ECONOMIC STUDIES

DEPARTMENT OF ECONOMICS
SCHOOL OF BUSINESS, ECONOMICS AND LAW
GÖTEBORG UNIVERSITY
170

Essays on Microeconometrics and Immigrant Assimilation

Alpaslan Akay

ISBN 91-85169-29-3
ISBN 978-91-85169-29-0
ISSN 1651-4289 print
ISSN 1651-4297 online

GÖTEBORG UNIVERSITY

To my father
and dear Merih

Contents

Abstract

Paper I.

Asymptotic bias reduction for a conditional marginal effects estimator in sample selection models.

In this article we discuss the differences between the average marginal effect and the marginal effect of the average individual in sample selection models, estimated by the Heckman procedure. We show that the bias that emerges as a consequence of interchanging the measures, could be very significant, even in the limit. We suggest a computationally cheap approximation method, which corrects the bias to a large extent. We illustrate the implications of our method with an empirical application of earnings assimilation and a small Monte Carlo simulation.

Paper II.

Local Unemployment and the Earnings-Assimilation of Immigrant Men in Sweden: Evidence from Longitudinal Data, 1990-2000.

The earnings-assimilation of first-generation immigrant men in Sweden was analyzed using eleven waves of panel-data, 1990-2000. Employment-probabilities and earnings were estimated simultaneously in a random-effects model, using Mundlak's formulation to control for both individual effects and panel-selectivity due to missing earnings-information. Assuming equal-period effects produced bias which could distort the findings. To correct the bias, local unemployment-rates were used to proxy for changing economy-wide conditions. Labour-market outcomes differed considerably across immigrant arrival cohorts, region and country of origin, and educational levels.

Paper III.

Monte Carlo Investigation of the Initial Values Problem in Censored Dynamic Random-Effects Panel Data Models.

Three designs of Monte Carlo experiments are used to investigate the initial-value problem in censored dynamic random-effects (Tobit type 1) models. We compared three widely

used solution methods: naive method based on exogenous initial values assumption; Heckman's approximation; and the simple method of Wooldridge. The results suggest that the initial values problem is a serious issue: using a method which misspecifies the conditional distribution of initial values can cause misleading results on the magnitude of true (structural) and spurious state-dependence. The naive exogenous method is substantially biased for panels of short duration. Heckman's approximation works well. The simple method of Wooldridge works better than naive exogenous method in small panels, but it is not as good as Heckman's approximation. It is also observed that these methods performs equally well for panels of long duration.

Paper IV.

Dynamics of Employment- and Earnings-Assimilation of First-Generation Immigrant Men in Sweden,1990-2000.

The employment- and earnings-assimilation of first-generation immigrant men in Sweden was estimated using a dynamic random-effects sample-selection model with eleven waves of unbalanced panel-data during 1990-2000. Endogenous initial values were controlled for using the simple Wooldridge method. Local market unemployment-rates were used as a proxy in order to control for the effect of changing macroeconomic conditions. Significant structural (true) state-dependence was found both on the employment-probabilities and on the earnings of both immigrants and native Swedes. The size of structural state-dependence differed between immigrants and Swedes. Failure to control for the structural state-dependence could have caused bias not only in the assimilation measures but also in the cohort-effects. For example, standard (classic) assimilation model seriously overestimates short-run marginal assimilation-rates and underestimates long-run marginal assimilation-rates. The model controlling for structural state-dependence shows that the earnings of all immigrants in Sweden (except Iraqies) eventually converge to those of native Swedes, but only Nordics and Westerners are able to reach the employment-probability of native Swedes.

Keywords: *Average marginal effect, Marginal effect of the average individual, Employment and earnings assimilation, Quasi-fixed effects approach, Initial value problem, Dynamic censored random-effects model, Monte Carlo experiment, Heckman's approximation, Simple method of Wooldridge, Dynamic random-effects sample-selection model, wage-curve method.*

J.E.L Codes: C13, C15, C23, C25, C33, J15, J40, J61.

Preface

My dear friend Merih Ipek writes the following in the preface of her new book which I now understand:[1]

"The Myth of Sisyphus[2], a remembrance (or a delusion) when my book is finally finished... Why?! Because there were many obstacles alongside the roads on which I walked. The book was turned upside-down for different reasons each time when I tried to finish it, just as the rock of Sisyphus that was rolling back again and again even if he ceaselessly pushed it to the top of "the hill". As Camus, I consider the emotional state of Sisyphus when his rock was rolling back to the foot of the hill and conclude that "the struggle itself towards the heights is enough to fill a man's heart. One must imagine Sisyphus happy".

The rock is still rolling. Fortunately, during my Ph.D. many people have helped me when I was carrying the rock. My deepest gratitude goes to my supervisor Professor Lennart Flood for his great help in each part of this thesis. I would like to thank him, before all, for his enthusiasm on econometrics which is a great support by its own. He has always been very generous to me with his time and knowledge and helped me with whatever I gave to him. I am greatly indebted to him for the discussions on econometrics and computational issues, and for introducing Fortran software to me (I was playing with toys before).

There are many others that have significantly helped me during the process of writing this thesis. First of all, I am greatly indebted to my coauthors, Kerem Tezic and Elias Tsakas. I specially thank to Olof-Johansson Stenman, Peter Martinsson, Fredrik Carlsson, Thomas Sterner and Gunnar Köhlin for their continuous support to me in all aspects. Olof always kept his door open to me and generously helped me with all issues. Special thanks to Gunnar Köhlin for his support and deep understanding during the last period of my Ph.D. I am truly grateful.

I thank to all seminar participants at Södra Allegatan for their valuable comments and suggestions. I also owe special thanks to Jörgen Hansen, Roger Whalberg, Marcela Ibanez, Martine Visser and my discussant at the final seminar, Konstantin Tatsiramos. I am greatly indebted to Rick Wicks for his useful comments and editorial corrections on my papers.

I would like to thank my teachers during my Ph.D., Lennart Hjalmarsson, Ali Tasiran, Catalin Starica, Bo Sandalin, Ola Olsson, Dick Durevall, Katerina Nordblom and Renato Aguliar and many others. I thank to Andrea Mitrut, Miguel Quiroga, Percious Zikhali, Miyase Yesim, Annika Lindskog, Jorhe Garcia, Daniel Zerfu, Constantin Belu,

[1] Merih Ipek (2006), *Introduction to Statistics II: Probability and Deductive Statistics.* Beta, Istanbul.
[2] Albert Camus [1942], (2000), *The Myth of Sisyphus.* Penguin Books, London, England, 107-111

Daniela Andren, Karin Jonson, Hala Abou-Ali, Gustav Hansson, Innocent Kabenga, Florin Maican, Astrid Nunez, Qin Ping, Sven Tengstam and Wei Jiegen, you have always been great friends to me. I thank you Wlodek Bursztyn, Johan Lönnroth, Dominique Anxo, Håkan Eggert, Åsa Löfgren, Måns Söderbom, Anders Boman, Elina Lampi, Matilda Orth, Marcus Eliason, Abebe Shimeles, Jesper Stage, Alexander Herbertsson, Clara Villegas, Kofi Vondolia, Nizamul Islam and all other people in the Department of Economics for giving me such a stimulating and qualified working environment. I have benefited very much from the tremendous opportunities given to me at Göteborg University. I also owe thanks to Eva Jonason, Eva-lena Neth Johansson for their great administrative support, and Elizabeth Foldi who always supported me with her warm friendsip. I will newer forget the joy I got on her birthday party at her beautiful house.

I am lucky to have my dear friends Gokhan Karabulut and Pinar, Aylin Aktukun, Mehmet Hakan Satman, Baris Altayligil, Hakan Bilgehan, Ender Zafer Asik, Bruno, Ozan and Erkin, I thank them all. I specially thank to you Enis Siniksaran for being my great friend and introducing statistics to me. I hope we will meet in "Cumhuriyet" soon.

I owe special thanks to two individuals; my dear friends Merih Ipek and her son Kerem Tezic. Thank you Merih for everything that you have done for me. You never stop encouraging me about anything. Thank you Kerem, it would not be possible for me to come to this point without your friendship and solidarity. I always miss the nights that we spent in Istanbul and Göteborg and the long walks during which we talked about philosophy and art (especially about Jazz, echoes of Pink Floyd and the psychedelic side of the world).

One of the other contributions of the Ph.D. in Göteborg to me is that I made life lasting friendships: Elias Tsakas, Peter Martinsson and Jana Maruta Grins. I thank to you Elias (karagözi) and your beautiful family for their help and support. I will never forget the times that we spent together in Patras. Thank you Peter for your great friendship and for the long profound discussions in our second office, "Skål", on "feelings of absurdity". Thank you Jana that you have always been with me and supported me in any conditions.

The hardest part of my Ph.D. process was to be away from my family back home. I have greatly missed my mother, Gulseren, and my dear sisters, Ayse and Sohret, and my brother, Sadik. It is really hard for me to be far away from my nephews Ahmet, Fatih, Melisa and Mehmet. I fully appreciate the understanding and support of all my family members during the years that I was not able to be with them.

I dedicate this dissertation to my father, who deceased ten years ago. You always wanted me to get educated and devoted your life to this objective. I also dedicate it to my best friend Merih Ipek, you always wanted my best.

Alpaslan Akay
December, 2007

Applied Economics, 2007, 1–10, iFirst

Asymptotic bias reduction for a conditional marginal effects estimator in sample selection models

Alpaslan Akay* and Elias Tsakas

Department of Economics, University of Göteborg, P.O. Box 640, 405 30 Göteborg, Sweden

In this article we discuss the differences between the average marginal effect and the marginal effect of the average individual in sample selection models, estimated by the Heckman procedure. We show that the bias that emerges as a consequence of interchanging the measures, could be very significant, even in the limit. We suggest a computationally cheap approximation method, which corrects the bias to a large extent. We illustrate the implications of our method with an empirical application of earnings assimilation and a small Monte Carlo simulation.

