Neighborhood Effects among Migrants: Evidence from Bangkok, Thailand

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Abstract

This paper examines neighborhood effects among migrants in an urban labor market, using pooled cross-section data from Bangkok, Thailand, that has experienced large scale inflows of migrants from the rural areas. In particular, we test whether or not the labor–market performance of previous migrants has externalities to that of new migrants from the same origin provinces. Although it has been increasingly recognized in both economics and sociology that non-market interactions of agents play important roles in a number of activities such as job search and education, there is a gap between those theoretical conjectures and empirical tests. We use the Labor Force Survey from Bangkok that records both the length of stay for migrants to the city and provinces from which they migrated. From this information, it is possible to identify the effects of previous migrants on new migrants for each origin. Our empirical results, that control origin fixed effects are two fold: i) the relative size of migration positively affects employment probabilities of new migrants (scale effect), and ii) the estimated employment probabilities of previous migrants also raise those of new migrants. We also simulate the magnitude of the origin externalities, that prove its significance to the overall performance of the urban labor market, given the large proportion of migrants in the Bangkok labor force.

JEL Classifications: O12, O15, J61, J23
Key Words: Externalities, Migrants, Employment Probability, Bangkok

1. Introduction

When people search for job, they need to acquire information from many kinds of media, for example, an organization which offers information on jobs, job bank or from people around themselves. If a job searcher is a migrant, he or she is especially influenced by people who have already migrated from the same origin. (e.g. Banerjee, 1983) That is, there exist external effects through information spillovers among migrants. Migrants are often supported from people who have previously migrated, and try to obtain useful information on job search. There is a possibility that external effects determine migrants' employment probability. In developing countries where information infrastructure is not well developed, the external effects are more influential than in developed countries. Moreover, the externalities not only influence employment probability, but also the efficiency of local labor markets. The purpose of this paper is to identify the external effects from people who migrated from the same origins on new migrants' employment probability, using micro data from Bangkok, Thailand.

The positive spillovers from previous migrants to new migrants mean that the productivity per capita is increasing in the number of migrants from rural area to the urban area, given labor force in Bangkok. An increase in employment probability also suggests the accumulation of human resources through job experience. If a number of migrants to Bangkok who find jobs with support from the people from the same origins and who accumulate their human capital through job experience increases, there should be not only a short-term improvement of employment probability but also a long-term productivity effect through labor markets.

In labor economics, the studies of neighborhood effect have mainly focused on schooling investment or crime. Because neighborhood effects are invisible, it is hard to distinguish these effects from unobserved common factors. For example, Case and Katz (1991), Case (1992), Yamauchi (2001) and Topa (2000) [3] consider neighborhood effects as external effects among people living in the same areas. Borjas (1995), O'Regan and

[3] Case and Katz (1991) analyze neighborhood effects among youth (from ages 17 to 24) in Boston on their probability to commit crimes, use drags or loose jobs, etc. Case (1992) shows that there exists the neighborhood influence in farmers' attitudes toward the adoption of new technologies in Indonesia. Yamauchi (2001) considers neighborhood effects based on Bayesian learning and shows that households determine investments in child schooling by observing neighbors' incomes and that the schooling distribution of parents' generation influences to schooling investments in children. Topa (2000) shows spatial neighborhood effects in employment determination within adjacent areas.

Quigley (1996) [4] verified the external effects from people having the same characteristics such as ethnic background. In this paper, the neighborhood effect is of the latter type. Montgomery (1991)[5] showed the importance of informal network in the determination of employment, including social network. But the studies of employment probability among migrants are rare. Banerjee (1983) shows from a survey in Delhi that neighborhood effects exist in the decision-making on migration and that migrants, helped by someone around them, are likely to find their jobs. Caces, Arnold, Fawcett and Gardner (1985) [6] examine migration from the Philippines to Hawaii as behavior related to social network, not as independent individual behavior. However, as they concerned decision-making about migration, they did not show migrants' neighborhood effects in terms of employment probability after migration.

In theoretical studies, on the other hand, Carrington, Detragiache and Vishwanath (1996)[7] focus on the external effect in migrants' employment probability. We modify their model so that we clarify implications that are relevant to our empirical results on the determinants of employment probability in destinations. Not only the size of migration that is focused in their model, we analyze empirically the impacts of estimated employment probabilities among migrants from the same origin toward the employment probability for recent migrants. Thereby it will become clear from our results that the employed is a more significant information source than the unemployed.

In the next section, we will introduce the modified model of Carrington, Detragiache and Vishwanath (1996). Empirical methodology is discussed in Section 3. Section 4 describes data from Thailand, and Section 5 summarizes empirical results. Simulations on employment probability are conducted in Section 6, and concluding remarks are mentioned in the final section.

[4] Borjas (1995) shows ethnic-based spillovers such that the skills of children depend not only on parental skills, but also on the mean skills of their ethnic group in the parents' generation. O'Regan and Quigley (1996) find that the spatial isolation of minority and poor households contributes to differences in youth employment by race and ethnicity.

[5] The model of Montgomery (1991) considers the importance of employee referrals and offers a variety of explanations for their use.

[6] They introduce and develop the concepts of shadow households and competing auspices that clarify the role of households and families in the migration process.

[7] They analyze the migration from South to North in the United States from 1915 to 1960, taling into account moving costs as endogenous.

2. Origin Externalities and the Instability of Migration Process

This section shows the influence of migrants' employment probability to decisions about migration from rural to urban areas, based on Carrington, Detragiache and Vishwanath (1996)' s model. Here we modify their model so that only migrants' employment probability determines moving cost endogenously.

Suppose that individuals can choose to live either in the city or in the countryside. Normalize population in time zero in each area to be 1. M_t is the number of (originally) rural workers who live in the city at time t, so the rural population at t is $1-M_t$. Let π_t be profit per worker from agricultural production in time t, which depends on the rural population $\pi_t = \gamma^r(M_t)$. Let $E_t (E_t \leq M_t)$ be the number of the migrants who are employed in manufacturing industry at time t, and w_t be the industrial wage. The inverse labor demand function in manufacturing is $w_t = \gamma^m(E_t)$. γ^r is increasing in M_t and γ^m is decreasing in E_t, and $\gamma^m(0) > \gamma^r(0)$, so that the manufacturing wage is higher than the rural wage before any migration occurs. Workers choose their location to maximize the expected discounted value of income (net of migration cost).

