) incorporates multi-dimensional target parameter. In such a case, the multi-dimensionality is interpreted as task complexity.

job has the greater return diversity. Let us consider a worker who experienced one urban job in the first period. He receives one realization from $g(\ln w_1)$, $\ln w_1 = a + b_1\theta + u_1$. The estimate of θ after observing an information from job 1 will become

$$\begin{aligned} E[\theta|\ln w_1] &= \frac{b_1\sigma_\theta^2}{b_1^2\sigma_\theta^2 + \sigma_{u1}^2}(\ln w_1 - a) \\ &= \beta(\ln w_1 - a), \end{aligned} \tag{2}$$

where β represents precision of θ after he experienced job 1. Because θ is common to both *regions*, $\log w_1$ and $\log w_2$ are interdependent. Expected return from job 2 in the second period after the experience in job 1 in the first period is

$$E[\ln w_2|\ln w_1] = a + b_2\beta(\ln w_1 - a) + u_2 \tag{3}$$

The worker will move to *job* 2 if $E[\ln w_2|\ln w_1] > a$, that is, if expected earnings in *job* 2 (conditional on observation of job 1 earnings in period 1) exceeds that of *job* 1. Let L_1 denote expected lifetime earnings when *job*1 is chosen first,

$$\begin{aligned} L_1 &= a + \frac{1}{2}\left\{\ln w_1 + E\left[\ln w_2|\ln w_1 > a\right]\right\} \\ &\quad \text{or} \\ L_1 &= a + \int_{-\infty}^{a} \ln w_1 g\left(\ln w_1\right) + \frac{1}{2}E\left[\ln w_2|\ln w_1 > a\right] \end{aligned} \tag{4}$$

Using that $g(lnw_1)$ is normal, L_1 becomes

$$\begin{aligned} L_1 &= a + \left[\frac{a}{2} - \frac{\sigma_1}{\sqrt{2\pi}}\right] + \left[a + \frac{2b_2\beta\sigma_1}{\sqrt{2\pi}}\right] \\ &= 2a + (b_2\beta - 1)\frac{\sigma_1}{\sqrt{2\pi}}, \end{aligned} \tag{5}$$

In equation (5), if $b_2\beta > 1$, $L_1 > 2a$. Since $2a$ is expected lifetime income when the worker doesn't change jobs in the second period, the second term represents the surplus from allowing to change jobs.

$$L_2 = 2a + (1 - b_1\gamma)\frac{\sigma_2}{\sqrt{2\pi}} \tag{6}$$

where $\gamma = \frac{b_2\sigma_\theta^2}{b_2^2\sigma_\theta^2+\sigma_{u2}^2}$, which is the counterpart of β in case *job* 2 is chosen first. The worker will choose the first job depending on the inequality between L_1 and L_2. From equation (5), (6),

$$L_1 - L_2 = \frac{1}{\sqrt{2\pi}}[(b_2\beta - 1)\sigma_1 + (b_1\gamma - 1)\sigma_2] \tag{7}$$

When $\sigma_2 > \sigma_1$, $L_2 > L_1$.

To conclude, choosing riskier *job* in the first period makes his lifetime income greater. In the context of rural-to-urban migration, moving to urban area in the early stage of life, the migrant could gain his lifetime income compared to the case he spends his early days in the origin. Of course moving to urban area will increase earnings because of larger level of mean wage in the urban area. But the focus here is on the effect of uncertainty and learning, and it is shown that in the absence of mean wage difference, urban area which gives greater earnings uncertainty is advantageous for young workers. [3]