I. Introduction

A large amount of applied work using nonlinear microeconometric models has been carried out over the last few decades. One of the important characteristics of these models is their nature, which allows the calculation of individual marginal effects. In general, most empirical studies report one of the two established point estimators for marginal effects: (i) the average of the marginal effects of all individuals in the sample, and (ii) the marginal effect at the sample means. Neglecting their quantitative, and more importantly, conceptual differences is a quite common practice. Greene's (2003) discussion on the marginal effects in binary choice models stresses the fact that in many occasions the asymptotic equivalence of the two measures is taken for granted. Verlinda (2006) shows that arbitrarily interchanging them in a binary pro-bit model could create bias and lead to misleading conclusions, since the two measures estimate different quantities

In the present article we discuss the relationship between the two measures in the context of sample selection models, also known as Tobit type II (Heckman, 1976, 1979). Provided that one is interested in the average effect over the population rather than in the effect over the average individual, we show that evaluating the derivative at the sample means leads to biased predictions, even asymptotically. Since the other alternative (averaging the marginal effects for the whole sample) could be computationally inefficient, we propose an approximation technique which significantly reduces the bias, without significantly increasing the number of numerical operations. In order to accomplish this, we express the average marginal effect (AME) with the Taylor expansion around the mean values of the explanatory variables and prove that the conventionally used marginal effect of the average individual ($MEAI$) is actually equal to the first order Taylor approximation, while the order of magnitude is equal to the asymptotic bias. By shifting to the second order

*Corresponding author. E-mail: Alpaslan.Akay@economics.gu.se

Applied Economics ISSN 0003–6846 print/ISSN 1466–4283 online © 2007 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/00036840600994096

approximation, one can reduce the size of the bias without high computational cost, since the second term of the series is a function of the Hessian and the covariance matrix evaluated at the sample means.

Marginal effects in sample selection models have recently been discussed. Saha *et al.* (1997a) show that failure to account for changes in the inverse of Mill's ratio leads to biased marginal effects. Hoffmann and Kassouf (2005) introduce unconditional marginal effects in addition to the standard conditional ones. In any case, the clear distinction between AME and $MEAI$ is necessary regardless of the definition of the marginal effects.

In order to emphasize the necessity of a consistent estimator for the AME we present an empirical application of immigrant earnings assimilation using registered data from Sweden. We find that our approach corrects the bias to a large extent, and discuss the policy implications behind this relative difference.

The article has the following structure. Section II briefly describes Heckman's two step procedure. Section III introduces the theoretical results of our approach. In Section IV we apply the model to real data, and also include Monte Carlo simulations. Section V concludes the article.

II. Heckman Procedure and Marginal Effects

Consider the following sample selection (otherwise known as the Tobit type II) model:

$$Y_i^* = \mathbf{X}_i'\beta + \varepsilon_i \tag{1}$$

$$H_i^* = \mathbf{Z}_i\gamma + u_i \tag{2}$$

$$H_i = 1\left[H_i^* > 0\right] \tag{3}$$

$$Y_i = Y_i^* \cdot H_i \tag{4}$$

where $i = 1, \ldots, N$. Let the latent variables Y_i^* and H_i^* denote individual i's earnings and hours of work respectively. Assume also that the matrices $\mathbf{X}_i$ and $\mathbf{Z}_i$ include various observed individual characteristics, with $\mathbf{X}_i$ being a strict subset of $\mathbf{Z}_i$. Finally, the joint error term $(\varepsilon_i,\ u_i)$ follows the bivariate normal distribution with correlation coefficient ρ and normalized variance of the selection equation error term, $\sigma_u^2 = 1$. Our primary aim is to estimate the parameter vector β of the earnings equation. We know that strictly positive hours of work is a necessary and sufficient condition for participating in the job market, ie. $H_i^* > 0$. Then the participation decision takes the form of a binary choice, since *working* and *not working* are complementary events, and as such they can be written as the indicator function of the equation above.

Conditioning on the subset of the population that contains the individuals who actually work, the expectation of the earnings given participation would be given by the following formula (Greene, 2003):

$$\begin{aligned} E\left[Y_i^* | H_i = 1, \mathbf{X}_i, \mathbf{Z}_i\right] &= E\left[\mathbf{X}_i'\beta + \varepsilon_i | H_i^* > 0\right] \\ &= \mathbf{X}_i'\hat{\beta} + E\left[\varepsilon_i | u_i > -\mathbf{Z}_i'\gamma\right] \\ &= \mathbf{X}_i'\hat{\beta} + \hat{\rho}\hat{\sigma}_\varepsilon \frac{\phi\left(-\mathbf{Z}_i'\hat{\gamma}\right)}{1 - \Phi\left(-\mathbf{Z}_i'\hat{\gamma}\right)} \end{aligned} \tag{5}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the density and the cumulative distribution of the standard normal distribution respectively. After some notation simplification Equation 5 is rewritten as follows:

$$E\left[Y_i^* | H_i = 1, \mathbf{X}_i, \mathbf{Z}_i\right] = \mathbf{X}_i'\hat{\beta} + \hat{\rho}\hat{\sigma}_\varepsilon \hat{\lambda}_i(\hat{\alpha}_u) \tag{6}$$

where $\hat{\alpha}_u = -\mathbf{Z}_i'\hat{\gamma}$, while λ denotes the inverse of Mill's ratio, ie. $\lambda = \phi/(1 - \Phi)$. It is straightforward that Equation 6 cannot be estimated consistently with ordinary least squares (OLS) in the existence of correlation between ε_i and u_i ($\rho \neq 0$). On the other hand, although consistent, the maximum likelihood estimator (MLE) constitutes a computationally challenging task. Heckman (1976) introduced a method which can simultaneously handle consistency and computational efficiency. His procedure consists of two separate steps. First, estimate the participation probability by applying a binary probit model

$$P[H_i = 1 | \mathbf{Z}_i] = \Phi(\mathbf{Z}_i'\gamma) \tag{7}$$

and use the estimated choice probabilities to calculate $\hat{\lambda}_i(\hat{\alpha}_u)$. In the second step, apply OLS on the earnings equation, while perceiving the estimated inverse Mill's ratio as another explanatory variable. Thus, one gets rid of the omitted variable problem that would otherwise emerge, and the estimator of the parameter vector in the target equation becomes consistent.

The *ceteris paribus* estimated marginal effect[1] of an infinitesimal change of an arbitrary individual characteristic k on individual i's earnings is given

[1] A more precise terminology would require defining it as *conditional marginal effect*, since it refers only to the individuals who actually work.

by the following equation for an explanatory variable $x_{k,i}$:

$$\widehat{ME}_{k,i} = \frac{\partial E[Y_i^*|H_i = 1, \mathbf{X}_i, \mathbf{Z}_i]}{\partial X_{k,i}} = \hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\hat{\sigma}_\varepsilon \hat{\delta}_i(\hat{\alpha}_u) \tag{8}$$

where $\hat{\delta}_i(\hat{\alpha}_u) = \hat{\lambda}_i^2(\hat{\alpha}_u) - \hat{\alpha}_u \hat{\lambda}_i(\hat{\alpha}_u)$. The (total) marginal effect of a variable in a sample selection model can be separated into two parts (Greene, 2003). The *direct effect* ($\hat{\beta}_k$) shows the marginal effect of an explanatory variable on the earnings without taking into account the effect of selectivity in the data. The second term in Equation 8 is called *indirect effect* and is a function of the observed individual characteristics. Due to this functional relationship, marginal effects vary across individuals. Omitting the indirect effect would linearize the marginal effect, which is rather convenient in practical terms, but it also creates nonnegligible bias. Such a problem would not arise if the estimated correlation coefficient between the errors of the first and second stage estimation equations (ρ) were equal to zero (Saha *et al*., 1997a).

Since policy decisions upon an action that changes an explanatory variable affecting the whole population, the existence of such nonlinearity allows the use of different measures for the marginal effects. In general, economists are interested in the AME of this action over all individuals. Using an inconsistent estimator for the AME could therefore potentially lead to wrong conclusions and undesired effects of the policy application. A consistent estimator for AME is given by the following expression:

$$\widehat{AME}_k = \frac{1}{N}\sum_{i=1}^{N} \widehat{ME}_{k,i} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\hat{\sigma}_\varepsilon \hat{\delta}_i(\hat{\alpha}_u)\right) \tag{9}$$

This follows directly from Khinchine's weak law of large numbers. Namely,

$$\operatorname{plim}_{N\to\infty}\widehat{AME}_k = E\Big[\hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\hat{\sigma}_\varepsilon \hat{\delta}_i(\alpha_u)\Big] = \hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\hat{\sigma}_\varepsilon E\Big[\hat{\delta}_i(\hat{\alpha}_u)\Big] \tag{10}$$

for every k.

However, due to factors such as computational inefficiency or unavailability of software routines for the calculation of $\widehat{AME}$, researchers usually report the marginal effect of the average individual ($\widehat{MEAI}$), which is equivalent to evaluating the marginal effects at the sample means:

$$\widehat{MEAI}_k = \widehat{ME}_{k,i}|_{\mathbf{Z}_i=\bar{\mathbf{Z}},\mathbf{X}_i=\bar{\mathbf{X}}} = \hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\hat{\sigma}_\varepsilon \bar{\delta} \tag{11}$$

where $\bar{\delta} = \hat{\delta}_i(-\bar{\mathbf{Z}}'\hat{\gamma})$. Notice that $\widehat{MEAI}$ is a consistent estimator for its population counterpart ($MEAI$),

$$\operatorname{plim}_{N\to\infty}\widehat{MEAI}_k = E\left[\hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\frac{\hat{\sigma}_\varepsilon}{\hat{\sigma}_u}\hat{\delta}_i(\bar{\mathbf{Z}}'\hat{\gamma})\right] = \hat{\beta}_k - \hat{\gamma}_k \hat{\rho}\hat{\sigma}_\varepsilon \hat{\delta}_i(\mathbf{M}'\hat{\gamma}) \tag{12}$$

but not for the AME, since $E[\hat{\delta}_i(\hat{\alpha}_u)] \neq \hat{\delta}_i(\mathbf{M}'\hat{\gamma})$. That is, $\widehat{AME}$ and $\widehat{MEAI}$ not only differ quantitatively, but also conceptually, since they estimate different things. Hence, the researcher who arbitrarily interchanges them could be led to misleading conclusions.