A move to the city does not guarantee employment. New migrants have to search for jobs, and there exists the externality such that they are helped during this search by the presence in the city of former migrants who are themselves employed. Let $p(E_{t-1})$ be the probability of migrant finding employment at time t. When $p'(\cdot) > 0$, the externality exists.

For simplicity, we assume that anyone born in the city or who has ever found a job in the city is employed with certainty. Let $V^m(M_t, E_{t-1}, u)$ be the expected discounted value of future income for a worker who is unemployed in the city at time t. ┌ is the value for an employed worker, and ┌ is the value of staying in the rural area at time t. We take the wage to be zero if a manufacturing job is not found Thus, the expected discounted income of an unemployed migrant to the city, with discount rate δ, is

$$V^m(M_t, E_{t-1}, u) = p(E_{t-1})V^m(M_t, E_{t-1}, e) + \delta[1-p(E_{t-1})]V^m(M_{t+1}, E_t, u). \quad \cdots(1)$$

The expected income of an employed urban resident is

$$V^m(M_t, E_{t-1}, e) = \gamma^m(E_t) + \delta V^m(M_{t+1}, E_t, e)\,. \qquad \cdots(2)$$

The expected income of a worker remaining in the countryside is therefore,

$$V^r(M_t, E_{t-1}) = \gamma^r(M_t) + \delta Max\{V^m(M_{t+1}, E_t, u), V^r(M_{t+1}, E_t)\}. \qquad \cdots(3)$$

Then, a worker currently living in a rural area will decide to move to the city under the condition that

$$V^m(M_t, E_{t-1}, u) \geq V^r(M_t, E_{t-1})\,. \qquad \cdots(4)$$

The process finally halts when the wage gap has diminished sufficiently so that there are no further incentives to move. In this steady-state $M_t = M_{t+1} = M$ all who have migrated find employment (as $t \to \infty$), so that $M = E$. Workers are indifferent between staying in the city and in the rural area at the steady state. Therefore,

$$\frac{\gamma^m(M) - \gamma^r(M)}{1-\delta} = \frac{\gamma^m(M)(1-p(M))}{1-\delta(1-p(M))}\,. \qquad \cdots(5)$$

The present discounted value of the urban-rural wage gap is just equal to the cost of migration.

We define as $p^*(M^*)$ employment probability in the steady state equilibrium (5). Consequently, the stability of (5) depends on the slopes of the right-hand side and the left-hand side. When the externality is weak and therefore the slope of employment probability function $p^*(M^*)$ is small, then a change of moving costs becomes smaller than the wage gap between rural and urban area. If the number of migrants increases historically from zero, the benefit from migration becomes larger than moving costs (left-hand side of M^*). In this case, we reach the equilibrium M^* stably.

If the number of migrants increases from the above equilibrium, moving costs become higher than the benefit from migration (right-hand side of M^*), and people go back to the countryside. It converges to the equilibrium M^* stably. The effect of the number of migrants on employment probability is small and the labor force distribution between rural and urban area is stable.

However, when the slope of employment probability function $p'(M^*)$ is relatively large, an opposite case emerges. In this case, even if some migrants move from rural area to urban area, as moving cost is higher than the benefit from migration (left-hand side of M^*). People go back to the rural area and the number of migrants in urban area M converges to zero. If the number of migrants increases from the equilibrium (5), the benefit from migration becomes larger than moving costs. As the number of migrants M is right to the equilibrium, M increases to the limit. As the number of migrants affects strongly employment probability, the external effect becomes accelerated.

Though employment probability function involves dynamical labor migration, it is an empirical question whether or not the external effect exists. Even if external effect exists, the size of effect has not been identified quantitatively in empirical contexts. The next section will show empirical methodology on the identification of the migrants' employment probability function $p(M)$.

3. Empirical Methodology

This section shows an identification methodology of the employment probability function. As the status of employment is a binary variable, that is employed or unemployed, we use Logit and Probit Models. Employment status is either employed ($y_i = 1$) or unemployed ($y_i = 0$),

$$y_i = \begin{cases} 1 & y_i^* > 0 \\ 0 & y_i^* \leq 0 \end{cases}$$

where a latent variable y_i^* is determined by $y_i^* = x_i'\beta + z_i'\gamma + \varepsilon_i$. ε_i follows the standard normal distribution or logistic distribution. Amemiya(1981) shows the identification between Logit and Probit Model. When data is binary, it is hard to identify the distribution because the standard normal distribution and logistic distribution are very similar. And also the result is hardly different. This paper does not assume the shape of distribution in advance, but estimate both of Logit and Probit Model.

Estimation equation is

$$\text{Prob}(y_i = 1) = \Phi(x_i'\beta + z_i'\gamma)$$

where in probit $\Phi(\cdot)$ is a standard normal distribution, whereas in logit $\Phi(\cdot)$ is a logistic distribution function, $y = 1$ if employed and = 0 if unemployed, x_i = a set of externality variables to be discussed later, z_i = a set of individual attributes such as sex, age, years of schooling and the number of household members.

In general, it is hard to distinguish between externalities and region-specific fixed factors, that are the common factor shared among people from the same origin. For instance, if people in a region have strong interests in education, investing more in child schooling than other regions, migrants from this region are more likely to be employed in Bangkok than those from other regions. Both previous and recent migrant workers are equally likely to be employed. Between these two groups occurs the presence of positive correlation. If such region-specific effect is not controlled in estimation, there is a risk to accept this positive, not causal, correlation as statistical evidence for externalities. Since those often unobserved region-specific effects are included in the error terms, it is likely that the size of previous migrants or the estimated employment probabilities among previous migrants have correlations with the error term, namely $E[x_i \varepsilon_i] \neq 0$.