5 Specification, Estimation

For the empirical specification, we make several simplifying assumptions. Firstly, potential migrants base their migration decision on their on-arrival wage distribution. That does not mean that they are myopic, instead, they follow the strategy described in the previous section. They choose regions to maximize their lifetime earnings, using the information only from the first period. Secondly, migration decision is not nested, in a way that decisions are two-fold, to-move-or-not-to-move and to which region to go. We focus on migration between only two areas, the Bangkok Metropolis and the rest of the country and assume that the only decision the workers make is whether or not to move to Bangkok. The third is that the migrants observe information on a particular job only after moving to the destination. Suitability of this assumption may be somewhat questionable considering the case of India mentioned earlier. However, the assumption, no pre-fixed urban job, is considered to be relatively suitable for the sample of the analysis in this section for the following reasons. The sample is restricted to the workers with relatively low education, junior-high school graduates and lower from the sample size. In addition, under these assumptions, the sort of knowledge the potential migrants would need is information about jobs

[3] Jovanovic, Nyarko(1997) derive similar result.

in Bangkok as a whole, rather than jobs on particular industries or occupation group.

Finally, we assume that potential migrants put their basis of migration decision on the earnings information of actual Bangkok migrants with similar attributes as their own, i.e., same sex, similar ages and education. The on-arrival wage distribution of those past migrants will be the observation from which the potential migrants infer their own. We let the variance of expected on-arrival log wage of migrants represent the risk associated with migration, or diversity of signals concerning the return to attributes.

For the assumptions above, the focus is on distribution of wages on-arrival of the past migrants. Since the wage data entry is in terms of current wage of migrant workers with various working experience in Bangkok, the first step is to subtract experience effects from their wages to estimate their wages at the time they moved to Bangkok. The current log wage of migrant i can be specified as

$$\ln w_i = X_i\beta + \sum_k d_i^k + \mu_i + \sum_{l=1}^{75} origin_i^l + \sum_{m=94.1}^{96.3} year^t + \varepsilon_i, \tag{8}$$

where X_i includes attributes of Bangkok migrants except educational attainment, namely sex_i age_i, age_i^2, and working experience in Bangkok, $exprnce_i$, $exprnce_i^2$. d_i^k represents education dummies for each education group k, $k = 1, ..., 9$. $k = 1, ..9$ represents no education, years of schooling $2, 4, 6, 9, 12, .14, 16$ and 18 respectively. μ_i is unobservable individual ability, and ε_{ij} is heterogeneity of reward specific to worker-job match which is normally distributed with mean 0.

Origin fixed effects, for which the origin dummies are intended to control, are considered to arise from the difference in the distance from the origin. In addition, possible origin fixed effect could arise, for instance, from Bangkok information acquired through neighbors in the origin villages, i.e., neighborhood effect. Year/round dummies $year^t$, $t = 94.1, 94.3,$ ... ,$96.1, 96.3$ ($98.1, 99.3$,...,$2000.1, 2000.3$ in post-crisis data subset) represent each years rounds of survey respectively. Round 1 corresponds to the survey held in February, and round 3 to August.

Since $E[\mu] \neq 0$ and μ is not available from the data set, variation of μ will be included in the error term. μ is also correlated with d_i^k. In order to avoid the bias caused by omitted μ, within-group estimation is applied to equation (8). Specifically the following equation is estimated for migrant workers i with working experience less than 5 years after the relocation.

$$\begin{aligned} \ln w_i - \overline{\ln w_i}^k &= (X_i - \overline{X_i}^k)\beta + \sum_k (d_i^k - \overline{d_i^k}^k) \\ &+ \sum_{l=1}^{75} (origin_i^l - \overline{origin_i^l}^k) + \sum_{m=94}^{96} (year_t - \overline{year_t}^k) \\ &+ (\mu_i - \overline{\mu_i}^k) + (\varepsilon_i - \overline{\varepsilon}^k) \end{aligned} \tag{9}$$

Upper bars represent means by education group k. The whole observation is divided by education group k, and all the variables are converted into deviations from means within education group k. Then, $d_i^k - \overline{d_i^k}^k = 0$ for all k. Assuming unobservable ability is symmetrically distributed within each k, $E[\mu_i - \overline{\mu_i}^k] = 0$ for all k, and $\mu_i - \overline{\mu_i}^k$ is randomly distributed. Also, $E[\varepsilon_i - \overline{\varepsilon}^k] = 0$ and $\varepsilon_i - \overline{\varepsilon}^k$ is randomly distributed. Therefore, OLS estimate of β will be unbiased.