III. Approximating Average Marginal Effects

As we discussed above, interchanging $\widehat{AME}$ and $\widehat{MEAI}$ produces bias and leads to inconsistent estimation of AME. In this section we suggest an approximation method for estimating AME that is computationally efficient and that significantly reduces the bias emerging from the use of $\widehat{MEAI}$. In order to extract the asymptotic bias we expand the Taylor series of $\hat{\delta}_i(\mathbf{Z}_i'\hat{\gamma})$ around the mean of the explanatory variables, $\mathbf{M}$:

$$\begin{aligned}\hat{\delta}_i(\mathbf{Z}'_i\hat{\gamma}) &= \hat{\delta}_i(\mathbf{M}'\hat{\gamma}) + \sum_k\left(\left.\frac{\partial\hat{\delta}_i(\mathbf{Z}_i'\hat{\gamma})}{\partial Z_k}\right|_{\mathbf{M}} \cdot (Z_{k,i} - M_k)\right)\\ &+ \frac{1}{2!}\sum_{k_1}\sum_{k_2}\left(\left.\frac{\partial^2\hat{\delta}_i(\mathbf{Z}_i'\hat{\gamma})}{\partial Z_{k_1,i}\partial Z_{k_2,i}}\right|_{\mathbf{M}} \cdot (Z_{k_1,i} - M_{k_1})(Z_{k_2,i} - M_{k_2})\right)\\ &+ \ldots = \hat{\delta}_i(\mathbf{M}'\hat{\gamma})\\ &+ \sum_{j=1}^{\infty}\left[\frac{1}{j!}\sum_{k_1,\ldots,k_j}\left(\left.\frac{\partial^j\hat{\delta}_i(\mathbf{Z}_i'\hat{\gamma})}{\partial Z_{k_1 i},\ldots,\partial Z_{k_j,i}}\right|_{\mathbf{M}}\right.\right.\\ &\left.\left.\cdot\,(Z_{k_1,i} - M_{k_1})\ldots(Z_{k_j,i} - M_{k_j})\right)\right].\end{aligned} \tag{13}$$

After plugging the previous expression into Equation 8 and taking expectation, we conclude that the AME is approximated by the following formula

$$\begin{aligned}AME_k &= \hat{\beta}_k - \hat{\gamma}_k\hat{\rho}\hat{\sigma}_\varepsilon E[\hat{\delta}_i(\mathbf{Z}_i'\hat{\gamma})] \\ &= MEAI_k - \hat{\gamma}_k\hat{\rho}\hat{\sigma}_\varepsilon \sum_{j=1}^{\infty} \\ &\quad \times \left[\frac{1}{j!}\sum_{k_1,\dots,k_j}\left(\left.\frac{\partial^j\delta_i(\mathbf{Z}_i'\hat{\gamma})}{\partial Z_{k_1,i},\dots,\partial Z_{k_ji}}\right|_{\mathrm{M}} \cdot \Psi^j_{k_1,\dots,k_j}\right)\right] \\ &= MEAI_k + B_k^1(\Psi^1, \Psi^2, \dots) \qquad (14)\end{aligned}$$

where $\Psi^j_{k_1,\dots,k_j} = E[(Z_{k_1,i} - M_{k_1})\dots(Z_{k_j,i} - M_{k_j})]$ denotes the jth order joint moment about the means, while B_k^1 denotes the size of the first order approximation asymptotic bias as a function of the joint moments, Ψ^j, of the individual characteristics. Therefore by using the $\widehat{MEAI}_k$ to estimate the AME_k, one implicitly takes into account only the first order approximation while neglecting the higher orders, which ultimately leads to bias equal to $\hat{B}_k^1(\Psi^1, \Psi^2, \dots)$. If instead one used an additional term of the Taylor polynomial, the *second order approximation of the AME* ($\widehat{SOAME}_k$) would substitute the $\widehat{MEAI}_k$. That would be given by the following formula:

$$\begin{aligned}\widehat{SOAME}_k = \widehat{MEAI}_k - \frac{1}{2}\hat{\gamma}_k\hat{\rho}\hat{\sigma}_\varepsilon \sum_{k2} \\ \times \sum_{k_2}\left(\left.\frac{\partial^2\hat{\delta}_i(\mathbf{Z}'_i\hat{\gamma})}{\partial Z_{k_1,i}\partial Z_{k_2,i}}\right|_{\bar{\mathbf{z}}} \cdot \widehat{\mathrm{Cov}}(Z_{k_1,i}, Z_{k_2,i})\right) \qquad (15)\end{aligned}$$

By using the second order approximation, which does not significantly increase the number of numerical operations since it only involves the elements of the entrywise product of the Hessian evaluated at $\bar{\mathbf{Z}}$ and the covariance matrix, one would substantially reduce[2] the bias of the estimates.

In the following section we empirically show that neglecting the bias could create misleading results that could significantly affect the policy implications of the model.

IV. Empirical Applications

We divide our applications into two parts: a study of earnings assimilation of immigrants in Sweden, where we with the use of real data illustrate the necessity of bias reduction in the estimation of marginal effects, and a Monte Carlo simulation where we examine the limiting properties of our approximation technique.

Earnings assilmation of immigrants in Sweden

The economic performance of immigrants is one of the major interests of policy makers in most highly immigrated Western countries. The question in such a study would typically be whether immigrants entered the host country with an earnings difference relative to natives and whether their earnings converge to those of the natives while years since migration (YSM) increase (Borjas, 1985, 1999; Longva and Raaum, 2003). Then, based on the answer, policies targeting to different individual characteristics of the immigrants are designed, in order to adjust the speed of assimilation closer to what is desired by the policy makers.

The data used in the present study comes from the registered nationally representative longitudinal individual data set of Sweden (LINDA), which comes in panel form and is rich in individual socioeconomic characteristics (Edin and Frederiksson, 2001). The principal data sources are income registers and population censuses. Family members are included in the sample only as long as they stay in the household. LINDA contains a sub-panel of about 20% of the foreign-born population. The working sample includes 3136 male individuals, aged 18–65 (1962 immigrants[3] and 1174 natives) followed for 11 years from 1990 to 2000.

Table 1 shows the mean characteristics of the sample. The earnings and the income from other sources are considerably higher among natives than among immigrants. Natives are more likely to be employed (0.82 vs. 0.57), are slightly older (38.4 vs. 37.1), but are also less likely to be married (0.39 vs. 0.43) and they have fewer children at home (0.44 vs. 0.48). They also acquire a higher level of education: 76% of natives are high school graduates, while the number is 71% among immigrants.

The immigrant arrival cohorts are classified into five year intervals except for the first and the last ones, which include the years before 1970 and the 1995–2000 period (six years), respectively. These two cohorts are slightly un-derrepresented in the sample (7 and 6% respectively). The immigrants are categorized according to their country of origin as follows: Nordic countries, USA, Western countries except USA (EU-15, Canada, Australia and New Zealand), Eastern Europe, Middle East, Asia, Africa and Latin America.

[2] The expected second order of magnitude is larger than the third one (Nguyen and Jordan, 2003).
[3] We define an immigrant as an individuals who was born abroad (first generation).

Table 1. Mean characteristics of immigrants and natives

Variables	Immigrants		Natives	
	Mean	SD	Mean	SD
Log earnings	8.5707	5.2519	10.7750	3.7428
Log nonlabour income	0.5656	1.9748	0.7746	2.3281
Employment	0.5713	0.4991	0.8221	0.4871
Age	0.3714	0.1103	0.3837	0.1127
Age squared	0.1501	0.0866	0.1599	0.0907
Big city (>250 000)	0.6347	0.4815	0.7349	0.4414
Number of children	0.4840	0.9875	0.4407	0.8959
Married/cohabiting	0.4344	0.4957	0.3891	0.4876
YSM	0.0794	0.0918	–	–
YSM squared	0.0147	0.0247	–	–
Education (highest level)				
Lower-secondary	0.2955	0.4852	0.2389	0.4911
Upper-secondary	0.4454	0.4970	0.4867	0.4998
University	0.2591	0.4381	0.2744	0.4462
Arrival cohort				
<1970	0.0669	0.2496	–	–
1970–1974	0.1176	0.3221	–	–
1975–1979	0.1574	0.3642	–	–
1980–1984	0.1372	0.3441	–	–
1984–1989	0.2237	0.4351	–	–
1990–1994	0.2335	0.4411	–	–
1995–2000	0.0637	0.1857	–	–
Geographical origin				
Nordic	0.1239	0.3609	–	–
W. Europe (incl. EU)	0.1188	0.2353	–	–
USA	0.1312	0.2485	–	–
Eastern Europe	0.1276	0.3337	–	–
Middle East	0.1434	0.3505	–	–
Asia	0.1245	0.3412	–	–
Africa	0.1250	0.3418	–	–
Latin America	0.1056	0.3097	–	–

Based on working indicators in the data, an employment dummy is defined that takes a value of 1 if the individual is employed and 0 otherwise. The earnings variable used in the study is obtained from the national tax registers and is measured in thousands of Swedish Kroner (SEK) per year, adjusted to 2000 prices.

The model specification for the immigrants is given by the following standard sample selection model:

$$\begin{aligned} Y_i^* &= \mathbf{X}_i'\beta + \phi AGE_i + \delta YSM_i + \sum_j \psi_j C_i^j + \sum_k \theta_k \Pi_i^k + \varepsilon_i \\ H_i^* &= \mathbf{Z}_i\gamma + u_i \\ H_i &= 1[H_i^* > 0] \\ Y_i &= Y_i^* \cdot H_i, \end{aligned} \tag{16}$$

where i denotes each cross section, and Y^* is the natural logarithm of the latent earnings. The individual characteristics included in the $\mathbf{X}_i$ matrix are individual i's number of children, marital status, size of permanent residence, education, and geographical origin. The variables AGE and YSM denote the age and the years since migration respectively.[4] Finally C_i^j and Π_i^k are indicator variables for the j-th immigrant arrival cohort and the k-th year. C_i^j becomes 1 if the individual arrived at the j-th cohort and 0 otherwise. Similarly, Π_i^k takes the value 1 if the individual is observed in the k-th period, and the value 0 otherwise. The $\mathbf{Z}_i$ matrix includes the same characteristics plus the logarithm of nonlabour income.[5] The model specification for the natives does not differ from the one estimated for the immigrants, with the exception of the variables that are not applicable, e.g. years since immigration, arrival cohort and geographical origin.