This problem can be solved through i) pooling several cross-sections over time, and ii) including origin fixed effects. Using panel or pooling several cross-section data, region-specific fixed effects can be estimated by region dummy variable. Then, to verify whether the number of previous migrants from the same origin or their employment probability raises new migrants' employment probability, we control for region-specific fixed effects by using origin province dummy variables. It should be noted that the external effects estimated in the above method are only identified from within-province variations, not from cross-province differences in employment status.

4. Data

This paper uses Labor Force Survey (LFS) from Thailand, from the National Statistical Office (NSO) in 1994 to 1996. Labor Force Survey is recently conducted every quarter: February, May, August, November. This paper uses data from February (First round) and August (Third round) in the three years [8]. For our purpose of this research, we only use Bangkok sample.

The definitions of variables in this paper are as follows. Labor force is defined as people who can work, not being housekeepers or students (from 1994 to 1996,

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[8] National Statistical Office conducts Labor Force Survey for all over Thailand three times in every year from1971. First round is done from January to March (the agricultural off-season), second round is from July to September, and third round is from October to December (the agricultural peak-season). From 1984, survey has been done four times a year (February, May, August and October). From first and third round in1994, as great demands for data in prefecture level, they expanded sample size. Survey is done per household and sample size in Bangkok is 3000 households.

compulsory education is up to age 13 in Thailand). Migrants are defined as people who live in Bangkok region for less than 5 years, after moving from the other regions. In the survey, we know the length of living in the destination up to 9 years. However, since previous provinces are not recorded for those who have stayed for more than 5 years, we restrict our definition of migrants as above. Migrants' origins (previous provinces) are divided into 76 provinces and foreign. The distribution of migrants by origin regions is shown in Figure 1. From north is 20.19% of all migrants, the north-east 11.08%, the south 21.54% and central including Bangkok 25.80% (Figure 1)

Elementary school is 6 years, under compulsory education from 1994 to 1996. Junior high school and high school are 3 years for each. College needs 4 years. Medical and dental schools take 6 years. In Thailand there are three kinds of vocational schools. They can enter after junior high school (3 years), or after high school (2 years), or for teachers (2 years). In this paper, we define vocational schools as all of the three. The distribution of years of schooling is shown in Figure 2.

As Labor Force Survey focuses on labor, there are many useful variables on employment such as working hour, wage, fringe benefits and so on. Also, as the in-depth data on migrants such as origin and reason of migration are available, this survey is suitable for the purpose of this paper.

Externality variables used for estimation is the share of people from a particular province in total migrant population in Bangkok, the share of the employed who moved from a particular province in the total migrant population from the province in Bangkok[9], and their square and cubic terms if necessary, in order to examine the nonlinear shapes of employment probability functions. We also use the interactions with individual attributes such as sex, age, and years of schooling. In particular, schooling may augment the externalities.

To estimate the number of migrants from a particular province, we need sample weights and the population of migrants in Bangkok at each round from 1994 to 1996. We use the ratios of migrants from a particular province to migrant population in Bangkok r_j using sample weights [10]. That is,

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[9] As the number of former migrants could be got only the number in sample, the rate was calculated by using weight.

[10] By using sample weight, the rate of the people from the same origin out of migrants' population in Bangkok can be found. If migrant population in Bangkok at each time point times this, real "number of the people from the same origin can be calculated.

$$r_j = \frac{\sum_{i \in n_j} w_i}{\sum_{m \in n} w_m} \ .$$

where n_j = the group of people from origin j who have stayed in Bangkok for more than a year but less than 5 years, and n = the group of people who migrated from outside Bangkok and have stayed for more than a year and less than 5 years. Figure 1 shows the share distributions over four regions.

We also calculated the employment probability among the people from a particular region:

$$\hat{p}_j = \frac{\sum_{i \in n_j} w_i I(work_i)}{\sum_{i \in n_j} w_i} \qquad \text{where } I(work_i) = 1 : \text{work}, \quad = 0 : \text{not work} \ .$$

We will analyze the effects of these externality variables on the employment probabilities of recent migrants, those who have stayed in Bangkok for less than a year.

Individual attributes that we consider are male dummy, age, age squared, years of schooling, its squared, the number of household members, single dummy and some educational attainment dummies. With the interaction terms of externality variables and these attributes, it is possible to examine whether the externality differs for different groups of people. For instance, the one who is highly educated (thus, can read and write) can have a higher ability in collecting more information than uneducated people, so the external effect on her/ him can be larger.

We use round-year fixed effects to remove price variations, seasonality and/or macroeconomic shocks in Bangkok region. We pool 6 rounds (first round and third round from1994 to 1996), and assume that origin region fixed effects are constant over time in three years.

Descriptive statistics are shown in table 1. Migrants refer to those who stayed in Bangkok for more than a year and less than 5 years. The table shows the average numbers per province.

5. Estimation Results

Estimation results [11] from Probit analysis are shown in Tables 2 and 3. Results of Logit analysis are shown in Tables A1 and A2, that also confirm our basic findings. Results without province fixed effects are also shown for comparison in each case. In either case, similar results are basically obtained. The model, which explains the data most effectively, is selected by the largest pseudo R squared. As a result, the model that includes cubic terms was selected in each case. We will show estimation results in detail below.

Table 2 shows the effects of the percentage of migrants from same province in migrants' population in Bangkok on the employment probability of migrants who migrated to Bangkok recently. Form these estimation results, the case with a cubic term, that captures flexible non-linearity of employment probability function, is most statistically preferred. It can be said that the employment probability function takes a convex shape at first and becomes concave as the size of previous migrants increases. External effect [12] to employment probability increases gradually when the percentage is small and reaches a critical point, beyond which the marginal effect decreases. The coefficients are larger when we control province fixed effects, compared to those without. It means that there exists a negative correlation between province fixed effects included in the error terms and the percentage of the migrants from the same origin.

