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Internal Migration, Earnings, and the Importance of Self-selection

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This paper analyses the impact of internal migration on earnings within the human capital model framework. Since migrants constitute a non-random sample of population, the endogenous nature of migration decision warrants necessary correction for the selectivity bias in their earnings function. The Mincer-type earnings model is thus augmented to determine the extent of this bias. Besides estimating the standard Mincerian earnings model, the paper also attempts to verify the learn-as-you-go proposition by introducing migration duration variables in the earnings model. Based on the household level Population, Labour Force, and Migration (1979-80) survey data, the analysis yields the following important conclusions: (i) the data allowed a meaningful estimation of Mincerian earnings function for migrants and non-migrants; (ii) the level of schooling was one of the important determinants of the distribution of income both for migrants and non-migrants–the four categorical variables of education were in general statistically significant with expected signs, implying that the hypothesis of a positive relationship between income and education was accepted; (iii) the rates of return to education improved systematically with higher levels of education, thus confirming the notion that education serves as a signalling device; (iv) the age-income profile was almost linear for migrants but showed concavity for non-migrants; (v) the presence of sample-selection was observed for migrants; and (vi) even after controlling for the influence of personal characteristics, i.e., education and experience, the long-standing migrants earned relatively more at the destination than the more recent migrants.

I. INTRODUCTION

The economic theory which perceives migration as investment in human capital is based on the maximisation behaviour of individuals [Sjaastad (1962)]. It measures the responsiveness of migration to the difference in earnings at different locations. Accordingly, individuals move from one region to another as long as the marginal revenue from change in location continues to exceed the marginal cost. In this framework, migration acts as an adjustment mechanism as the prospective migrants are able to improve their earnings potential through productivity-raising self-investment.

The gains from migration are traditionally measured by treating migration as one of the right-hand-side variables in the earnings model,[1] using household-level data. However, it is now widely recognised that issues like individual self-selection, including the migration decision, are not random; rather, these are the outcome of the maximisation behaviour of economic agents. Heckman (1976) and Lee (1976) have shown that

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[1] See Haque (1977, 1984); Waldorf and Waldorf (1983) and Khan and Irfan (1985).

unless the *endogenous* nature of these decisions is duly recognised, the OLS estimates may turn out to be inconsistent. In the light of this argument, an *augmented* Mincerian earnings model will be estimated in this paper which explicitly recognises the endogenous nature of the migration decision. The extended model will correctly establish whether or not there are gains from individual characteristics of migrants as compared to non-migrants.

The second objective of this study is to measure the extent of "assimilation" effect on the migrants by verifying the learn-as-you-go proposition. We anticipate that due to possible disruption and adaptation effects, the earnings of recent migrants will be low as compared to those who have migrated for a sufficiently long time and have acquired the knowledge of location-specific-capital. To capture the gains from a lengthy stay at the destination, migration duration will be introduced as an additional explanatory variable in the earnings model.

The empirical analysis will rely on the nation-wide household-level Population, Labour Force, and Migration (PLM 1979-80) survey data, which are based on a random sample of 11,300 households. For each household, the survey recorded information on income, expenditure, labour force participation, migration, and fertility history. The head of the household or any other responsible person in the house (usually a man) completed the questionnaires related to migration, labour force, and income and expenditure, while women between ages 13 and 49 completed the fertility-related questionnaire.[2] We understand that the choice of micro data on rural-urban migration flows is more appropriate as the objective is to verify a theory which is individual-based. Moreover, such data explicitly take into account the heterogeneity in the population [Robinson and Tomes (1982)].

The rest of this paper is arranged in the following order. The second section develops a theoretical framework of an earnings model within the traditions of the human capital school. The operational model for empirical analysis is presented in the third section. The methodology and the empirical results are discussed in the fourth section, and the final section concludes the study by summarising the major findings.

II. THE ANALYTICAL MODEL

Until recently, the returns to migration were estimated by treating income or a relevant proxy for income as a dependent variable and migration as one of the explanatory variables. However, as indicated above, the decision to migrate is not an outcome of a controlled experiment in which the randomly selected experimental group is allowed to migrate and the control group stays in the area of origin. Rather, migration takes place as a consequence of the maximisation behaviour of individuals. Therefore, an estimation of earnings which does not take into account the endogenous nature of the migration decision results in inconsistent estimates due to the selectivity bias.

To overcome this problem, a model is developed in this paper where individual earnings and the migration decision are jointly determined in a simultaneous framework.[3] While the earning capacity of migrants and non-migrants is defined to conform

[2]Further details of the data are provided in Ahmed (1991) and Ahmed and Sirageldin (1993).