The assimilation model given by (16) aims to identify the three important effects (aging, arrival cohort and period effect) on the earnings assimilation simultaneously. However, this model is not identified in any given cross section, since the calendar year in which the cross section is observed is the sum of YSM in the host country and the calendar year in which the individual immigrated. Thus the identification restriction imposed in the present study is that the period effect in the immigrant earnings equation is equal to that of the natives ($\Pi_i^I = \Pi_i^N, \forall i = 1, \ldots, 11$), which is a standard assumption in the assimilation literature (Borjas, 1985, 1999).

The estimation results and the bias analysis for the probit equation (first step) and the target equation (second step) are presented in respectively, along with the $\widehat{AME}$, the $\widehat{MEAI}$, the $\widehat{SOAME}$ and the first and second order bias ($\widehat{FOBIAS}$ and $\widehat{SOBIAS}$), which denote the difference between the consistent estimator $\widehat{AME}$ and its first ($\widehat{MEAI}$) and second order ($\widehat{SOAME}$) approximations respectively. For example, the $\widehat{AME}$ for the variable AGE for the immigrants is estimated to 0.1 53, while the corresponding $\widehat{MEAI}$ and $\widehat{SOAME}$ are equal to 0.235 and 0.175 respectively, which constituting a 73% improvement of the bias.

Taking a closer look at the first and second order bias estimates of the selection and the earnings equation (respectively), one can easily notice the rather significant improvement in all variables, not only in relative but also in absolute terms.

[4] The exact functional forms for age and years since migration are quadratic. The second order terms are omitted for notation simplicity purposes.

[5] The exclusion restriction adopted in this article is that the nonlabour income affects the probability of being employed but not the earnings.

Table 2. Estimates and analysis of bias for the employment equations

Variables	Est.	*AME*	*MEAI*	*SOAME*	*FO Bias*	*SO Bias*
Immigrants						
Constant	−1.3258	−0.3387	−0.5195	−0.3871	0.1808	0.0485
Log nonlabour income	−0.7741	−0.1977	−0.3033	−0.2260	0.1055	0.0283
Age	0.1259	0.1530	0.2347	0.1749	−0.0817	−0.0289
Age squared	−0.0016	–	–	–	–	–
Big city (>250 000)	0.1115	0.0285	0.0437	0.0326	−0.1520	−0.0041
Number of children	−0.0170	−0.0044	−0.0067	−0.0050	0.0023	0.0006
Married/cohabiting	0.3598	0.0919	0.1410	0.1051	−0.0490	−0.0132
YSM	0.0477	0.0122	0.0187	0.0139	−0.0065	−0.0017
YSM squared	−0.0001	–	–	–	–	–
Education (highest level)						
Upper-secondary	0.3657	0.0934	0.1433	0.1068	−0.0499	− 0.0134
University	0.5363	0.1370	0.2101	0.1566	−0.0731	− 0.0196
Arrival cohort						
1970–1974	−0.2306	−0.0589	−0.0904	0.0314	−0.0673	0.0084
1975–1979	−0.2826	−0.0722	−0.1107	−0.0825	0.0385	0.0103
1980–1984	−0.3285	−0.0839	−0.1287	−0.0959	0.0448	0.0120
1985–1989	−0.3510	−0.0897	−0.1375	−0.1025	0.0479	0.0128
1990–1994	−0.7965	−0.2035	−0.3121	−0.2326	0.1086	0.0291
1995–2000	−0.6630	−0.1694	−0.2598	−0.1936	0.0904	0.0242
Geographical origin						
Nordic	−0.8735	−0.2231	−0.3422	−0.2551	0.1191	0.0319
W. Europe (incl. EU)	−0.9631	−0.2461	−0.3774	−0.2813	0.1313	0.0352
USA	−0.3394	−0.3422	−0.5248	−0.3912	0.1826	0.0490
Eastern Europe	−0.3023	−0.3327	−0.5103	−0.3803	0.1776	0.0476
Middle East	−1.5686	−0.4007	−0.6146	−0.4581	0.2139	0.0573
Asia	−1.1450	−0.2925	−0.4486	−0.3344	0.1561	0.0419
Africa	−1.4546	−0.3716	−0.5699	−0.4248	0.1983	0.0532
Latin America	−1.1511	−0.2941	−0.4510	−0.3362	0.1569	0.0421
Natives						
Constant	−1.8781	−0.2753	−0.5145	−0.4719	0.2392	0.1966
Log nonlabour income	−0.8216	−0.1204	−0.2251	−0.2064	0.1046	0.0860
Age	0.1480	0.0016	0.0029	0.002741	−0.0014	−0.0011
Age squared	−0.0018	–	–	–	–	–
Big city	0.0801	0.0118	0.0220	0.0201	−0.0102	−0.0084
Number of children	0.0551	0.0080	0.0151	0.0139	−0.0070	−0.0058
Married/cohabiting	0.3974	0.0583	0.1089	0.0999	−0.0506	−0.0416
Education (highest level)						
Upper-secondary	0.3803	0.0557	0.1042	0.0956	−0.0484	−0.0398
University	0.4964	0.0728	0.1360	0.1247	−0.0632	−0.0520

Notes: The estimated average marginal effects (*AME*), marginal effects for the average individual (*MEAI*), the second order approximation of the average marginal effects (*SOAME*), and first (*FO Bias*) and second (*SO Bias*) order bias are presented in the table. The estimated SEs can be provided upon request.

This becomes even more worth mentioning since it is observed in the key variables. For instance, having a university degree improves the earnings of the immigrants by 0.340 log points, according to the $\widehat{AME}$. On the other hand, using the $\widehat{MEAI}$ yields an estimate equal to 0.370 log points. Finally, the $\widehat{SOAME}$ is equal to 0.348, which is substantially closer to the $\widehat{AME}$ (73% bias correction).

A really interesting result, though not surprising given the structure of the Taylor series, is that the percentage change in the bias level by shifting to the second order approximation remains constant across explanatory variables. Table A1 shows the size of the relative improvement when the second order approximation is used.

As we mentioned earlier, the hypothesis that one is usually willing to test in this specific type of study is *whether the earnings of the immigrants catch up with those of the natives with enough years spent in the host country, and if so how long this assimilation process takes*. Assume that the aging variables are defined as a function of time ($AGE(t)$ and $YSM(t)$). Then the relative earnings for immigrant i with respect to

Table 3. Estimates and analysis of bias for the earnings equations

Variables	Est.	*AME*	*MEAI*	*SOAME*	*FO Bias*	*SO Bias*
Immigrants						
Constant	11.5815	11.1524	11.0788	11.1330	0.0737	0.0195
Age	0.0290	0.0130	0.0132	0.0131	−0.0001	−0.00004
Age squared.	−0.0002	–	–	–	–	–
Big city (>250 000)	−0.0541	−0.0181	−0.0119	−0.0165	−0.0062	−0.0016
Number of children	−0.0117	−0.0172	−0.0181	−0.0174	0.0009	0.0002
Married/cohabiting	0.0217	0.1381	0.1581	0.1434	−0.0200	−0.0053
YSM	0.0075	0.0229	0.0256	0.0236	−0.0026	−0.0007
YSM squared	0.0003	–	–	–	–	–
Education (highest level)						
Upper-secondary	−0.0242	0.0941	0.1145	0.0995	−0.0203	−0.0054
University	0.1665	0.3401	0.3699	0.3479	−0.0298	−0.0079
Arrival cohort						
1970–1974	0.0966	0.0220	0.0092	0.0186	0.0128	0.0033
1975–1979	0.1712	0.0797	0.0640	0.0756	0.0157	0.0042
1980–1984	0.2659	0.1597	0.1414	0.1548	0.0183	0.0048
1985–1989	0.3291	0.2155	0.1960	0.2103	0.0195	0.0052
1990–1994	0.4727	0.2150	0.1707	0.2032	0.0443	0.0117
1995–2000	0.6263	0.4118	0.3750	0.4021	0.0368	0.0097
Geographical origin						
Nordic	−0.4172	−0.6998	−0.7484	−0.7127	0.0485	0.0128
W. Europe (incl. EU)	−0.3966	−0.7082	−0.7618	−0.7223	0.0535	0.0142
USA	−0.3288	−0.7622	−0.8367	−0.7819	0.0744	0.0197
Eastern Europe	−0.4382	−0.8596	−0.9320	−0.8788	0.0723	0.0191
Middle East	−0.5098	−1.0174	−1.1045	−1.0404	0.0872	0.0231
Asia	−0.4402	−0.8107	−0.8744	−0.8276	0.0636	0.0168
Africa	−0.4732	−0.9439	−1.0247	−0.9653	0.0808	0.0213
Latin America	−0.5268	−0.8993	−0.9633	−0.9162	0.0640	0.0169
Natives						
Constant	12.1808	11.3733	11.1341	11.3868	0.2392	−0.0135
Age	0.0043	0.0147	0.0159	0.0146	−0.0012	0.0001
Age squared	0.0080	–	–	–	–	–
Big city	−0.0708	−0.0363	−0.0261	−6.7524	−0.0102	0.0006
Number of children	−0.0445	−0.0208	−0.0138	−0.0212	−0.0070	0.0004
Married/cohabiting	0.0260	0.1969	0.2475	0.1941	−0.0506	0.0029
Education (highest level)						
Upper-secondary	−0.0106	0.1529	0.2014	0.1502	−0.0484	0.0027
University	0.2361	0.4496	0.5128	0.4460	−0.0632	0.0036

Note: See the note of Table 2.

native j, t years after migration, are given by the following equation:

$$\Delta Y_{i,j}(t) = E^I\left[Y_i|H_i = 1, AGE(t_0+t), YSM(t), \mathbf{X}_i, \mathbf{Z}_i\right] - E^N\left[Y_j|H_j = 1, AGE(t_0+t), \mathbf{X}_j, \mathbf{Z}_j\right] \quad (17)$$

where t_0 is the age at migration,[6] while E^I and E^N denote the conditional expectations of the assimilation model of the immigrants and the natives respectively. Evaluating $\Delta Y_{i,j}(t)$ at $t=0$ yields the initial earnings difference, otherwise called entry effect upon arrival.