On the interaction terms with attributes, we find that sex (male dummy) and schooling year are significant when province fixed effects are controlled. Therefore, migrants who are male and/or more educated are influenced effectively from previous migrants from the same origin and their employment probabilities rise. Above all, there is a possibility that well educated migrants can become accustomed to new environments quickly and has a more ability in gathering effectively the information about employment.

Table 3 shows the effects of estimated employment probabilities of previous migrants on those of current migrants. It is found that the probability influences significantly the employment probability of recent migrants when province fixed effects are controlled. The coefficients are larger than those without fixed effects.

In the case with the cubic term, estimation result is most significant. That is, the

[11] Before this, we estimated the scale of externality; the number of people from the same origin and the number of employed people from the same origin and could get significant results as well.
[12] It was confirmed that inflection point is interior.

previous migrants' employment probability raises the employment probability of recent migrants gradually and reaches a critical point, then the marginal effect decreases eventually.

On the effects of individual attributes, single dummy influences positively the employment probability in all estimation results. Age and age squared are also significant; age affects positively migrants' employment probability, but with a diminishing marginal effect. When we control province fixed effects, those university-educated and vocational school educated have larger employment probabilities.[13]

6. Simulation

From our estimation results, it is clear that the more people from a particular origin migrated to Bangkok, the larger the subsequent migrants' employment probability is and therefore the more migrants go to Bangkok. Now, return to the employment probability at steady state $p^*(M)$, which was shown in Section 2, and consider the size of external effect. I use the specifications with cubic terms, as they are most statistically preferred.

Figures 3 and 4 quantify changes of the employment probability when attributes are fixed as their means. In these figures, when the percentage of migrants from same origin and the employment probability of previous migrants are smaller than their means respectively, employment probability rises largely. It is implied that at the initial stage of migration flow, the externalities work strongly to invite more migrants from rural areas. However, since this paper does not estimate wage functions in rural and urban areas, the slopes of both sides of Eq (5) in Section 2 cannot be compared directly. The question on the stability of equilibrium cannot be answered. However, the finding that there exist substantial external effects to the new migrants' employment probability supports a possibility that the benefit from migration can surpass moving

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[13] It is one of interesting topics for future research to study whether, as a large variety of human resources or various industries are concentrated in the cities, there are knowledge spillovers across industries promoting economic development. From previous studies on the United States (For example, Rauch, 1992[13]; Glaeser, Kallal, Scheinkman and Shleifer, 1992[13]), we may conjecture that this phenomenon occurs also in Bangkok. People from different areas, having different human resources concentrate in the city and therefore accumulate further human resources. Glaeser (1999a) insisted that there is a factor for facilitating skill acquisition in cities. Since various industries concentrate in Bangkok, there can be accumulative spillover effects. As a result, it may be that labor force of high productivity is built up in Bangkok. We leave the examinations of this issue to future research.

costs.

7. Conclusion

This paper shows that there exists the external effect from previous to new migrants in the determination of employment probability in labor markets. It also becomes clear, as interaction terms with male dummy and years of schooling are significant, that the externalities in employment probability in the Bangkok labor market differ for different genders and educational attainment. These interesting results are robust, or even stronger when we include origin province fixed effects, that capture the presence of correlations with unobserved region factors.

It is implied from our results that, if employment in the destination market helps migrants acquire skills and accumulate human capital in the long-run, the average labor productivity can differ through the labor-market externalities. Therefore, not only short-term welfare of migrants, but subsequent long-term effects on development can also differ, with the presence of the externalities. Since an increase in labor force may or may not lead to an increase in the number of the employed, market-wide unemployment rate and macroeconomic efficiency are also influenced through the employment externalities that we prove in our empirical analysis.

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Table1 Descriptive Statistics

Whole Kingdom	1994 R-1	1994 R-3	1995 R-1	1995 R-3	1996 R-1	1996 R-3
#obs all	183892	177821	176581	176130	175109	170639
migrants	21914	20576	20720	21060	20827	19690
migrants (less than 1 yr)	5741	6251	5149	6452	5469	5799
population from same province	205.40	198.30	195.69	179.84	183.35	174.79
	(262.44)	(228.41)	(241.10)	(223.99)	(225.22)	(237.68)
the employed from same province	140.14	136.74	138.47	130.39	133.38	129.03
	(177.48)	(153.96)	(178.60)	(175.35)	(176.87)	(191.20)
employment probability	0.71	0.79	0.69	0.82	0.73	0.83
	(0.45)	(0.41)	(0.46)	(0.39)	(0.44)	(0.38)
male dummy	0.58	0.59	0.59	0.60	0.60	0.60
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
age	26.91	26.84	27.91	27.69	28.63	28.11
	(10.07)	(10.36)	(10.61)	(10.63)	(10.77)	(10.72)
years of schooling	6.30	6.16	6.56	6.35	6.30	6.25
	(3.32)	(3.10)	(3.47)	(3.21)	(3.49)	(3.31)
household size	4.16	4.54	4.10	4.52	4.07	4.32
	(1.86)	(1.92)	(2.62)	(4.30)	(2.19)	(2.28)
single dummy	0.36	0.38	0.39	0.34	0.33	0.35
	(0.48)	(0.49)	(0.49)	(0.47)	(0.47)	(0.48)

Bangkok	1994 R-1	1994 R-3	1995 R-1	1995 R-3	1996 R-1	1996 R-3
#obs all	6451	5949	7193	7210	6910	6693
migrants	641	609	848	718	774	634
migrants (less than 1 yr)	98	122	169	122	153	111
population from same province	7.38	9.09	8.25	6.86	8.09	6.95
	(8.84)	(9.93)	(9.51)	(7.70)	(8.51)	(7.89)
the employed from same province	5.66	7.03	6.87	5.30	6.31	5.56
	(7.69)	(8.28)	(8.88)	(6.84)	(7.13)	(6.87)
employment probability	0.88	0.66	0.76	0.63	0.80	0.91
	(0.33)	(0.48)	(0.43)	(0.49)	(0.40)	(0.29)
maledummy	0.62	0.44	0.49	0.44	0.55	0.50
	(0.49)	(0.50)	(0.50)	0.50	(0.50)	(0.50)
age	24.90	25.73	26.86	24.49	28.60	26.26
	(8.29)	(9.84)	(10.03)	(11.01)	(10.82)	(9.64)
years of schooling	6.37	6.34	6.47	6.83	6.03	5.59
	(2.83)	(2.75)	(3.20)	(3.70)	(3.10)	(2.99)
household size	3.02	5.00	3.60	3.56	3.36	3.05
	(1.04)	(2.46)	(2.42)	(1.07)	(2.04)	(1.70)
single dummy	0.56	0.36	0.54	0.35	0.45	0.52
	(0.50)	(0.48)	(0.50)	(0.48)	(0.50)	(0.50)

Means and standard deviations (parentheses) are shown. Population from same province is the estimate of the population from a particular province with the length of stay, more than 1 year and less than 5 years. The employed from same province is that of those who are employed.