With $\hat{\beta}$ in hand, the next step is to estimate parameters of expected wage distribution confronted by each potential migrants in terms of wage distribution at the time each of them moved to Bangkok. Potential migrants are assumed to base the criteria of their decision on mean and variance of expected Bangkok wage, which they infer from wage observations of past migrants. Further, we assume that they consider those variables to depend on observable attributes. Since they know their own attributes, they only need to observe wages of past migrants with attributes similar to themselves. In order to control attributes of migrants, we take means and variance of past migrants' wage observation by attribute group h.

$$E^h[\ln w_i^{ar}] = E^h[\ln w_i - \hat{\beta}(exprnce_i + \sum_{l=1}^{75} origin_i^l + \sum_{m=94}^{96} year^m)]. \qquad (10)$$

The portion of wage difference between groups attributed to workers' sex, age and educational attainment remains uncontrolled, and the mean is taken by attribute group instead. Rural workers are considered to have different (implicit) reservation wage for migration depending on their attributes. They know their own attributes and take it in account when they make a decision. For a particular group with high reservation wage, for instance, expected Bangkok wage associated with migration must be also high for them. In this regard, the effect of their attributes on expected on-arrival wage must remain included in the information they observe. Similarly, for diversity of expected on-arrival log wage,

$$sd^h[\ln w_i^{ar}] = sd^h[\ln w_i - \hat{\beta}(expence_i + \sum_{l=1}^{75} origin_i^l + \sum_{m=94}^{96} year^m)], \qquad (11)$$

where $sd^h[\cdot]$ stands for standard deviation. For the argument described above, the contribution of worker attributes remain in inter-group wage difference, but completely controlled within attribute groups. Those parameters of on-arrival wage distributions, $E^h[\ln w_i^{ar}]$ and $sd^h[\ln w_i^{ar}]$ are the bases of decision for potential migrants affiliated to each h. An important point to notice is that since we have controlled the effect of experience, year and origin, as seen from equation (9), the remaining variation in $E^h[\ln w_i^{ar}]$ and $sd^h[\ln w_i^{ar}]$ is that from variation in ability μ_i and job specific noise ε_i. Particularly, $sd^h[\ln w_i^{ar}]$, seen from a worker in a specific attribute group, represents the sum of variation in individual ability and job specific noise within that group. Of those two sources of variation, we assume the extent to which noise affect wages is common to all attribute groups. This assumption is the counterpart of the one in the theoretical framework, in which we supposed the job specific noise is common to both Bangkok and non-Bangkok jobs. With this assumption, $sd^h[\ln w_i^{ar}]$

serves as signal for the migrant workers to refer to their own ability. Finally, migration equation that explains migration decision by mean and variance of expected on-arrival Bangkok wage is estimated with Probit estimation. Let us assume unobservable reservation wage $\ln w_i^*$ for each (potential) Bangkok migrant such that

$$\begin{cases} mig_j = 1 \ \ when \ \ \ln w_j \geq \ln w_j^* \\ mig_j = 0 \ \ otherwise \end{cases},$$

where sample j includes Bangkok migrants with period of stay less than 5 years, and rural workers, who choose to stay in the origin, both of age. Sample i includes Bangkok migrants within the past five years as described above. We suppose migration decision is made according to the following migration equation,

$$\begin{aligned} mig_j &= \zeta\, E^h[\ln w_j^{ar}] + \eta\, var^h[\ln w_j^{ar}] + X_j\beta \\ &\quad + \sum_{t=94.1}^{96.3} year^t + \sum_{m=1}^{76} origin_j^m + \xi_j. \end{aligned} \tag{12}$$

Migration equation (12) explains the propensity to migrate by parameters of expected wage distribution. Our focus is on η, the parameter of wage uncertainty on arrival. Mean on arrival wage is included in the equation in order to control the level effect on wage diversity. Prediction of the theory is that the parameter estimates are positive both for $E^h[\ln w_i^{ar}]$ and $sd^h[\ln w_i^{ar}]$. It must be noted that the difference of those parameters is captured in terms of difference between attribute groups. On the other hand, in the theoretical framework discussed in section 3, we compared diversity of wage distribution by region, and concluded that workers will choose regions with greater wage diversity. This means that we implicitly assume that any non-Bangkok wage is constant agricultural wage that is unique to each attribute groups. Thus, for groups with greater diversity of expected Bangkok wage, it is more likely that the diversity is greater in Bangkok than at the origin.