Then the estimated marginal rate of assimilation ($\widehat{MRA}$), which shows the rate of earnings convergence between the i-th immigrant and the j-th native at time t (Barth *et al.*, 2004), is given by the following equation:

$$\widehat{MRA}_{i,j}(t) = \frac{\partial E_i^I}{\partial t} - \frac{\partial E_j^I}{\partial t} \quad (18)$$

or in terms of marginal effects:

$$\widehat{MRA}_{i,j}(t) = \widehat{ME}^I_{AGE,i}(t) + \widehat{ME}^I_{YSM,i}(t) - \widehat{ME}^N_{AGE,j}(t) \quad (19)$$

[6] The entry age in the present study is assumed to be constant across immigrants and equal to 20.

We thus reach a point where the marginal effects are in question again. Given the fact that we are interested in the average total years of assimilation ($\widehat{ATYA}$), one should estimate the average marginal rate of assimilation ($\widehat{AMRA}$). Namely,

$$\begin{aligned}
\widehat{AMRA}(t) &= \sum_{i=1}^{I}\sum_{j=1}^{J}\frac{1}{I}\frac{1}{J} \\
&\quad\times\left(\widehat{ME}^{I}_{AGE,i}(t)+\widehat{ME}^{I}_{YSM,i}(t)-\widehat{ME}_{AGE^{N},j}(t)\right) \\
&= \frac{1}{I}\sum_{i=1}^{I}\widehat{ME}^{I}_{AGE,i}(t)+\frac{1}{I}\sum_{i=1}^{I}\widehat{ME}^{I}_{YSM,,i}(t) \\
&\quad-\frac{1}{J}\sum_{j=1}^{J}\widehat{ME}^{N}_{AGE,j}(t) \\
&= \widehat{AME}_{AGE}(t)+\widehat{AME}^{I}_{YSM}(t)-\widehat{AME}^{N}_{AGE}(t)
\end{aligned} \tag{20}$$

where I and J denote the total number of immigrants and natives respectively. One can similarly calculate the estimators for the marginal rate of assimilation for the average individual ($\widehat{MRAAI}$) and the second order approximation of the average marginal rate of assimilation ($\widehat{SOAMRA}$), by substituting the corresponding marginal effects in Equation 20.

Then the estimator of the average total years of assimilation ($\widehat{ATYA}$) is the upper limit that equates the following integral with the average initial earnings difference:

$$\int_{0}^{\widehat{ATYA}}\widehat{AMRA}(t)\,\mathrm{d}t=\Delta Y(0) \tag{21}$$

Table A2 shows the estimation results. The $\widehat{ATYA}$ is reported in the first column for each group of immigrants. According to this estimator, the earnings of the immigrants from for example Africa catch up to the level of the natives *on average* 25.3 years after arrival. The second column of the table reports total years of assimilation for the average immigrant ($\widehat{TYAAI}$). The corresponding estimate for the *average* African immigrant is 23.6 years, which is 1.7 years shorter than the ($\widehat{ATYA}$). Finally, by using the method we propose in the present article, the second order approximation of the average total years of assimilation ($\widehat{SOATYA}$) yields an estimate of 24.4 years, which is 54% closer to the targeted result.

Monte Carlo simulation

As we have already discussed, the bias that emerges when using the $\widehat{MEAI}$ as a point estimator of the AME is not a consequence of a small sample, which would disappear in the limit. Regardless of the sample size, the second order approximation leads to bias reduction compared to the first one. The purpose of this section is to provide empirical evidence for the size of the bias reduction through a Monte Carlo experiment.

Assume a standard sample selection model of the form of Equation 1, with $\mathbf{X}_i$ being a singleton and $\mathbf{Z}_i=(Z_{1,i},Z_{2,i})$ coming from the bivariate normal distribution with mean $\mu_i=(\mu_1,\mu_2)$ and covariance matrix Σ. Assume also the following parameter values: $\beta=1$, $\gamma=(3,-2)$, $\sigma_{\varepsilon}=0.5$, $\sigma_u=1$, $\rho=-0.8$, $\mu=(0.5,1.5)$ and $\Sigma=\left[\begin{smallmatrix}0.5 & -0.1\\ -0.1 & 1\end{smallmatrix}\right]$. By using pseudo-random numbers, we then repeatedly evaluate the first and the second order bias, while increasing the sample size in steps of 100 observations. The results are presented in Table A3.

Figure 1 illustrates the same point as Table A3, namely that it becomes clear that the bias that emerges when using the $\widehat{MEAI}$, is corrected to a rather large extent, without a corresponding

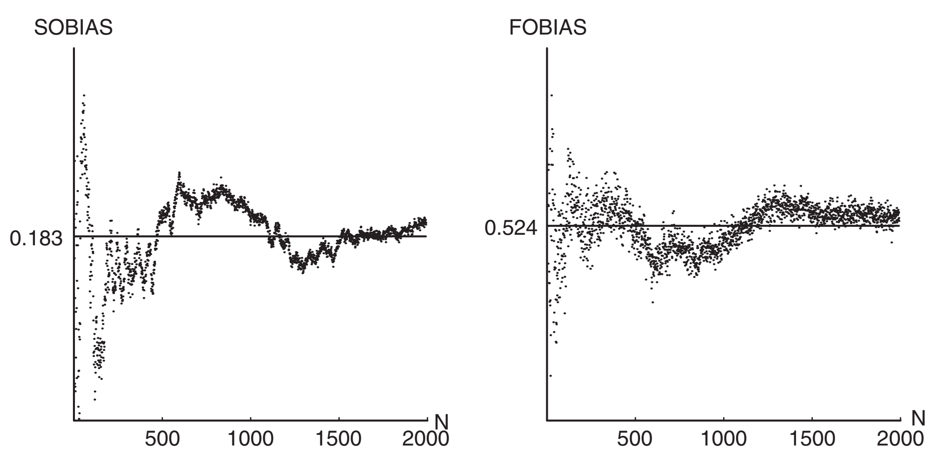


Fig. 1. First and second order bias in Monte Carlo experiment

computational cost. Notice that bias reduction is observed not only for small samples, but also asymptotically.

V. Concluding Discussion

In this article we discuss the differences between two point estimators of the marginal effect of an explanatory variable on the population, in a sample selection model estimated by Heckman's two step procedure. We show that contrary to a rather widespread perception that neglects any differences between them, the AME is significantly different from the marginal effect of the average individual, even asymptotically. Thus, it should be clear that there is not only a quantitative distinction but also a conceptual one between these measures. Given that the usual aim is to extract information about the average effects on the population, a clear bias would emerge if using the marginal effect of the sample average individual. Hence, we suggest an approximation method based on the Taylor expansion, which should correct the bias to a rather remarkable extent, while increasing the number of computational operations relatively little. Such an example is presented in the article, along with a Monte Carlo experiment, both supporting the previous argument. Before closing, we would like to make clear that we do not argue in favour of the AME and against the marginal effect of the average individual. Instead, our aim is to stress that once the AME has been chosen as an informative tool for policy making, the sample marginal effect of the average individual provides inconsistent estimations which can be corrected to a large extent by the proposed method.

Acknowledgements

We are indebted to Lennart Flood, Marcela Ibanez, Florin Maican and Kerem Tezic for their benefitting comments. We would also like to specially thank an anonymous referee for his valuable suggestions. All mistakes and misprints are exclusively ours.

References

Barth, E., Bratsberg, B., Raaum, O. (2004) Identifying earnings assimilation of immigrants under changing macroeconomic conditions, *Scandinavian Journal of Economics*, **106**, 1–22.

Borjas, G. J. (1985) Assimilation, changes in cohort quality, and the earnings of immigrants, *Journal of Labor Economics*, **3**, 463–89.

Borjas, G. J. (1999) *The economic analysis of immigration Handbook of Labor Economics*, Vol. 3A (Eds) O. Ashenfelter and D. Card, pp. 1697–760.

Chiswick, B. R. (1978) The effect of Americanization on the earnings of foreign-born men, *Journal of Political Economy*, **86**, 897–921.

Edin, P. A. and Frederiksson, P. (2001) LINDA – Longitudinal individual data for Sweden, Working Paper, Uppsala University, Department of Economics 2001:6.

Greene, W. H. (2003) *Econometric Analysis*, 5th edn, Prentice Hall, Saddle River.

Heckman, J. J. (1976) The common structure of statistical models of truncation, sample selection and limited dependent variables, and a simple estimator for such models, *Annals of Economic and Social Measurement*, **5**, 475–92.

Heckman, J. J. (1979) Sample selection bias as a specification error, *Econometrica*, **47**, 153–62.

Hoffmann, R. and Kassouf, A. L. (2005) Deriving conditional and unconditional marginal effects in log earnings equation estimated by Heckman's procedure, *Applied Economics*, **37**, 1303–11.

Longva, P. and Raaum, O. (2003) Earnings assimilation of immigrants in Norway-a reappraisal, *Journal of Population Economics*, **16**, 177–93.

Nguyen, X. and Jordan, M. I. (2003) On the concentration of expectation and approximate inference in layered networks, *Advances in Neural Information Processing Systems (NIPS)*, 16.

Saha, A., Capps Jr, O. and Byrne, P. J. (1997a) Calculating marginal effects in models for zero expenditures in household budgets using Heckman-type correction, *Applied Economics*, **29**, 1311–6.

Saha, A., Capps Jr, O. and Byrne, P. J. (1997b) Calculating marginal effects in dichotomous-continuous models, *Applied Economics Letters*, **4**, 181–5.

Verlinda, J. A. (2006) A comparison of two common approaches for estimating marginal effects in binary choice models, *Applied Economics Letters*, **13**, 77–80.