[3]With reference to selectivity modelling and estimation in Pakistan, probably the first attempt was made by Haque (1984) for work status choice. Later on, Haque (1986) applied this technique to test the labour market segmentation hypothesis in Pakistan. More recently, Kozel and Alderman (1990) have used this procedure to determine work participation and labour supply decisions in urban areas of Pakistan.

with the human capital theory [Becker (1964); Becker and Chiswick (1966) and Mincer (1974)], the decision to migrate largely depends on the theory of individual migration [Todaro (1969) and Harris and Todaro (1970)]. We start with specification of the earning functions for migrants and non-migrants.

Taking an explicit account of the endogeneity of the migration decision rule, this information is disaggregated by the choice of the individuals to participate in a controlled experiment. Accordingly, self-selectivity results in migration if gains to migration exceed other alternatives. We assume that the potential earnings of the i^{th} individual are not only influenced by observable personal characteristics Z_i and by unobservable factors that are summarised by u_i, but that the gains from migration are additionally influenced by factors which determine the cost of migration (C_i). Thus, the earnings of the two groups can be specified as:

$$Ln\ Y_{mi} = \alpha_0 + Z_i\alpha_1 + W_i\alpha_2 + u_{mi} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2.1)$$

$$Ln\ Y_{ni} = \beta_0 + Z_i\beta_1 + u_{ni} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2.2)$$

where $Ln\ Y_{mi}$ and $Ln\ Y_{ni}$ are the logarithm of earnings of migrants and non-migrants respectively, W_i includes those factors which influence the cost of migration, u_{mi} and u_{ni} are the random disturbance terms associated with unconditional earning functions of the two categories of workers.

Since these earnings are conditional on whether or not a person migrates, a new variable representing the migration decision rule (I_i) which measures the relative gains of migration has to be constructed. That is,

$$I_i^* = Ln\ Y_{mi} - Ln\ Y_{ni} - C_i \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2.3)$$

For estimation purposes, the reduced-form migration decision rule is derived by substituting expressions (2.1) and (2.2) in (2.3). By collecting and re-labelling terms we get:

$$I_i^* = X_i\,\pi_I - \varepsilon_{1i} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2.4)$$

where ε_{1i} includes the random disturbance term associated with cost function and u_s; and $X_i = [Z_i, W_i]$.

The reduced-form decision rule in its present form contains the latent dependent variable (I_i^*) which is unobservable. In fact, what we observe is

$$I_i = 1 \quad \text{if } I_i^* > 0$$

$$I_i = 0 \quad \text{if } I_i^* < 0$$

which implies that the individual who gains from migration (i.e., $I_i^* > 0$) for him $Y_i = Y_{mi}$. On the other hand, if $I_i = 0$ (or $I_i^* < 0$) then $Y_i = Y_{ni}$. That is, the expected earnings of migrants and non-migrants specified below are thus conditional on the decision rule:

$$E[Y_{mi}\,|I_i = 1] = \alpha_0 + Z_i\alpha_1 + W_i\alpha_2 + E[u_{mi}\,|I_i = 1] \quad \ldots \quad \ldots \quad \ldots \quad (2.5)$$

$$E[Y_{ni} \mid I_i = 0] = \beta_0 + Z_i\beta_1 + E[u_{ni} \mid I_i = 0] \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2.6)$$

A simple inspection of these expressions will reveal that the standard OLS technique can not be applied to estimate (2.5) and (2.6). The conditional means of income disturbance terms are non-zero as there is a truncation of the sample because of the migration decision. The correct estimation procedure, in this case, is simultaneous estimation of the qualitative dependent variable of the migration decision along with the earning functions. The two-step estimation procedure as suggested by Heckman (1976) and Lee (1976) requires that, in the first step, consistent estimates of π_i are derived through the probit maximum likelihood technique. These estimates are used to construct instruments for conditional disturbance terms, which in turn are used in the earning functions to resolve the specification error. Assuming joint normality of u_{mi} and u_{ni}, the estimates of these conditional disturbance terms will be:

$$E\,[u_{mi} \mid I_i = 1] \;=\; [\frac{\sigma_{u_{mi}\varepsilon_{1i}}}{\sigma_{\varepsilon_{1i}}}]\;[\,-\frac{\varphi(X_i\hat{\pi}_i\,/\,\sigma_{\varepsilon_{1i}})}{\Phi(X_i\hat{\pi}_i\,/\,\sigma_{\varepsilon_{1i}})}]$$

$$E\,[u_{ni} \mid I_i = 0] \;=\; [\frac{\sigma_{u_{ni}\varepsilon_{1i}}}{\sigma_{\varepsilon_{1i}}}]\;[\frac{\varphi(X_i\hat{\pi}_i\,/\,\sigma_{\varepsilon_{1i}})}{1-\Phi(X_i\hat{\pi}_i\,/\,\sigma_{\varepsilon_{1i}})}]$$

where $\sigma_{um\varepsilon}$ and $\sigma_{un\varepsilon}$ are the elements of co-variance matrix, and $\varphi(.)$ and $\Phi(.)$ are the standard normal probability and cumulative density functions, respectively. To save space, define λ_i as