Table 2 Employment Probability Function (1) – Probit

	FE	No FE	FE	No FE	FE	No FE
Share of the same	7.20645	−6.473987	10.70341	7.389731	55.20995	85.97343*
origin population	(0.236)	(−0.200)	(0.289)	(0.187)	(1.371)	(2.126)
squared			−68.36725	−260.2742	−2368.445	-4145.691*
			(−0.234)	(−0.720)	(−1.510)	(−2.329)
cubic					26750.87	43942.43*
					(1.528)	(2.158)
Interactions with						
male	31.80545*	27.44806*	31.19917*	25.75696*	31.93848*	29.43436*
	(2.280)	(2.027)	(2.277)	(2.038)	(2.465)	(2.372)
age	−0.5400775	−0.3348443	−0.5481338	−0.3568933	−0.5346657	−0.3720454
	(−0.668)	(−0.364)	(−0.676)	(−0.394)	(−0.677)	(−0.410)
years of schooling	0.2668186	3.638096	0.2396748	3.606967	0.3919848	4.005441
	(0.126)	(1.557)	(0.112)	(1.549)	(0.179)	(1.664)
Individual attributes						
single	0.703591**	1.041305**	0.7034672**	1.036598**	0.6985769**	1.03114**
	(3.595)	(4.437)	(3.608)	(4.466)	(3.566)	(4.430)
univ grad	0.5462143	1.845742*	0.5448642	1.833863*	0.6284964	1.898858*
	(1.034)	(2.282)	(1.029)	(2.241)	(1.153)	(2.263)
vocational sch	0.6231606	3.067873*	0.6305862	3.08806*	0.7366673	3.265077*
	(0.714)	(2.379)	(0.718)	(2.415)	(0.825)	(2.559)
male	−0.1012578	0.2298218	−0.0972869	0.2474462	−0.1308265	0.2101841
	(−0.424)	(0.711)	(−0.408)	(0.771)	(−0.545)	(0.656)
age	0.1170822*	0.1652059*	0.1173046*	0.1663809*	0.1193243*	0.1689389*
	(2.412)	(2.524)	(2.429)	(2.565)	(2.481)	(2.633)
age squared	-0.001721*	-0.0023879**	-0.001722**	-0.0023983**	-0.0017561**	-0.0024314**
	(−2.677)	(−2.830)	(−2.691)	(−2.884)	(−2.729)	(−2.905)
years of schooling	-0.3190634**	−0.1655933	-0.3196825**	−0.1654028	-0.3305427**	−0.1697573
	(−2.790)	(−1.336)	(−2.808)	(−1.335)	(−2.877)	(−1.405)
yr sch squared	0.0099048	−0.0043053	0.0099584	−0.0043678	0.0103299	−0.0048405
	(1.426)	(−0.468)	(1.436)	(−0.477)	(1.471)	(−0.539)
householdsize	−0.0375363	−0.0956025	−0.0379354	−0.0924863	−0.047437	-0.1017587*
	(−0.816)	(−1.803)	(−0.829)	(−1.732)	(−0.988)	(−1.989)
# obs	769	664	769	664	769	664
quasi- R sq	0.1755	0.3914	0.1756	0.3922	0.1812	0.4001
Chi-sq (d.f.)	6.65(4)	10.24(4)	7.07(5)	11.07(5)	11.00(6)	16.11(6)
p-value	[0.1556]	[0.0366]	[0.2158]	[0.0499]	[0.0883]	[0.0132]

Asymptotic t values (z) are inparenthese. For construction of the population share, see the text.

* – 5 percent, ** – 1 percent significant

Chi sq statistics are for testing the hypothesis that all parameter values for the externalitiy variables are jointly zero.