Appendix

Table A1. Relative reduction of the bias

	Immigrants	Natives
Selection equation	0.714	0.143
Earnings equation	0.943	0.735

Table A2. Estimates and analysis of bias for the assimilation period

Variables	Earn. diff.	*ATYA*	*TYAAI*	*SOATYA*	*FO Bias*	*SO Bias*
Nordic	0.2916	13.6973	12.7850	13.1966	0.9123	0.5006
W. Europe (incl. EU)	0.1851	8.6961	8.1169	8.3782	0.5792	0.3178
USA	0.1895	8.9012	8.3083	8.5758	0.5929	0.3253
Eastern Europe	0.3285	15.4322	14.4043	14.8682	1.0279	0.5641
Middle East	0.5099	23.9514	22.3561	23.0760	1.5953	0.8754
Asia	0.4449	20.8989	19.5069	20.1351	1.3920	0.7639
Africa	0.5392	25.3264	23.6395	24.4007	1.6869	0.9256
Latin America	0.4047	19.0115	17.7452	18.3166	1.2663	0.6949
Total	0.3617	16.9894	15.8578	16.3684	1.1316	0.6210

Notes: The initial earnings difference, the estimated average total years of assimilation (*ATYA*), total years of assimilation for the average immigrant (*TYAAI*), the second order approximation of the average total years of assimilation (*SOATYA*) and first (*FO Bias*) and second (*SO Bias*) order bias are presented in the table. The estimated SEs can be provided upon request.

Table A3. Bias convergence in Monte Carlo simulation

Number of obs.	*AME*	*MEAI*	*SOAME*	*FO Bias*	*SO Bias*	Rel. improv.
1000	1.4034	1.0060	1.2033	0.3974	0.2001	0.4965
10 000	1.5300	1.0100	1.3900	0.5160	0.1400	0.7308
50 000	1.5303	1.0 080	1.3392	0.5222	0.1910	0.6342
100 000	1.5343	1.0084	1.3500	0.5259	0.1843	0.6496
250 000	1.5321	1.0082	1.3436	0.5239	0.1886	0.6401
500 000	1.5338	1.0083	1.3488	0.5255	0.1850	0.6479

Note: See the note of Table 2.

Local Unemployment and the Earnings-Assimilation of Immigrant Men in Sweden: Evidence from Longitudinal Data, 1990-2000*

Alpaslan Akay† and Kerem Tezic‡

Department of Economics, Göteborg University

SLI, Swedish Institute for Food and Agricultural Economics

December 15, 2007

Abstract

The earnings-assimilation of first-generation immigrant men in Sweden was analyzed using eleven waves of panel-data, 1990-2000. Employment-probabilities and earnings were estimated simultaneously in a random-effects model, using a quasi-fixed effects to control for both individual effects and panel-selectivity due to missing earnings-information. Assuming equal-period effects produced bias which could distort the findings. To correct the bias, local unemployment-rates were used to proxy for changing economy-wide conditions. Labour-market outcomes differed considerably across immigrant arrival cohorts, region and country of origin, and educational levels.

Keywords: *Immigrants, earnings-assimilation, unbalanced panel, selection-bias, random-effects, Mundlak's formulation, local unemployment-rates.*

JEL Codes: C33, J15, J61.

---

*The authors thank Lennart Flood, Roger Wahlberg, Elias Tsakas, Marcela Ibanez, Peter Martinsson, and seminar participants in Göteborg for their valuable comments.

†Department of Economics, Göteborg University, Box 600 SE 405 30 Göteborg, Sweden. Tel: +46-(31) 773 5304 Email: Alpaslan.Akay@Economics.gu.se

‡SLI, Swedish Institute for Food and Agricultural Economics, Box 730, SE 22007 Lund, Tel: +46(46)2220785 Email: Kerem.Tezic@sli.lu.se.

1 Introduction

The economic assimilation of immigrants has become an important topic in highly- immigrated Western countries. Governments generally desire to assimilate immigrants as rapidly and completely as possible, and thus need to know how their country-specific skills and resultant earnings develop after arrival. We estimated immigrant earnings in the context of the Swedish labour-market for the period 1990-2000, improving the existing (conventional) methods in order to control for several potential sources of bias.

Sweden has experienced large migration-waves since World War II, originally from southern Europe in response to high demand for labour. Since the mid-1970s, immigration to Sweden has largely switched from economic to political, partly due to a decline in economic growth and because of resultant immigration-restrictions. At the same time Sweden's liberal rules for political refugees led to a new influx of immigrants from non-European countries (at first from Chile; later from Iraq, Iran, Afghanistan, and many African countries in the 1980s; then from the former republics of Yugoslavia in the 1990s).

Thus the composition of the immigrant-population by country of origin changed substantially, while the employment-possibilities and earnings of immigrants also declined relative to native Swedes.

This occurred despite the boom in the Swedish economy during the 1980s, and then got worse during the slump in the early 1990s. Probably both supply and demand-side factors were responsible for the worsening income-gap between immigrant and native Swedes. A structural shift in the Swedish economy from industrial to service-oriented increased demand for employees with language and interpersonal skills, including the culture-specific ability to deal with authorities and labour-market organizations. Such demand for informal competence made it difficult for immigrants to compete even if they had the same level of formal education.

Beyond the income-inequality itself and stresses that immigrants have placed on public services and income-transfer programs, their economic status is a matter of interest since it relates to the persistence of social problems. Assimilation can be even more difficult for children if their parents were not only immigrants but low-income as well.

Many studies have assessed the economic assimilation of immigrants, for North America: Chiswick, 1978; Borjas, 1985, 1989; LaLonde and Topel, 1991, 1992; Baker and Benjamin, 1994; and Duleep and Regets, 1999; for Europe: Aguilar and Gustafson, 1991; Bauer and Zimmermann, 1997; Bell, 1997; Longva and Raaum, 2003. But because of data limitations these studies were prone to some important potential biases. The synthetic panel methodology which has been standard for assimilation-studies ignores the influence of unobserved factors on immigrants' economic performance; if these factors are correlated with immigrants' observed characteristics, the results will be biased. The possibility of sample-selection bias has also been neglected. And whether synthetic or not, identification of any model which aims to separate assimilation-, cohort-, and period-effects needs some parameter-restrictions (Mason et al., 1973; Glenn, 1981). Further, the results can be quite sensitive to what restrictions are made (Glenn, 1976). The restriction usually used in assimilation studies is that period-effects (assumed representative of overall macroeconomic conditions) be the same for immigrants and natives (Borjas, 1985, 1995). However, Barth et al. (2002a, 2002b, 2004) show that if the earnings of immigrants and natives have different sensitivities to varying economy-wide conditions, then this assumption leads to bias which can distort the earnings-predictions for immigrants. They found different unemployment elasticities not only between immigrants and natives, but also among immigrant-groups from different world regions. Longva and Raaum (2002) found that the earnings of immigrants and natives were affected differently by regional unemployment rates in Norway; McDonald and Worswick (1997) found a similar result for the immigrants to Canada using aggregate unemployment rates.

We used eleven waves (1990-2000) of the register-based Longitudinal Individual Dataset (LINDA) which allowed us to overcome the problems just discussed. We estimated the employment- and earnings-equations simultaneously while also extending the standard approach using panel methodology with a random-effects model augmented by Mundlak's (1978) formulation. Thus we allow for correlation between persistent unobserved and observed individual characteristics while also correcting for sample selection. Following Blanchflower and Oswald (1994), Card (1995) and Barth at al. (2004), we also used wage-curve methodology with local unemployment rates to avoid inappropriate restrictions.

The next section develops the models used and discusses econometric issues, while Section 3 presents the data. Section 4 gives the estimation results. Section 5 summarizes and draws conclusions.

2 Econometric specifications

2.1 The assimilation model

Our econometric strategy was chosen both to exploit the panel-aspect of the data to correct for potential sample-selection bias. Sample-selection bias[1]can arise from self-selection by the individuals under investigation or from sample-selection decisions made

[1] A simple sample-selection test (suggested by Verbeek and Nijman, 1992) was also performed by adding the lagged selection-indicator ($r_{i,t-1}$) to the equation, estimating the model by fixed effects on the unbalanced panel, and doing a t-test for the significance of $r_{i,t-1}$. For all groups, $r_{i,t-1}$ was significant.

by data-analysts. Such sample-selectivity can be a major problem with cross-sectional as well as panel data (Matyas and Sevestre, 1995; Kyriazidou, 1997). It has been common in many economic analyses of panel-data to study only a balanced sub-panel without correcting for selectivity-bias.

Another big concern in empirical work is unobserved individual-effects (heterogeneity), which may be correlated with explanatory variables. It is desirable to consider both sample-selectivity and unobserved heterogeneity simultaneously, which can be done in various ways. We estimated a random-effects model (as suggested by Zabel, 1992) in which income-generation by immigrants (I) is given by

$$y_{it}^{*I} = x_{it}\beta^I + \phi^I AGE_{it} + \delta\ YSM_{it} + \textstyle\sum_j \psi_j C^j + \sum_k \theta_k^I \Pi^k + \eta^I \log UR_{it}^{mI} + u_i^I + \varepsilon_{it}^I$$

$$r_{it}^I = 1\left\{z_{it}\gamma^I + v_i^I + \omega_{it}^I > 0\right\} \tag{1}$$

$$y_{it}^I = y_{it}^{*I} \times r_{it}^I$$

and income-generation by native Swede is given (N) by

$$y_{it}^{*N} = x_{it}\beta^N + \phi^N AGE_{it} + \textstyle\sum_k \theta_k^N \Pi^k + \eta^N \log UR_{it}^{mN} + u_i^N + \varepsilon_{it}^N$$

$$r_{it}^N = 1\left\{z_{it}\gamma^N + v_i^N + \omega_{it}^N > 0\right\} \tag{2}$$

$$y_{it}^N = y_{it}^{*N} \times r_{it}^N$$

where y_{it}^* denotes the log of latent earnings; i denotes individuals; t denotes the year; x_{it} and z_{it} are vectors of socio-demographic characteristics such as educational attainment, marital status, and non-labour income; AGE denotes the age of the individual; YSM is years since migration;[2] C denotes arrival-cohort; Π is also an indicator variable indicating income in year t; UR_i^m is the local unemployment rate for municipality m in year t; r_{it} is a selection-indicator measuring the benefit of being employed relative to unemployed; u_i and v_i are unobserved persistent individual-specific effects; ε_{it} and ω_{it} are idiosyncratic error-terms and $\beta, \phi, \delta, \psi, \theta, \eta$ and γ are vectors of unknown parameters of interest.