$\lambda_{mi} = [\,-\frac{\varphi(X_i\hat{\pi}_I\,/\sigma_{\varepsilon_{1i}})}{\Phi(X_i\hat{\pi}_I\,/\sigma_{\varepsilon_{1i}})}]$ and $\lambda_{ni} = [\frac{\varphi(X_i\hat{\pi}_I\,/\sigma_{\varepsilon_{1i}})}{1-\Phi(X_i\hat{\pi}_I\,/\sigma_{\varepsilon_{1i}})}]$. In the second step, the "selection effect" is incorporated in (2.5) and (2.6) so that the resulting models satisfy the assumptions of the classical least square. In this case, the final estimable form of the earnings functions for migrants and non-migrants will be:

$$[Y_{mi} \mid I_i = 1] = \alpha_0 + Z_i\alpha_1 + W_i\alpha_2 + \frac{\sigma_{u_{mi}\varepsilon_{1i}}}{\sigma_{\varepsilon_{1i}}}\,\lambda_{mi} + v_1 \quad \ldots \quad \ldots \quad \ldots \quad (2.7)$$

$$[Y_{ni} \mid I_i = 0] = \beta_0 + Z_i\beta_1 + \frac{\sigma_{u_{mi}\varepsilon_{1i}}}{\sigma_{\varepsilon_{1i}}}\,\lambda_{ni} + v_2 \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2.8)$$

where the introduction of λ_i allows a consistent estimation of the earning equations by OLS as the disturbance terms (v_i) are now normally distributed.

III. THE OPERATIONAL MODEL

Since the estimation of structural earnings functions (2.7) and (2.8), in their "general" form, is not possible, we now specify variables which are either direct or proxy measures of these theoretical constructs, namely, earnings, education, work experience, regional variables, and year of migration. We shall also discuss the economic rationale that justifies their inclusion in the operational specification of the model.

Earnings

In the earnings equation, monthly earnings of the head of the household, whether migrant or non-migrant, are used as the dependent variable. Two issues require special attention towards the choice of the dependent variable. First, it may be noted that the logarithm of monthly earnings is made up of two choice mechanisms: a labour supply decision and the productivity effect (the monthly wage rate), which the Becker-Mincer earnings functions attempt to estimate.[4] In this case, the issue of censoring becomes relevant because maximisation of monthly or yearly gains depends on whether or not an individual has command not only on a certain wage but also on his choice of hours of work.[5]

Second, in estimating the human capital model, Blinder (1973) encourages the use of "wage rate" rather than earnings as the dependent variable, as the use of former may result in biased estimation because there is no control for labour supply. In the present study, this problem is partially mitigated by restricting the sample to a group of men aged 16 years or above who have positive monthly earnings. Secondly, only those respondents are included in the working sample who did not report their monthly income as below one hundred rupees. These restrictions are intended to reduce the bias that may arise by the inclusion of part-time workers in the sample.[6]

Education

One of the important determinants of the Becker-Mincer earnings model is the level of schooling of the respondent. In the human capital model of earnings, education is considered as self-investment the rewards of which, of course, accrue in terms of greater earnings for the remaining work-span. Of course, this does not deny the consumption benefits of education.

While computing rates of return to education, two concepts are generally adopted. In the first case, a quadratic term for years-of-schooling is added in the simple earnings model; and in the second case, different educational levels are specified in the model by means of a series of dummy variables.[7] Since the second procedure adds a great deal of sensitivity to the model, we have disaggregated years of schooling into four categories; i.e., (a) primary education which requires five years of schooling, (b) middle school requiring eight years, (c) high school which requires ten years of schooling, and (d) further years of schooling are categorised as college-university education.

Work Experience

The second source of accumulation of human capital is through on-the-job training, which is consistent with Arrow's learning-by-doing hypothesis. In this case, a worker acquires job-specific or general skills which enhance his productivity as

[4]For example, see Heckman (1974), where separate equations have been estimated for hours of work and wages.

[5]For an elaborate discussion of this point, see Haque (1986, 1986a).

[6]Despite these restrictions, we understand that under-estimation of individual earnings due to moonlighting will be offset by over-estimation of earnings of part-time workers.

[7]For a detailed discussion on the computation of rates of return to education, see Psacharopolous (1981).

compared to his colleagues. Thus, the earnings of workers may differ because of productivity differentials.

In the absence of direct information in the PLM survey about *actual* years of work experience, this variable is constructed on the basis of information concerning the respondent's current age and education. The *potential* years of work-experience in this paper is, therefore, obtained as a residual from current age, completed years of schooling and six; where it is assumed that schooling starts at the age of six. "Potential experience" is probably a reasonable approximation for male workers because of their higher labour force participation rates.