X_j are attributes of workers, namely, sex, age, years of schooling. Year/round dummies become $\sum_{t=98.1}^{00.3} year^t$ for post-crisis sub-sample. Origin dummies are intended to capture mainly two things. The first is the difference in distance to Bangkok. The other is neighborhood effect of migration. Storetton (1983) reports on Philippines construction industry that the origins of migrant workers in Manila are concentrated in few particular districts. This is because of information flows between neighbors in the origin.

6 Empirical Results

The parameter estimates of migrant wage equation (9) for both pre-crisis and post-crisis periods are shown in Table 1. There is no qualitative change around the two periods, except that number of observation in post-crisis period is around half the size of that in pre-crisis, partly because of deterred mobility to Bangkok. The decrease of the sample size is also because number of wage observation decreased due to increased unemployment rate among migrant workers in post-crisis period.

[Table 1. Within-group estimates of wage equation parameters]

The coefficients are used to yield experience-controlled Bangkok wage distributions by attribute groups, as described in equation (10) and (11). The calculated parameters of Bangkok wage distributions for each attribute groups are shown in table 2 in comparison between pre-crisis and post-crisis periods. Table 2(a) is for male migrants with pre-crisis period in the left half, and post-crisis period in the right. Table 2(b) is for female migrants.

In comparison by ages at migration, the conditional Bangkok wage diversity is the greatest among those who moved in their teens and twenties, while mean wages are greater at higher ages of relocation. Such relations are particularly obvious for those with educational attainment of four, six and nine years, which are core group composing migrant labor force. Those observations are consistent with our prediction that the degrees in which wages reflect unobserved heterogeneity among individuals are greater for younger migrants, the most likely cohort or mobility.

Comparing between two periods, in most cases, destination wage diversity is increased in post-crisis period or otherwise unchanged. The degree of uncertainty is remarkably magnified especially for primary school graduators (with six years of schooling). The within-group wage variations, in our framework, consist of variation in return to unobserved attributes of workers within the group, and noise variance in wage signal. Although we cannot distinguish between those factors from the data, it is conceivable that job specific factors which are accounted as noises, especially difference between industries contribute more in the post-crisis period. Behrman, Deolalikar, Tinakorn and Chandoevwit (2001) reports that adjustment of employment in post-crisis Bangkok was attained mostly in construction industry. Expanded difference in inter-industry prospects are considered to have increased the contribution of noise variance in the within-group wage diversity.

[Table2(a) Parameters of Bangkok wage distributions
by attribute group, male]

[Table2(b) Parameters of Bangkok wage distributions
by attribute group, female]

On the basis of the destination wage distribution parameters shown in table 2, I estimate migration equation as described in equation (12). The parameter estimates are shown in table 3 for 1994-1996 and 1998-2000.

[Table 3. Parameter estimates of migration equation]

The sample for migrants is limited to attribute groups with at least ten observations in order to avoid small sample bias. Also for stayers, attribute groups that correspond to migrant sample is included. Within the sample, migration rate from all over the country into the Bangkok Metropolis is 1.10 per cent in period 1994-1996 and 1.04 per cent in 1998-2000. For 1994-1996, the parameters of wage diversity are positive and significant, supporting the prediction of the theory. The other parameters are also plausible and significant. For 1998-2000, the effects of mean wage on relocation is no longer significant, and the wage diversity negatively affect relocation.