2.2 Identification of the model and quasi-fixed effects approach for the unobserved individual-effects

The models given in (1) and (2) have two identification problems. First of all, a simultaneous focus on employment and earnings immediately implies one has to take a stance

[2] The model also includes the squared-age and squared-years since migration; and interactions of local unemployment-rates with both years since migration and squared-years since migration (but not shown in (1) and (2), for simplicity).

on selection. A credible analysis of selection requires a robust identifying instrument (an exclusion-restriction). The second problem arises because the model (1) aims to separate years since migration, arrival-cohort, and period-effects.

Identification of selection-bias depends on the exclusion restriction or identifying instrument: At least one explanatory variable in the selection equation must be excluded from the earnings equation. The number of variables usable for this purpose in empirical applications is very limited; it is not easy to find a defensible and robust identifying instrument. The restriction adopted here is that *temporary capital (non-labour) income* is assumed to only affect participation, whereas the *permanent* capital (non-labour) income can affect earnings, through human capital investment.

Consider the capital income y_{it}^{nl} of individual i during t, which can be split into two uncorrelated components, $\beta y_{it}^{nl} + \varphi \overline{y}_i^{nl}$, where $\overline{y}_i^{nl} = (1/T_i)\sum_1^{T_i} y_{it}^{nl}$ is the average over time. This can also be written as $\beta(y_{it}^{nl} - \overline{y}_i^{nl}) + (\beta + \varphi)\overline{y}_i^{nl}$. The first part of the expression is the difference from the within individual means, and represents *temporary shocks* on the capital income and the second part is *permanent capital income* or *level effect*. It was assumed that temporary shocks affected only current participation but not the earnings, and it was therefore excluded from the earnings equations and used as identifying restriction.

The period-effect in equations (1) and (2) is a linear combination of the effects of arrival-cohort and years since migration.[3] It is not possible to analyze the effects of age, cohort, and period simultaneously. An additional restriction must be imposed, either period-effect is the same for both immigrants and Swedes, or cohort-effect is the same across arrival cohorts. The changing pattern of immigration over time generated by political conflicts in source-countries and changes in immigration policy in Sweden makes the constant cohort-effects unrealistic. The restriction imposed in this paper is that period-effect in the immigrants' earnings generating process is equal to the one that is in the earnings generating process of natives. If in fact they were not equally affected by the trend in economy-wide conditions, then this restriction could lead to severe bias in estimates of the effects of arrival-cohort and years-since-migration (Barth et al., 2004). This restriction does not mean that labour-market and social conditions were unchanged during the observation period, but that the earnings of immigrants and natives Swedes were equally affected (Borjas, 1985). Our observation period covers the eleven years between 1990 and 2000 in which Sweden experienced an economic downturn. As shown in Figure 1, there is positive trend in the unemployment rates. In this period unemployment

[3] The calendar year of any given cross-section is the sum of years since migration and the year in which the individual immigration occurred.

rates reached its historical maximum at 8.2 % in 1993.

Figure 1 *about here*

To attempt to control for this bias, at least partially, local market unemployment-rates were used by following the *wage-curve model* suggested in Card (1995) and Barth et al., (2004). To include the changes in the sensitivities to changing macroeconomic over time, the model was also augmented by interacting the years-since-migration with local unemployment rates. The augmented wage-curve model was also restricted by equal-period-effects assumption. However, it was assumed that the period-effects could be identified (at least partially) by controlling for local unemployment rates.

In this paper, we will follow a fully parametrized random-effects approach with maximum likelihood estimator. However, the random-effects approach is inconsistent and seriously biased if the probability distribution of the unobserved individual-effects which is conditioned on observed individual characteristics is misspecified ($E\left[u_i|x_{it}\right] \neq 0$). For example, *ability* which can be considered as unobserved factor influencing the employment probabilities and earnings may be correlated with education level while *motivation* can be correlated with immigrant status. In this case, treating the individual effects as i.i.d. errors would also lead to biased and inconsistent estimators.

To deal with this issue, we follow a quasi-fixed effects approach which is allowing correlation between unobserved and observed individual-characteristics. Thus, the correlated random-effects approach of Mundlak (1978) and Chamberlain (1984) is adopted by parameterizing the fixed-effects as linear projection on the *within*individual means of *time-varying* regressors,

$$u_i = \xi \overline{x}_i + \zeta_i$$

and

$$v_i = \vartheta \overline{z}_i + \kappa_i$$

where $\overline{x}_i = (1/T_i)\sum_1^{T_i} x_{it}$ and $\overline{z}_i = (1/T_i)\sum_1^{T_i} z_{it}$; T_i is the number of periods an individual is observed; ζ_i and κ_i are the new unobserved individual-effects which are assumed as not correlated with observed explanatory variables. ξ and ϑ are parameters. Adding these expressions to the earnings and selection equations, the composed error terms become $\widetilde{\varepsilon}_{it} = \varepsilon_{it} + \zeta_i$ and $\widetilde{\omega}_{it} = \omega_{it} + \kappa_i$, with it assumed

$$\widetilde{\varepsilon}_{it} \sim N\left[0, \sigma^2_{\widetilde{\varepsilon}_{it}}\right], \qquad i = 1, ..., N; t = 1, ..., T$$

$$\widetilde{\omega}_{it} \sim N\left[0, 1\right], \qquad i = 1, ..., N; t = 1, ..., T$$

$$\rho_{\widetilde{\varepsilon}\widetilde{\omega}} = Corr(\widetilde{\varepsilon}_{it}, \widetilde{\omega}_{it})$$

The error-terms $\widetilde{\varepsilon}_{it}$ and $\widetilde{\omega}_{it}$ are assumed to be non-autocorrelated and the selectivity is assumed to show-up through the correlation of these composite error terms. The model was estimated by a simulated maximum likelihood estimator with smooth recursive simulator (GHK) using 100 random draws.

2.3 The estimator of assimilation

Just as it would be with cross-sectional data the conditional mean function for the sample selection model here is not changed by the presence of random effects:

$$E\left[y_{it}|x_{it}, z_{it}, r_{it} = 1\right] = x_{it}\beta + \rho_{\widetilde{\varepsilon}\widetilde{\omega}}\sigma_{\widetilde{\varepsilon}}\frac{\phi\left(z_{it}\gamma\right)}{\Phi\left(z_{it}\gamma\right)} \tag{3}$$

where ϕ and Φ probability density and distribution function of standard normal random variable, respectively; the variance of the augmented error-term is $\sigma^2_{\widetilde{\omega}} = 1$ due to the normalization. In this paper, the earnings assimilation is measured as a situation where immigrant earnings catch up over time with native earnings by following Borjas (1985, 1999). Then, the expected earnings-difference between immigrant group k and native Swedes at any time t after arrival, evaluated at the mean values is

$$\Delta y_k = E^I - E^N$$

or

$$\begin{aligned}\Delta y_k(t) = {} & E^I\left[y_{it}|AGE(t_0+t), YSM(t), x_{it}, z_{it}, r_{it} = 1\right] \\ & - E^N\left[y_{it}|AGE(t_0+t), x_{it}, z_{it}, r_{it} = 1\right]|_{x=\overline{x}, z=\overline{z}}\end{aligned} \tag{4}$$

where t_0 is labour-market entry age of the individuals. The *initial earnings-difference* (or *entry-effect*) is calculated by $\Delta y_k(0)$. Then, the estimator of the *marginal rate of assimilation* (MRA) for any time t after arrival is

$$\widehat{MRA_k}(t) = \frac{\partial E^I}{\partial t} - \frac{\partial E^N}{\partial t}$$

or in terms of estimated marginal effects of the variables age $ME(AGE(t))$ and year since migration $ME(YSM(t))$,[4]

$$\widehat{MRA_k}(t) = (ME(YSM(t)) + ME^I(AGE(t_0+t))) - ME^N(AGE(t_0+t)) \tag{5}$$

[4] Note that the model in (1) and (2) has non-linear conditional expected value, and thus the estimated parameters are no longer equal to the marginal effects.

Clearly, if $\widehat{MRA_j}(t) > 0$ in any time after arrival, then assimilation occurs. Given that the initial earnings difference is negative $\Delta y_k(0) < 0$ and $\widehat{MRA_k}(t) > 0$ is positive, immigrants close the earnings gap with this marginal rate. The estimator of *total years for assimilation* (TYA), that is the time spend needed to catch-up with the earnings of an average native, as a continuous function on the real time axis, is constructed in the following way: TYA is the upper-limit of the integral which accumulates the $\widehat{MRA_k}(t)$ of each time points to initial earnings-difference of the immigrant group (or equivalently, the time needed for the immigrant group in which the age-earnings profiles of the immigrants and natives intersect):

$$\int_0^{\widehat{TYA_k}} \widehat{MRA_k}(t) = \Delta y_k(0) \tag{6}$$

Using a numerical method for finding the roots, equation (6) can be solved for an estimate of $\widehat{TYA_k}$.

In order to create the same estimators for employment assimilation, the above steps are repeated by using the conditional expected value of probit model,

$$E\left[r_{it}|z_{it}, \overline{z}_i\right] = \Phi(z_{it}\gamma) \tag{7}$$

3 The data

The study was based on the 1990-2000 panel of the Swedish register-based Longitudinal Individual Data-set (LINDA), which contains two distinct random samples: a population sample, which includes 3.35% of the entire population each year, and an immigrant sample, which includes almost 20% of immigrants to Sweden.[5] There is no overlap between samples. Apart from being a panel which is representative for the population, the sampling procedure ensures that the data are representative for each year. The sampling frame consists of everyone who lived in Sweden during a particular year, including those who were born or died, and those who immigrated or emigrated. The data is updated with current household information each year with information from the population and housing censuses and the official Income Register, as well as a higher-education register. The Income Register information, based on filed tax returns, is contingent on the tax rules for that year (For more details see Edin and Frederiksson, 2001).