Table 3 Employment Probability Function (2) – Probit

	FE	No FE	FE	No FE	FE	No FE
employment prob	4.635729 *	4.877253*	0.7120598	1.113432	9.999539*	12.24542*
	(2.610)	(2.233)	(0.262)	(0.293)	(1.798)	(1.814)
squared			2.753166*	2.895768	-16.78076*	−21.30536
			(2.512)	(1.445)	(−1.835)	(−1.607)
cubic					11.84116*	14.51738*
					(2.212)	(1.780)
Interactions with						
male	0.0160352	−0.0482827	0.0836816	−0.0476015	0.1195202	−0.1291059
	(0.017)	(−0.040)	(0.093)	(−0.040)	(0.123)	(−0.102)
age	−0.0691215	−0.0888254	−0.0616961	−0.0829705	−0.0715253	−0.0889101
	(−1.550)	(−1.561)	(−1.470)	(−1.446)	(−1.552)	(−1.487)
years of schooling	0.1620613	0.3029197	0.2051872	0.3061294	0.2027709	0.3245195
	(0.875)	(1.360)	(1.157)	(1.450)	(1.094)	(1.472)
Individual attributes						
single	0.6577708**	0.8189493**	0.6405541**	0.8022573**	0.7371734**	0.8529726**
	(4.355)	(3.929)	(4.213)	(3.859)	(4.214)	(3.910)
univ grad	1.23885	2.848497*	1.489357*	2.904227**	1.414824*	2.917162*
	(1.553)	(2.580)	(1.883)	(2.746)	(1.778)	(2.768)
vocational sch	1.711641	3.200429*	1.735485	3.188963*	1.675133	3.169461*
	(1.653)	(2.496)	(1.735)	(2.541)	(1.579)	(2.529)
male	0.3627623	0.5514069	0.3218864	0.5535177	0.2804335	0.6061013
	(0.469)	(0.558)	(0.445)	(0.568)	(0.366)	(0.594)
age	0.1934534**	0.2145697*	0.1966357**	0.2166934*	0.2046132**	0.2244542**
	(2.953)	(2.601)	(3.122)	(2.641)	(3.323)	(2.770)
age squared	-0.002053**	-0.0021802**	-0.0021774**	-0.0022813**	-0.0021787**	-0.0023292**
	(−3.292)	(−2.844)	(−3.581)	(−3.006)	(−3.827)	(−3.131)
years of schooling	-0.3582765*	-0.3813806*	-0.3686079**	-0.3769846*	-0.3546471*	-0.3777241*
	(−2.529)	(−2.095)	(−2.787)	(−2.136)	(−2.610)	(−2.068)
yr sch squared	0.0066381	−0.0016142	0.0055762	−0.001608	0.0047112	−0.002249
	(1.242)	(−0.160)	(1.020)	(−0.158)	(0.863)	(−0.220)
householdsize	−0.0056178	−0.0731969	0.0002016	−0.0610168	−0.0163733	−0.0635758
	(−0.185)	(−1.316)	(0.006)	(−1.051)	(−0.493)	(−1.076)
# obs	769	664	769	664	769	664
quasi- R sq	0.3992	0.4443	0.4060	0.4474	0.4148	0.4528
Chi–sq (d.f.)	98.11(4)	33.18(4)	156.36(5)	43.75(5)	134.45(6)	41.1(6)
p–value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Asymptotic t values (z) are inparenthese. For construction of the population share, see the text.

* – 5 percent, ** – 1 percent significant

Chi sq statistics are for testing the hypothesis that all parameter values for the externalitiy variables are jointly zero.

Table A1 Employment Probability Function (3) – Logit

	FE	No FE	FE	No FE	FE	No FE
Share of the same	13.77121	−16.04136	18.34854	17.61417	92.36468	170.7964*
origin population	(0.255)	(−0.272)	(0.288)	(0.250)	(1.347)	(2.381)
squared			−89.54085	−601.9964	−3889.591	-8022.54*
			(−0.183)	(−0.865)	(−1.428)	(−2.439)
cubic					43457.55	81336.38*
					(1.451)	(2.289)
Interactions with						
male	63.31326*	56.39279*	62.145*	51.67692*	59.96358*	57.48574*
	(2.365)	(2.161)	(2.301)	(2.125)	(2.538)	(2.575)
age	−0.9741749	−0.5758363	−0.9794227	−0.6303771	−0.9401061	−0.570272
	(−0.709)	(−0.360)	(−0.712)	(−0.400)	(−0.699)	(−0.378)
years of schooling	0.2049928	6.819026	0.1589025	51.67692*	0.5100591	7.426506
	(0.053)	(1.558)	(0.041)	(2.125)	(0.129)	(1.680)
Individual attributes						
single	1.207766**	1.998258**	1.208537**	1.998939**	1.207759**	2.021759**
	(3.441)	(4.501)	(3.472)	(4.562)	(3.424)	(4.442)
univ grad	0.8174619	4.139136*	0.8157773	4.130277*	0.9423432	4.288974*
	(0.866)	(1.868)	(0.862)	(1.832)	(0.966)	(1.850)
vocational sch	1.236949	5.742771*	1.244198	5.786481*	1.40702	6.168992*
	(0.746)	(2.110)	(0.748)	(2.134)	(0.841)	(2.294)
male	−0.2416536	0.3965464	−0.23306	0.4543918	−0.2702822	0.3967011
	(−0.582)	(0.693)	(−0.558)	(0.800)	(−0.655)	(0.702)
age	0.2071937*	0.3028405**	0.2074108*	0.3059028**	0.2107159*	0.3144222**
	(2.429)	(2.638)	(2.447)	(2.721)	(2.482)	(2.784)
age squared	-0.003084**	-0.0043616**	-0.003084**	-0.0043855**	-0.0031367**	-0.0045019**
	(−2.663)	(−2.837)	(−2.672)	(−2.926)	(−2.683)	(−2.955)
years of schooling	-0.6193722**	−0.305698	-0.6200051**	−0.3108139	-0.6409709**	−0.3310044
	(−2.708)	(−0.934)	(−2.717)	(−0.938)	(−2.722)	(−1.035)
yr sch squared	0.020493	−0.010308	0.0205572	−0.0102331	0.0212927	−0.0107959
	(1.598)	(−0.402)	(1.603)	(−0.394)	(1.603)	(−0.428)
householdsize	−0.0641007	-0.1967723*	−0.064523	-0.1872886**	−0.0807509	-0.2051817*
	(−0.801)	(−1.974)	(−0.809)	(−1.864)	(−0.964)	(−2.170)
# obs	769	664	769	664	769	664
quasi- R sq	0.1807	0.4004	0.1807	0.4017	0.1859	0.4111
Chi-sq (d.f.)	6.65(4)	10.05(4)	6.92(5)	10.86(5)	10.72(6)	16.39(6)
p-value	[0.1558]	[0.0395]	[0.2266]	[0.0542]	[0.0975]	[0.0118]

Asymptotic t values (z) are inparenthese. For construction of the population share, see the text.

* – 5 percent, ** – 1 percent significant

Chi sq statistics are for testing the hypothesis that all parameter values for the externalitiy variables are jointly zero.