In our Bayesian framework, any change in the learning environment is attributed to the change in variance of subjective belief, noise variance of the signal, or change in the mean of subjective belief itself. Employment structure in Bangkok have largely changed in the post-crisis period and it is conceivable that rural workers think the relevant ability have changed. That is especially likely for young ones with little relocation experience in the past. This sort of change in the situation corresponds to the change in mean and variance of subjective belief.

Likewise, as described in table 2, increase in variance of urban wage signals at least partly reflects the magnified noise variance. Although workers cannot distinguish variance of wage signal between the portion that reflecting heterogeneity and that come from noise, the deterred migration is presumably because of the decline in the reliability of urban wage as signals for return to unobserved attributes.

Additionally, workers' risk aversion parameters that are not incorporated in our framework might have also changed after the crisis. In that case, the uncertainty of urban wages that reflects unknown attributes works against the relocation. Even without change in degrees of risk aversion, non-Bangkok workers with liquidity constraint refrain from moving to Bangkok to take risks that come from magnified uncertainty in urban wages.

7 Conclusion

In this paper, we discussed the relation between rural-to-urban migration decision and the risk of migration associated with wage diversity in the destination, along with examining the structural change in the relocation decision around the financial crisis in 1997.

Observation from Thai data shows extensive mobility of young cohorts into Bangkok for whom destination wage uncertainty is greater and mean is lower compared to migrants at higher ages. The baseline of analysis is the relevance of urban wage diversity as a motive for relocation. For workers who learn about their own ability that is unknown ex-ante, greater diversity of urban wage can be favorable. Wages from such diverse distribution are more accurate signal for their unobserved heterogeneity. This enables greater lifetime income through regional/occupational choice in the later stage of life.

Consistent with such argument, conditional wage diversity is the greatest among young workers in their teens and twenties, the cohort that compose the core group of migrant labor force. Subject to migration, urban wage diversity as a proxy for degree to which wages accurately reflect unobserved heterogeneity positively explains the relocation decision of workers to Bangkok in the pre-crisis period. The role of wage signal accuracy in relocation decision, however, is not found relevant in post-crisis period. After the crisis, our results show that conditional wage diversity negatively affect migration, and even mean wages are no longer relevant.

Those changes in migration motives owe largely to the change in learning environment. Conditions in Bangkok labor market have changed around the financial crisis, concerning job opportunity for migrant workers. Such change is thought to have risen through changes in job creation and destruction, or even without change in job opportunity itself, through changes in relevant attributes that affect urban wages. Those changes increased the extent of noisiness of urban wage signal. In other words, reliability of urban wages as signals are considered to have declined after the crisis.

Along with that, workers' prior perception have also changed, as well as its vagueness being magnified, on their return to unobserved ability in urban jobs. Although it is not incorporated in our framework, changes in workers' attitude towards uncertainty have affected their migration behavior.

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Table 1. Within-group estimates of wage equation parameters[4]

	(1)			(2)	
	1994-96			1998-2000	
	coef.	t		coef.	t
sex_i	0.1652	7.54		0.103	2.71
age_i	0.0403	7.18		0.0360	3.61
age_i^2	-0.000505	-6.15		-0.000441	-3.1
$exprnce_i$	0.0320	5.01		0.0463	4.39
$year_{94.1}$	-0.0567	-1.76	$year_{98.1}$	0.35	0.39
$year_{95.1}$	-0.0440	-1.44	$year_{99.1}$	0.439	0.49
$year_{96.1}$	0.143	5.26	$year_{00.1}$	0.323	0.24
$year_{94.3}$	-	-	$year_{98.3}$	0.514	0.57
$year_{95.3}$	0.0896	2.91	$year_{99.3}$	0.446	0.49
$year_{96.3}$	0.206	7.54	$year_{00.3}$	-	-
$origin_{1-76}$	suppressed		$origin_{1-89}$	suppressed	
intercept	0.0296	0.25		0.0239	0.26
number of obs.	2697			1426	
R squred	0.482			0.461	

[4]Note: Parameters are estimated by weighted OLS. In order to control ability bias, all the variables are converted to deviation from education group mean to yield within-estimator (see equation (9)). Heteroschedastisity of residuals are allowed in calculating standard errors. Coefficients of origin dummies are suppressed to save space.