The economic theory of optimisation behaviour suggests that the investment in human capital declines beyond a certain age. Thus, the peak age hypothesis results in a hump-shaped age profile of productivity.[8] In order to test this hypothesis, a quadratic term for experience is also included in the model. Assuming that the age-income profile is concave from below, it is expected that the coefficient for experience will be positive and its squared term will appear with a negative sign.

Residence (Dummy) Variables

Previous research has shown that there are significant differences in the earnings in rural versus urban areas of Pakistan.[9] These two sectors differ not only in terms of cost of living but also in terms of the available opportunities for education and jobs. The same is true for the standard of living across provinces. To control for the inter-sectoral and inter-provincial differences, dummy variables are included in the earnings model. We anticipate higher earnings for the residents of the Province of Punjab as compared to those living in the other provinces because of the former's perceived relative prosperity.

Migration Duration

Since the year of migration varies for different migrants, the gains from migration can be assessed by considering the time that has passed since migration. It is expected that, other things being equal, recent migrants possessing similar characteristics earn less as compared to those who have migrated for a sufficiently long duration and have thus acquired relatively more of the necessary skills of location-specific capital. The migration duration variables are therefore important in verifying the learn-as-you-go proposition.

Selection Effect

The extent of selectivity-bias in earnings is assessed on the basis of the significance of both λ_{mi} and λ_{ni}. Since by definition $\lambda_{mi} < 0$, this suggests that the observed mean of initial earnings will be greater or less than its population mean as $\sigma_{u_m\varepsilon} \lesseqgtr 0$. Similarly, since $\lambda_{ni} > 0$, the positive or negative selection bias in the initial earnings for non-migrants will be determined on the basis of $\sigma_{u_n\varepsilon} \gtreqless 0$. Positive coefficients for both λ_{mi} and λ_{ni} will be consistent with the "comparative advantage" hypothesis, which allows for the role of talent in determining the observed outcomes [Roy (1951) and

[8]See, for example, Browning, Deaton and Irish (1985); Ghez and Becker (1975) and Ahmad *et al.* (1993).

[9]See, for example, Khan and Irfan (1985); Kozel and Alderman (1990); Shabbir and Khan (1991) and Shabbir (1994).

Willis and Rosen (1979)].

On the basis of the preceding discussion of variables, it is now possible to present the operational model for the two categories, that is, migrants and non-migrants, for empirical analysis. The sign below each variable reflects the expected effect of these explanatory variables on the dependent variable.

$$\begin{array}{rcl} Y_{ni} & = & \text{f[EDH2, EDH3, EDH4, EDH5, EXP, EXPSQ,} \\ & & \quad (+) \quad (+) \quad (+) \quad (+) \quad (+) \quad (-) \\ & & \text{OCH, URDUM, PRDUM]} \\ & & \quad (+) \quad (+) \quad (+) \end{array}$$

and

$$\begin{array}{rcl} Y_{mi} & = & \text{g[EDH2, EDH3, EDH4, EDH5, EXP, EXPSQ,} \\ & & \quad (+) \quad (+) \quad (+) \quad (+) \quad (+) \quad (-) \\ & & \text{OCH, URDUM, PRDUM, MGDR]} \\ & & \quad (+) \quad (+) \quad (+) \quad (+) \end{array}$$

where

Y_{mi} = Monthly income of migrants measured in rupees,
Y_{ni} = Monthly income of non-migrants measured in rupees,
EDH2 = Dummy variable that takes a value of One if husband possesses primary education and zero otherwise,
EDH3 = Dummy variable that takes a value of One if husband possesses eight years of schooling and zero otherwise,
EDH4 = Dummy variable that takes a value of One if husband possesses secondary school education and zero otherwise,
EDH5 = Dummy variable that takes a value of One if husband's education is beyond high school and zero otherwise,
EXP = Experience (Current Age – Years of Schooling – 6),
EXPSQ = Experience squared,
OCH = Dummy variables taking a value of One if the occupation of husband belongs to professional, clerical, sales, agriculture, or skilled, etc., category and zero otherwise,
PRDUM = Dummy variable taking a value of One if the respondent lives in the Province of Punjab and zero otherwise,
MGDR = Dummy variable(s) reflecting migration duration.

Given the above operational specification of the model, we now turn to estimate these relationships for migrants and non-migrants.