Table A2 Employment Probability Function (4) – Logit

	FE	No FE	FE	No FE	FE	No FE
employment prob	7.565163*	6.974432	0.3994353	1.173815	18.87079	22.27285
	(2.044)	(1.645)	(0.072)	(0.171)	(1.531)	(1.741)
squared			5.024895*	4.737007	−33.47913	−41.1352
			(2.319)	(1.163)	(−1.715)	(−1.697)
cubic	0.072494	−0.033097	0.0211376	0.0011835	23.36415*	27.65471*
	(0.038)	(−0.015)	(0.012)	(0.001)	(2.095)	(1.837)
Interactions with						
male	−0.1160878	−0.1394046	−0.0979683	−0.1325838	0.1924807	−0.1246993
	(−1.408)	(−1.445)	(−1.292)	(−1.384)	(0.096)	(−0.052)
age	0.3531985	0.7898316	0.4252031	0.7359947	−0.1194206	−0.1429735
	(0.833)	(1.510)	(1.072)	(1.473)	(−1.378)	(−1.403)
years of schooling	1.191721**	1.587433**	1.163256**	1.530696**	0.4170857	0.7401152
	(4.054)	(3.530)	(3.860)	(3.418)	(0.982)	(1.438)
Individual attributes						
single	2.379734	6.461835*	2.835087	6.247088*	1.342529**	1.613701**
	(1.297)	(2.128)	(1.534)	(2.114)	(3.881)	(3.557)
univ grad	3.21098	6.368977*	3.219758	6.16981*	2.659431	6.155443*
	(1.582)	(2.234)	(1.635)	(2.202)	(1.452)	(2.101)
vocational sch	0.6352334	0.9842823	0.6820922	0.9562309	3.043423	5.964054*
	(0.424)	(0.563)	(0.492)	(0.552)	(1.475)	(2.127)
male	0.3383858**	0.3628509*	0.3401627**	0.3670803*	0.5227703	1.044634
	(2.853)	(2.506)	(2.965)	(2.555)	(0.347)	(0.566)
age	-0.0036616**	-0.0037842*	-0.0038753**	-0.0039284**	0.3545666**	0.3813715**
	(−3.220)	(−2.670)	(−3.471)	(−2.818)	(3.205)	(2.713)
age squared	-0.6827183*	-0.8415378*	-0.6747528*	-0.7849955*	-0.0038352**	-0.0040284**
	(−2.286)	(−2.274)	(−2.519)	(−2.192)	(−3.740)	(−2.976)
years of schooling	0.0111594	−0.0072777	0.0080942	−0.0069739	-0.6284855*	-0.7695466*
	(0.963)	(−0.302)	(0.640)	(−0.288)	(−2.219)	(−2.086)
yr sch squared	−0.0105751	−0.1548017	−0.002608	−0.1349175	0.0058152	−0.0075959
	(−0.193)	(−1.484)	(−0.046)	(−1.227)	(0.456)	(−0.315)
householdsize	−0.0105751	−0.1548017	−0.002608	−0.1349175	−0.0315044	−0.1355503
	(−0.193)	(−1.484)	(−0.046)	(−1.227)	(−0.545)	(−1.204)
# obs	769	664	769	664	769	664
quasi- R sq	0.3991	0.4471	0.4056	0.4493	0.4153	0.4552
Chi-sq (d.f.)	71.81(4)	28.03(4)	113.28(5)	33.53(5)	95.17(6)	32.28(6)
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Asymptotic t values (z) are inparenthese. For construction of the population share, see the text.

* – 5 percent, ** – 1 percent significant

Chi sq statistics are for testing the hypothesis that all parameter values for the externalitiy variables are jointly zero.