Table 2(a) Parameters of Bangkok wage distributions by attribute group, male

		1994-1996			1998-2000		
yr.sch.	mig. age	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.
0	16-18	6.156	0.337	6	6.279	0.619	7
4	13-15	6.011	0.331	9	6.424	0.205	5
	16-18	6.346	0.223	12	6.594	0.402	8
	19-21	6.404	0.166	24	6.875	0.215	14
	22-24	6.246	0.392	28	6.574	0.360	11
	25-27	6.396	0.225	57	6.617	0.633	11
	28-30	6.313	0.501	55	6.597	0.689	32
	31-33	6.223	0.361	32	6.760	0.364	27
	34-36	6.369	0.178	17	6.794	0.385	19
	37-39	6.405	0.236	21	6.776	0.259	22
	40-42	6.415	0.274	10	6.743	0.390	16
	43-45	6.428	0.148	8	6.795	0.334	10
6	13-15	6.281	0.297	159	6.601	0.412	56
	16-18	6.357	0.313	239	6.669	0.476	119
	19-21	6.391	0.310	175	6.740	0.460	97
	22-24	6.423	0.279	78	6.767	0.433	82
	25-27	6.465	0.261	32	6.790	0.408	51
	28-30	6.411	0.152	8	6.823	0.347	22

Table 2(a) ctnd.

yr. sch.	mig. age	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.
9	13-15	6.352	0.287	34	6.598	0.749	46
	16-18	6.399	0.210	86	6.798	0.346	66
	19-21	6.431	0.160	20	6.832	0.376	36
	22-24	6.356	0.340	16	6.776	0.344	31
	28-30	6.665	0.505	9	6.979	0.408	10
12	16-18	6.411	0.185	23	6.909	0.201	28
	19-21	6.448	0.339	23	6.997	0.276	21
	22-24	6.461	0.195	7	7.141	0.156	13
	25-27	6.475	0.480	5	6.843	0.385	5
14	19-21	6.649	0.247	11	7.286	0.443	13
	22-24	6.827	0.322	15	7.210	0.235	6
16	22-24	7.182	0.223	6	7.637	0.589	21
	25-27	7.261	0.481	12	7.982	0.363	8
18	22-24	6.829	0.288	7	7.284	0.155	7

Note: Attribute groups with at least five observation are reported in the table. In the estimation of migration equation, Sample is restricted to groups with at least ten observations to avoid small sample bias. Parameters are weighted with sampling probability by age and sex.

Table 2(b) Parameters of Bangkok wage distributions by attribute group, female

		1994-1996			1998-2000		
yr. sch.	mig. age	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.
4	19-21	6.471	0.314	19	6.888	0.170	5
	22-24	6.606	0.210	32	7.194	0.206	7
	25-27	6.562	0.259	60	7.001	0.267	12
	28-30	6.473	0.638	42	7.123	0.387	28
	31-33	6.631	0.291	35	6.986	0.300	25
	34-36	6.634	0.197	28	6.970	0.282	12
	37-39	6.571	0.182	18	7.114	0.274	18
	40-42	6.499	0.188	20	7.143	0.254	15
	43-45	6.662	0.222	16	7.352	0.537	8
	46-48	6.721	0.158	7	7.009	0.284	11
6	13-15	6.401	0.268	126	6.749	0.236	43
	16-18	6.419	0.294	172	6.854	0.450	76
	19-21	6.547	0.356	148	6.988	0.470	83
	22-24	6.605	0.255	112	7.052	0.256	92
	25-27	6.629	0.309	36	6.993	0.346	69
	28-30	6.561	0.176	18	6.903	0.469	25

Table 2(b) ctnd.