IV. EMPIRICAL RESULTS

Migration Decision Rule

Towards estimating the *selectivity-corrected* earnings models for migrants and non-migrants, the first step is to estimate the reduced-form migration decision rule (2.4)

which generates the estimates of Inverse Mill's ratios λ_{mi} and λ_{ni}.[10] Thus, the discussion of the main findings of the paper is initiated by a brief analysis of the results related to the reduced-form migration decision rule presented in Table 1.[11] According to these results, a negative and significant relationship between the age and the migration decision indicates that the probability of migration decreases as one grows older. On the other hand, the level of education which acts as a signalling device encourages migration. Similarly, the chances of migration increase if the respondent belongs to a professional category as compared to any other occupational group. The commitment and the cost-related variables, such as the ownership of house, number of school-going children, and self-employment of husband, deter individuals and families from moving. Finally, the sample under consideration indicates that contrary to general understanding, education of wife reduces the probability of migration, whereas her participation in the labour market has almost no effect on the family's migration decision. This may not be too surprising in Pakistani social set-up, where females are generally "tied" movers.

Structural Earnings Models

We now present the results related to earnings of migrants and non-migrants. Two types of models (both for migrants and non-migrants) are analysed here. In the first case, selectivity-corrected conditional earnings functions are estimated and the second type of results where no such correction is made enable us to determine the degree of selectivity bias in earnings.

Earnings of Migrants

Table 2 presents the structural-form estimates of earnings for migrants. The middle two columns of this table are for selectivity-corrected results and the two right-most columns are where selectivity is ignored.

Some of the "general conclusions" that are drawn from empirical results are as follows: (a) the PLM data allow a meaningful estimation of Mincerian earnings function for migrants and non-migrants in Pakistan; (b) the returns to education are positive and significant for all except in one case; (c) the initial rate of increase in earnings due to experience is slightly over one percent for migrants and over two percent for non-migrants; (d) the professional and technical workers gain relatively more from migration; and (e) the coefficient of determination ranges between 0.17 and 0.24 under alternative model specifications.

Concentrating on the selectivity-corrected results,[12] we find that except for prima-

[10]The solution procedure is available in LIMDEP, an econometric software, developed by Greene (1990).

[11]The specification of the migration decision rule is discussed in greater details in Ahmed and Sirageldin (1993).

[12]In evaluating the selectivity-corrected results, one should be careful about the sensitivity of these results. Although Heckman's two-step procedure correctly identifies the selectivity-bias problem, the results are quite sensitive to the normality assumption about the error term. This sensitivity is reduced to a greater extent if there are certain variables that influence sample selection but do not merit inclusion in the second-stage regression. To overcome this problem, the earnings functions in the present analysis excludes a number of variables that were included in the migration decision rule. Some of these variables are: ownership of assets (house and land), number of school-going children, wife's education, and her work experience.

Table 1

Maximum Likelihood Probit Estimates of Reduced Form Migration Decision Rule

Variables	Estimated Coefficients	*t*-Statistics
Constant	–0.373	–2.80**
AGE (H)	–0.013	–3.09*
Education[a] (H)		
Primary (1–5)	0.213	1.70***
Middle (6–8)	0.146	1.12
High (9–10)	0.379	3.11*
College/University	0.548	3.57*
Education[b] (W)	–0.025	–2.03**
Husband Self-employed	–0.403	–4.02*
Occupation[c] (H)		
Professional	0.389	2.48**
Clerical	–0.029	–0.18
Sales	0.093	0.63
Agriculture	0.272	1.38
Skilled	0.145	1.23
Other	0.117	0.81
LF Participation (W)	0.002	0.39
Ownership of House	–0.549	–6.66*
Children in School	–0.107	–2.23**
Province Dummy (Punjab=1)	0.342	4.35*

[a]Reference Group = Husband possesses no education.
[b]Reference Group = Wife possesses no education.
[c]Reference Group = Husband household worker or his profession not specified.

*Significant at one percent level.
**Significant at five percent level.
***Significant at ten percent level.

Summary Statistics	
Log Likelihood Ratio	–659.62
Restricted Log-L	–732.79
Chi-squared (17)	146.36
Significance Level	0.32173E–13
Sample Size	2126

Table 2

Structural Earnings Estimates of Migrants Based on Heckman's Two Step Procedure and the OLS Dependent Variable: Log (Monthly Income)