Figure 1 Origin Regions – Share

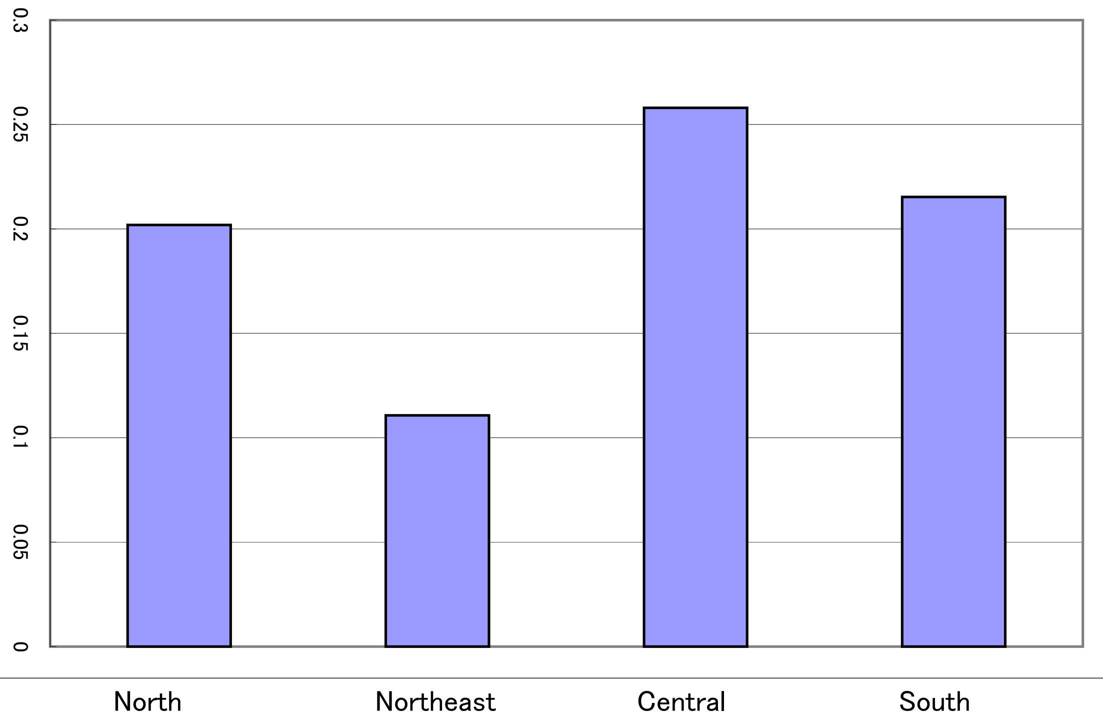

Figure 2 Educational Attainment
years of schooling

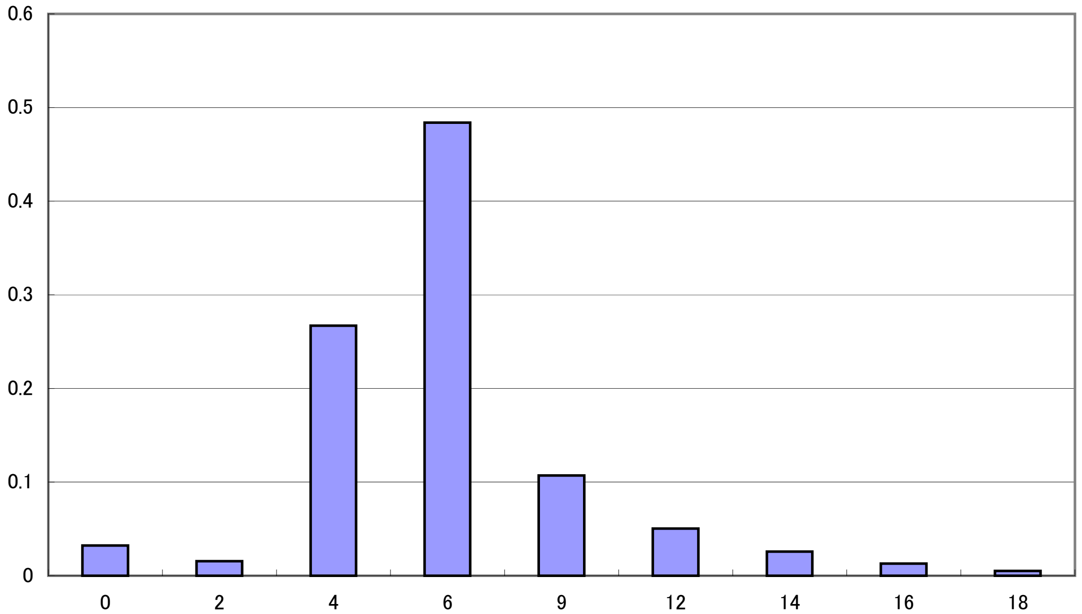

Figure 3 Employment Probability Function

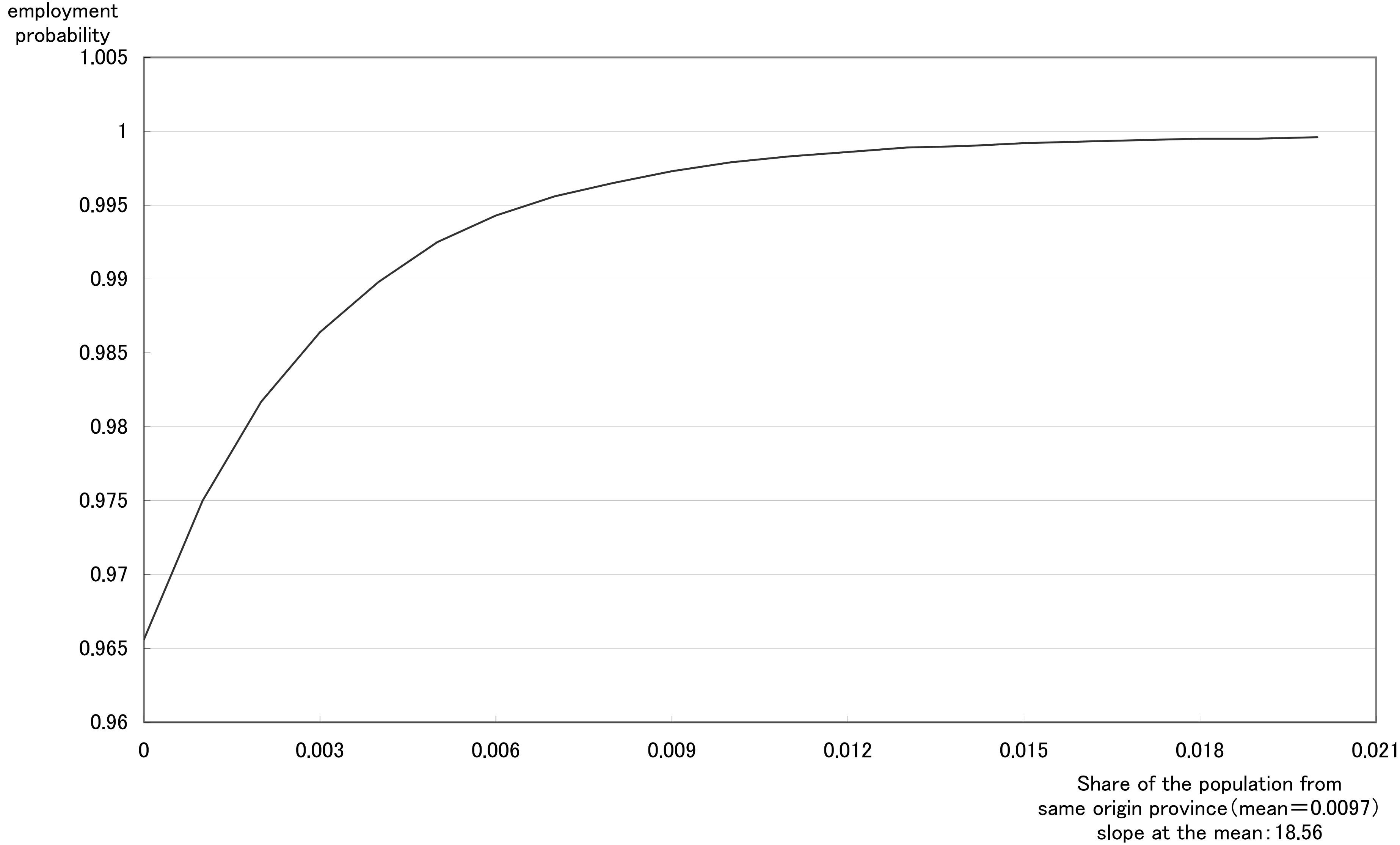

Figure 4 Employment Probability Function