yr. sch.	mig. age	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.	$E[\ln w_i^{ar}]$	$sd[\ln w_i^{ar}]$	obs.
9	13-15	6.484	0.313	24	6.712	0.496	31
	16-18	6.553	0.312	46	6.832	0.348	71
	19-21	6.683	0.346	30	6.987	0.441	22
	22-24	6.772	0.456	27	6.694	0.773	30
	25-27	6.694	0.279	23	6.999	0.411	22
	28-30	6.840	0.313	7	7.320	0.235	10
	31-33	6.775	0.248	5	6.937	0.660	9
12	16-18	6.584	0.170	25	7.049	0.356	27
	19-21	6.563	0.366	34	7.071	0.270	32
	22-24	6.739	0.223	15	7.199	0.301	25
	25-27	6.709	0.201	7	7.078	0.493	5
	28-30	6.708	0.327	6	7.120	0.399	7
14	19-21	6.777	0.208	19	6.920	0.303	7
	22-24	6.492	0.723	13	7.172	0.318	8
	25-27	6.572	0.358	10	7.324	0.610	2
16	22-24	7.270	0.533	9	7.713	0.773	15
	25-27	7.259	0.443	10	8.150	0.843	14
	28-30	8.445	1.051	8	8.067	0.436	3
18	22-24	7.212	0.305	6	7.597	0.284	5

Table 3. Parameter estimates of migration equation[5]

mig_i	(1) 1994-1996			(2) 1998-2000	
$\text{E}^h[\ln w_i^{ar}]$	4.69	10.43		-0.00633	-0.05
$\text{sd}^h[\ln w_i^{ar}]$	0.848	3.26		-0.265	-1.96
sex_i	-0.792	-12.08		-0.0447	-1.28
age_i	-0.311	-12.17		-0.0789	-5.25
age_i^2	0.0039	10.85		0.000602	2.64
yr.sch_i	-0.129	-6.95		-0.0123	-1.36
$\text{year}_{94.1}$	-0.234	-5.43	$\text{year}_{98.1}$	0.0988	2.29
$\text{year}_{95.1}$	0.126	2.17	$\text{year}_{99.1}$	0.0135	0.29
$\text{year}_{96.1}$	0.0807	1.9	$\text{year}_{00.1}$	-	-
$\text{year}_{94.3}$	-0.225	-4.79	$\text{year}_{98.3}$	0.07	1.54
$\text{year}_{95.3}$	0.0623	1.06	$\text{year}_{99.3}$	-0.00273	-0.06
$\text{year}_{96.3}$	-	-	$\text{year}_{00.3}$	0.0131	0.28
origin_{1-76}	suppressed		origin_{1-89}	suppressed	
number of obs.	250237			277326	
presudo R^2	0.234			0.134	

[5] Note: Parameters are estimated by Probit. Individual heterogeneity of error term is allowed to calulate standard errors.