Variables	Estimated Coefficients with *t*-statistics			
	Selectivity Corrected		Selectivity Ignored	
	Model 1	Model 2	Model 3	Model 4
Constant	0.586	5.720	6.230	6.216
	(18.66)*	(17.05)*	(25.68)*	(24.39)*
Education[a] (H)				
Primary	0.088	0.093	0.090	0.103
	(0.65)	(0.71)	(0.66)	(0.77)
Middle	0.304	0.384	0.325	0.374
	(2.14)**	(2.52)**	(2.28)**	(2.69)*
High	0.409	0.500	0.385	0.462
	(3.36)*	(3.92)*	(3.17)*	(3.66)*
College/University	0.835	0.738	0.777	0.669
	(6.32)*	(4.82)*	(6.05)*	(4.43)*
Experience	0.015	0.019	0.018	0.022
	(0.98)	(1.26)	(1.11)	(1.43)
Experience Squared	–0.0003	–0.0003	–0.0002	–0.0003
	(–0.82)	(–1.18)	(–0.72)	(–1.07)
Occupation[b] (H)				
Professional	–	0.272	–	0.223
		(1.80)***		(1.49)
Clerical	–	–0.367	–	–0.377
		(–2.45)**		(–2.51)**
Sales	–	–0.197	–	–0.126
		(–1.41)		(–0.92)
Agriculture	–	0.324	–	0.343
		(1.59)		(1.66)***
Skilled	–	–0.010	–	–0.014
		(–0.09)		(–0.18)
Other	–	–0.222	–	–0.272
		(–1.54)		(–1.90)***
Province Dummy[c]	–0.167	–0.126	–0.223	–0.203
(Punjab=1)	(–1.93)***	(–1.48)	(–2.76)*	(–2.61)*
LAMBDA	0.251	0.331		
(Inverse Mill's Ratio)	(1.77)***	(2.23)**	–	–
Summary Statistics				
R Squared	0.207	0.29	0.196	0.274
Adjusted R Squared	0.179	0.24	0.171	0.231
St. Error of Regression	0.583	0.552	0.598	0.576
Sample Size	232	232	232	232

[a]Reference Group = Husband possesses no education.
[b]Reference Group = Husband engaged in household work or his occupation is unspecified.
[c]Reference Group = Those who belong to rural areas.

*Significant at one percent level.
**Significant at five percent level.
***Significant at ten percent level.

ry education, the coefficients for all other categories of schooling are significant at one percent or five percent level. The only insignificant coefficient suggests that primary education is not sufficient to bring any valuable addition to migrant's earnings.[13] On the other hand, migrants having relatively more years of schooling are better off at the destination. For example, those with middle school education earn 2.16 percent more than those with primary education and the earnings of migrants with high school or college education are as high as 32.1 percent and 74.7 percent, respectively, as compared to migrants with primary education. These percentages would translate to an increase of Rs 324.00 to Rs 1120.00 per month for higher education if the monthly income for primary school migrants is assumed to be Rs 1500.00 per month.

The annual rates of return calculated from the coefficients of Model-1 range between 5.3 percent for secondary education and 10.7 percent for college-university graduates. These results are consistent with earlier empirical evidence from Pakistan where the rates of return to higher education range between 5.2 and 13.1 for secondary school and university graduates.[14]

The growth path of earnings over the life-cycle is explained by potential years of job experience and its squared term. While experience and earnings show a positive though insignificant relationship for migrants, the negative coefficient for the squared term confirms the concave nature of experience-earnings profile. The insignificance of these coefficients requires a word of caution in explaining these results.[15]

Contrary to our expectation, the provincial dummy variables indicate that the residents of the Punjab were not better off in terms of earnings than those living in other provinces. This was not only observed by Khan and Irfan (1985) and Shabbir (1994), who used the PLM 1979-80 data, but also by Kozel and Alderman (1990) and Ashraf and Ashraf (1993), who used entirely different data sets. So far as evidence from the PLM data is concerned, it may be noted that during the field-work for this survey, interviews in the NWFP and Balochistan provinces were conducted in relatively more accessible areas, leaving out the poorer population living in the remote areas. This sampling error could have falsely raised the living standard of these provinces. However, it is also possible that the population residing in these regions might have been more prosperous as they benefited the most from the remittances from out-migrants of this area working in the oil-producing Middle Eastern countries [Shabbir (1994)]. Furthermore, two recent studies on regional economic disparity have also confirmed a higher incidence and intensity of poverty in Punjab.[16]

The Mincerian earnings model was further extended to test alternative hypotheses. One such extension was to introduce controls for occupational groups to measure the impact of the differences in skills on earnings. The evidence confirmed that when the

[13]This phenomenon of market imperfection is also confirmed from the results of Table 4, where variables related to migration duration have been introduced in the model specification. The results indicate that as compared to natives, even those migrants who have migrated for a sufficiently longer duration are not preferred for jobs which require elementary education.

[14]Table 2 in Khan and Irfan (1985) provides such a comparison between different studies. However, none of the studies reported in the above table distinguishes between migrants and non-migrants.

[15]It may be pointed out that these results did not improve in any significant way when experience and its squared term were replaced by current age and its squared term.

[16]It may be interesting to note that both Ercelawn (1991) and Malik (1991) did not use any control for migration.

occupation of migrants disaggregated into various categories was included in the model, the possession of human capital remained a significant determinant of their earnings. However, only professionals were able gain from migration. The statistical significance of the professional dummy variable may also reflect the presence of information gap between occupational groups which could have forced workers belonging to other categories of occupation to join the informal sector, where the returns are usually low. Alternatively, due to the low demand for them, the non-professionals might have accepted lower-level public or private formal-sector jobs.