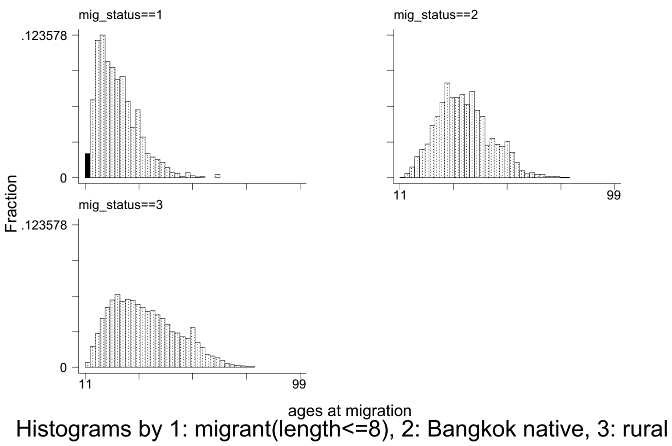

Figure 1: Age profiles of workers by migration status, 1998-2000

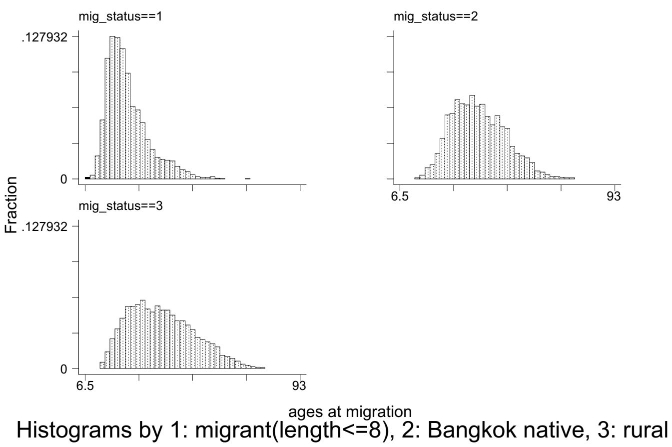

Figure 2: Age profiles of workers by migration status, 1998-2000

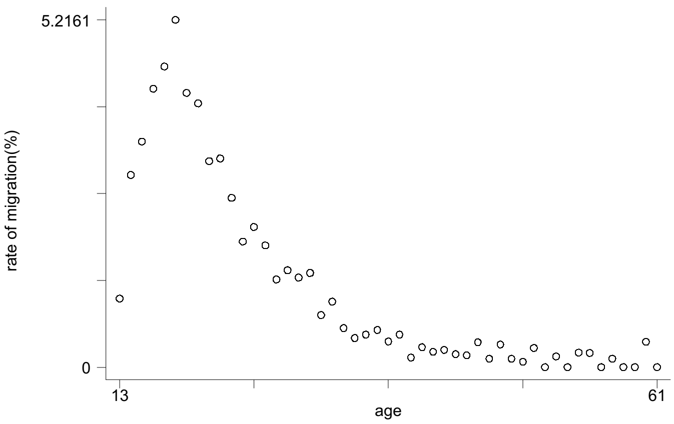

Figure 3: Rate of out-migration by age, 1994-1996

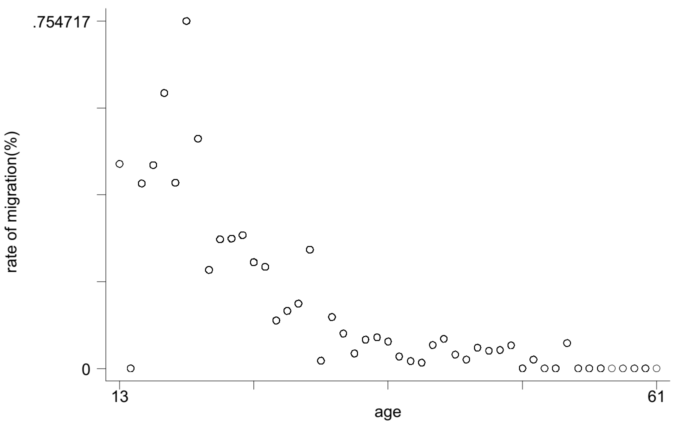

Figure 4: Rate of out-migration by age, 1998-2000

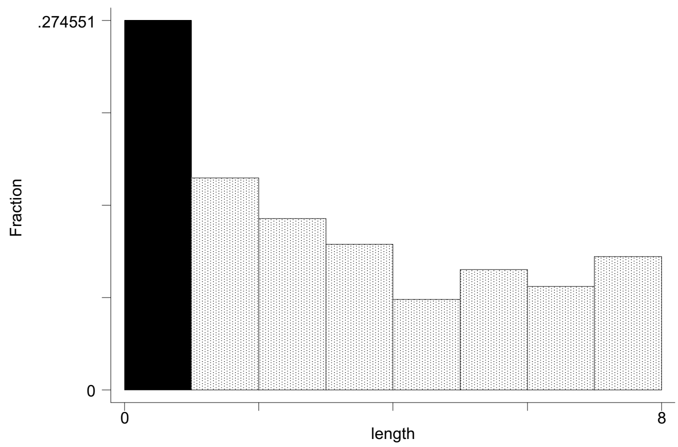

Figure 5: Years of schooling profile of migrant workers