Finally, a positive and significant coefficient for the selectivity variable of migrants was observed. This implied a negative selection bias for migrants' earnings, i.e., those who migrated earned less, *ceteris paribus,* at their destination than an average non-migrant had he also moved. This suggests that migrants who might have been above-average in the place of origin could hardly compete with average residents of the place of destination. Another reason for this unexpected result could be the fact that migrants in the sample are younger in age as compared to non-migrants, thus the experience-effect on earnings will have to be small. The subsequent discussion in the paper also confirms that the gains from migration take time to materialise. The cut-off period of December 1971 in th PLM survey, which determines the length of the migrants' stay at the destination, is probably too short to capture effectively the true benefits of migration since disruption, adaptation, and assimilation are stages which are quite time-consuming. Furthermore, the negative selection bias is not all too surprising as a similar phenomenon for the migrants was also observed in Malaysia [Lee (1989)].[17]

Another way of looking at the extent of such bias is through a comparison of selectivity-corrected results with those where selectivity is ignored. The results presented in the two right-hand columns of Table 2 indicate that even though the estimates from the two techniques are almost identical in terms of the level of significance and signs of various coefficients, nonetheless, the rates of return to education are lower if the calculations are based on results when selectivity is ignored (5.9 vs 6.4 and 7.2 vs 8.1 for the lowest to the highest category of education). This confirms that, without correction for the selection bias, the returns to investment in human capital such as education and on-the-job training are under-estimated.

Earnings of Non-migrants

The earnings estimates for non-migrants are presented in Table 3. Contrary to the migrants' case, job experience, which reflects accumulation of human capital by non-migrants, not only appeared with expected signs, but in the present case this variable is statistically significant also. The age-earning profile of non-migrants appears to be non-linear, with its peak appearing between 40 to 43 years, depending on the specification.[18]

[17]However, note that one of the problems with the selectivity variable is that it could indicate the presence of selection bias even when there was no selection bias. This problem arises when some of the explanatory variables used to determine the migration decision rule are also included in the conditional earning equations. In this case, since λ_i is a non-linear function, it is likely to pick up any non-linear terms omitted from the earnings function. The remedy to this problem, as suggested by Maddala (1983), is to include non-linear terms in the conditional equation. In the present study, this problem is resolved by introducing in the earnings function a squared term for experience which picks up non-linearities.

[18]This observation is due to the presence of self-employed workers in the sample.

Table 3

Structural Earnings Estimates of Non-migrants Based on Heckman's Two Step Procedure and the OLS Dependent Variable: Log (Monthly Income)

Variables	Estimated Coefficients with *t*-statistics			
	Selectivity Corrected		Selectivity Ignored	
	Model 1	Model 2	Model 3	Model 4
Constant	6.261	6.154	6.033	5.932
	(53.02)*	(51.47)*	(62.78)*	(61.10)*
Education[a] (H)				
Primary (1–5)	0.130	0.126	0.099	0.095
	(2.41)**	(2.40)**	(2.31)**	(2.25)**
Middle (6–8)	0.365	0.343	0.359	0.340
	(6.43)*	(6.13)*	(7.92)*	(7.49)*
High (9–10)	0.449	0.471	0.400	0.430
	(8.36)*	(8.40)*	(9.43)*	(9.54)*
College/University	1.042	1.064	0.953	1.004
	(16.45)*	(15.64)*	(19.33)*	(18.40)*
Experience	0.026	0.025	0.031	0.031
	(3.91)*	(3.86)*	(5.20)*	(5.15)*
Experience Squared	–0.0003	–0.0003	–0.0004	–0.0003
	(3.21)*	(3.15)*	(–3.88)*	(–3.82)*
Occupation[b] (H)				
Professional	–	0.200	–	0.108
		(2.58)**		(1.75)***
Clerical	–	–0.109	–	–0.135
		(–1.44)		(–2.18)**
Sales	–	0.180	–	0.222
		(3.52)*		(5.45)*
Agriculture	–	0.178	–	0.163
		(2.22)**		(2.52)**
Skilled	–	0.207	–	0.189
		(4.19)*		(4.73)*
Other	–	–0.007	–	–0.039
		(–0.11)		(–0.78)
Residence Dummy[c]	–0.801	–0.077	–0.144	–0.137
	(–2.19)**	(–2.15)**	(–5.26)*	(–5.06)*
LAMBDA (Inverse Mill's Ratio)	0.874	0.836		
	(5.36)*	(4.86)*	–	–

[a]Reference Group = Husband possesses no education.
[b]Reference Group = Husband engaged in household work or his occupation is unspecified.
[c]Reference Group = Those who belong to rural areas.

*Significant at one percent level.
**Significant at five percent level.
***Significant at ten percent level.

Summary Statistics				
R Squared	0.208	0.235	0.190	0.221
Adjusted R Squared	0.204	0.229	0.187	0.216
St. Error of Regression	0.586	0.576	0.593	0.583
St. Error Corrected for Selection	0.738	0.718	–	–
Sample Size	1894	1894	1894	1894

The returns to education, for this group, increased with higher level of schooling. The rates of return increased from 6.4 percent to 14.8 percent for college-university graduates. These rates, especially for the latter category, are higher as compared to migrants.

The results further show that for non-migrants the selectivity variable turns out to be significant and positive, which implies a positive selection bias for non-migrants' earnings. That is, those who do not migrate earn more than an average migrant had he not migrated. Even though this is surprising, yet similar findings on self-selection were reported by Lee (1989); Nakosteen and Zimmer (1980) and Robinson and Tomes (1982).

A comparison of selectivity-corrected results with those where selectivity is ignored shows that, once again, the significance of coefficients and their direction is more or less the same in the two cases. However, as for migrants, the rates of return to schooling are lower if calculated from the OLS estimates as compared to those where selectivity is corrected.

Assimilation Effect

The assimilation hypothesis or the learn-as-you-go proposition suggests that migrants take time to adjust to new surroundings. For this reason, the performance of recent migrants may not be as good as they would have desired before migration. However, with the passage of time, these migrants are assimilated into the new environment which leaves a positive influence on their socio-economic life. In order to capture this phenomenon, the Mincerian earnings model is further augmented by introducing two variables. One of these variables is for recent migrants and the other is for relatively long-standing migrants. As pointed out earlier, in the PLM survey data, the length of migration for a migrant could be assessed from the cut-off period of December 1971. A recent migrant was thus defined as the one whose migration duration was only about two years since 1979, and a relatively long-standing migrant was one who had migrated about seven years before the survey was conducted. The results presented in Table 4

Table 4

Structural Earnings Estimates of Migrants Based on Heckman's Two-step Procedure and the OLS Dependent Variable = Log (Monthly Income)

Variables	Estimated Coefficients with *t*-statistic	
	Selectivity Corrected	Selectivity Ignored
Long-standing Migrants	0.201	0.201
	(1.70)***	(1.72)***
Recent Migrants	0.065	0.031
	(0.53)	(0.25)
LAMBDA	0.248	–
(Inverse Mill's Ratio)	(1.74)***	
*Significant at one percent level.		
**Significant at five percent level.		
***Significant at ten percent level.		
R Squared	0.217	0.207
Adjusted R Squared	0.182	0.175
St. Error of Regression	0.579	0.596
Sample Size	232	232

confirm the importance of migration duration in the determination of earnings of migrants.[19] The statistically significant coefficient for long-standing migrants reveals that migrants indeed require time to acquire skills of location-specific capital. These skills and on-the-job training increase their productivity, which, in terms of earnings, bring them at par with natives.

V. SUMMARY AND CONCLUSIONS

An effort has been made in this paper to estimate Mincerian earnings functions for rural-to-urban migrants and non-migrants in Pakistan. In order to correct for the self-selection bias, a two-step estimation procedure was utilised. The empirical results provided the following important conclusions:

(i) The PLM data from Pakistan allowed a meaningful estimation of Mincerian earnings function for migrants and non-migrants.

(ii) The level of schooling was one of the important determinants of the distribution of income, both for migrants and non-migrants. The four categorical variables of education were, in general, statistically significant with expected signs, implying that the hypothesis of a positive relationship between income and education was accepted.

(iii) The rates of return to education improved systematically with higher levels of education, thus confirming the notion that education serves as a signalling device.

(iv) The age-income profile was almost linear for migrants but showed concavity for non-migrants. This phenomenon, although it confirmed the peak-age hypothesis, could partially be attributed to the presence of self-employed workers in the sample.

(v) Regional dummy variables and different categories of occupation were not insignificant in explaining the variations in income of the two groups.

(vi) The analysis indicated the presence of selectivity bias in earnings. However, the correction of bias had a marginal effect on the overall conclusions.

(vii) Migration duration was an important variable to capture the "assimilation effect". Although the survey data did not allow migration duration longer than eight years, the model, nonetheless, predicted higher earnings for long-standing migrants than those who had migrated relatively recently.

On the basis of these results, it is safe to conclude that human capital variables are important determinants of the earnings of migrants as well as non-migrants. Among these, education could be isolated as the major contributing factor. It was observed that substantial gains could be accomplished by investing in the human capital. However, as with any other type of investment, gains from migration also take time to materialise.

[19]Although Table 4 reports results for long-standing and recent migrants, the model specification included all the variables that were included in Models 1 and 3 in Table 2.

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