To avoid selection-problems due to retirement at age 65, the 33,504 immigrant men in LINDA aged 18-55 in 1990 were initially selected for the study, as well as an equal-sized

[5] Immigrants to Sweden enter the national register (and thus the sampling-frame) when they receive a residence permit. In general, immigrants may become Swedish citizen after a sufficient number of years.

control group of randomly-selected native Swedish men, matched for age and county (län) of residence.[6] An additional 20% of new immigrants, 2,000-4,000 were included in each year, as well as an equal number of randomly-selected but matched native Swedes. By 2000, these unbalanced panels consisted of 65,800 immigrant men (generating 521,761 annual observations) and slightly more native Swedes.

Edin et al. (2000) point out that the measures of immigrant-assimilation can be distorted if a significant fraction of immigrants return back to their home country. This did not seem to be a problem since less than 5% disappeared from the data during the observation period. In any case it would be difficult to model return migration with this data since it is not possible to distinguish emigrants from those who died.[7]

The immigrants were categorized as being from other Nordic countries, Western Europe (USA, Canada, Australia, and New Zealand), Eastern Europe, the Middle East, Asia, Africa, or Latin America.

The earnings-variable used is gross labour-income, measured in thousands of SEK per year, inflated by the consumer price index (2000-prices). To eliminate those with short employment periods or part-time jobs with low pay, we followed Antelius and Björklund (2000) in considering as employed only those earning at least 36,400 SEK.[8] The employment-indicator (r_{it}) was defined as 1 if the individual was employed and 0 otherwise.

The key explanatory variables were age and age-squared; years since migration and squared; marital status (cohabiting was considered married); number of children at home; highest education level; residence in Stockholm or elsewhere; other income; arrival-cohort; and local unemployment rates. Local unemployment rates were calculated by dividing the number of unemployed by the population in the municipality of residence, which was assumed to be exogenous to employment and income though conditional on individuals' observed and unobserved characteristics.[9]

No data on work-experience was available. In most U.S. studies this is handled by

---

6 The self-employed were excluded from the analysis since their employment- and earnings-conditions are considerably different from wage-earners.

7 Klinthäll (2003) found that 40% of immigrants arriving from Germany, Greece, Italy and the U.S., 40 percent left Sweden within five years. The main hypothesis which is borrowed from the U.S. Emigration Studies is that the least successful immigrants leave. However, as pointed out by Arai (2000), even low-earning immigrants may have strong incentive to stay due to a relatively high level of living standard in the lower range of the earnings distribution as compared to other countries. The difference in mean earnings between who disappeared (2,934 individuals) and those in the final sample was minimal.

8 This criterion, also adopted in LINDA is the "basic amount" that qualifies one for the earnings-related part of the public pension-system.

9 Because of the immigrant-placement policies implemented in 1985, immigrants' country of origin and their municipality of residence can be correlated (Edin et al, 2002 and 2003; Åslund and Rooth, 2003).

calculating "potential work experience" as age minus years of schooling minus six. But Swedish education-data is given in terms of highest level, not years, so such a calculation would introduce severe measurement-error.

Table 1 shows the mean values for these variables, for both native Swedes and immigrants.

Table 1 *about here*

Both the earnings and employment rate (82% vs. 37-68%) and were considerably higher for native Swedes. On the other hand, more immigrants were married or cohabiting (40% vs. 38-59 %). Native Swedes were generally better educated: About 77% had at least upper-secondary education, compared to 61-76% for immigrants. The earlier immigrant arrival-cohorts each had 9-12% of the total, whereas 1985-89 had 18% and 1990-94 had almost 25%. The Iran-Iraq war and various conflicts in former Yugoslavia occurred during the latter periods. The Nordic area accounted for 25% of all immigrants followed by the Middle East (23%), Eastern Europe (21%) and Western Europe (14%). Asia, Africa, Latin America each had 5-6%.

The immigrant population was clearly not homogenous: Employment rates and earnings were much higher for those from Nordic or Western countries. Middle-Eastern and African immigrants were far less likely to be employed, and had lower earnings if they were. Immigrants from non-Nordic Western countries had more education than all other groups (nearly 32% had a university degree), followed by Eastern Europeans. Despite the fact that Nordic immigrants, most of them from Finland, had less education, they had a higher employment-rate and earned more than the other groups. All this is generally in accord with previous studies on immigrants in Sweden.

4 Empirical analysis

Since immigrants to Sweden were heterogeneous across regions of origin, we estimated the model given in (1) and (2) for each group separately. Our primary interest is to determine whether they enter Sweden with an earnings differential relative to natives and whether their earnings converge to those of the natives as years since migration increases.

First let's consider evidence whether such period-effects on both employment-probabilities and earnings can be identified with local unemployment rates. Then, we will look at estimation results on employment and earnings assimilation. We will consider whether the quality of immigrants is declined by across-immigrant cohorts and finally we will address the effect of educational levels on employment probabilities and earnings.

4.1 Local unemployment-rates and the identification of economy-wide conditions on employment probabilities and earnings

Since, as we noted earlier, simultaneous identification of the effects of age, arrival cohort and economy-wide conditions is not possible, the last effect is generally assumed equal for both immigrants and natives. If this is not true, then the earnings-difference and marginal assimilation rates calculated using the classical assimilation model, which does not include local unemployment-rates, will be biased downward (or upward) depending on the positive (or negative) trend in the local unemployment rates. The hypothesis can be tested by using the local unemployment-elasticities obtained from jointly estimated earnings and employment equations.

The elasticities given in Table 2 (below) are the marginal effects from the log local unemployment rates of jointly estimated employment and earnings equations. Immigrants' employment probabilities and earnings were more responsive to the changes in local unemployment-rates than were the native Swedes. The employment-probabilities and earnings of Africans, Asians, Middle Easterners, Latin Americans and Eastern Europeans were especially negatively affected (Many Eastern Europeans immigrated in the mid- to late-1990s, which were high-unemployment years, so the high unemployment elasticities for this group are perhaps not surprising). The effect of labour-market conditions on the employment probabilities and earnings of natives was small.

Table 2 about here

Figure 2 (below) profiles the *age unemployment-rate employment probability* and *earnings* of African immigrants and native Swedes in three dimensions.[10] The both panels project employment probabilities and earnings age-profiles along the unemployment axis. The striking observation is that the employment probabilities and earnings of native Swedes were not responsive to changes in local unemployment rates, whereas the employment-probabilities and earnings of Africans declined substantially with local unemployment.

Figure 2 about here

Figure 3 (below) shows the effect of local unemployment on employment-probabilities and earnings for Africans and (dashed lines) for native Swedes under good and bad employment conditions, 1% and 5% unemployment. The employment-probabilities of African Immigrants were much higher with low unemployment, though not as high as those of

[10] We did the same simulation for all immigrant groups by region and country of origin classifications. As expected the results followed the sign and size of the unemployment-elasticity of each group.

native Swedes even with high unemployment. With low unemployment the earnings of those working were also much higher, as they improve their labour-market specific skills and wage-bargaining powers (Barth at al, 2004). It implies that *low* unemployment rate causes *fast* employment probability and earnings assimilation. The classical model with the equal-period-effect assumption ignores these facts and produces biased outcomes. Controlling for local unemployment rates adds back to the assimilation model what the identification restriction ignores in some extent depending on the impact of the labour-market conditions.

Figure 3 *about here*

4.2 Earnings and employment assimilation with local unemployment rates

Table 3 show changes in the earnings-differences of immigrants compared to native Swedes by region or country and by year since migration. The differences were calculated by setting the year since migration variable is equal to zero and evaluating all other right hand side variables at their average values (except for local unemployment rate, set to its median value). The initial age set to 20 and years since migration is increased by five years apart until the end of individuals working life (see Section 2.2). The total years for assimilation (TYA) are denoted FA (full assimilation) or PA (partial assimilation). Partial assimilation is the years it took to reach the minimum earnings-difference, if it never turned positive.

There are initially two main groups of immigrants to Sweden with respect to earnings assimilation: Nordics and Westerners with very small initial earnings-differences; and all the rest. The initial difference was quite negative for Middle Easterners, Africans and Asians as well as Eastern Europeans and (to lesser extent Latin Americans). However, Eastern Europeans and Latin Americans eventually reached full assimilation, whereas after 20-25 years since arrival, the earnings convergence of the others had stopped or gotten worse. These immigrants were never able to attain the earnings-parity with otherwise comparable native Swedes. For instance, Asians did best, but were only able to reduce the initial earnings-difference to 0.213 log points, in 26-30 years after arrival.

Table 3 *about here*

Nordics had smallest initial earnings-difference (-0.136), but it took 22.5 years to full assimilation, much longer than Western Europeans, and even longer than Eastern Europeans. It has been theorized that low initial earnings-differences would correlate with low earnings-growth and low marginal rates of assimilation like the Nordics experienced

(Duleep and Regets, 1997). But, Borjas (1998) points out that the relationship depends on the technology of skill-acquisition, including cultural, social, and institutional similarities between the immigrants and natives. Nordics countries and Western Europeans are closest in this regard.

Table 3 also shows earnings-differences by country of origin, which are very similar to those we just looked at. The Norwegians did best in Sweden, even earnings slightly more than the average matched Swede upon arrival but their marginal assimilation rates turned to negative in 2-3 years. Iranian and Turkish immigrants reached full assimilation while Iraqis (the other large Middle Eastern group) did much worse.

Table 4 reports the relative employment probabilities of immigrants by region and country of origin, obtained by jointly estimated probit equation. Only Nordics and Western Europeans were able to reach the employment probabilities of average Swedes. Assimilation in employment-probabilities occurred generally faster than in earnings, but rates turned negative after 10-15 years.

Table 4 about here

Figure 4 compares the predicted employment-probabilities and earnings of average immigrants and average native (dashed curves).

Figure 4 about here

Employment-probabilities and earning of Middle Eastern, Asian and African immigrants did not converge to those of native Swedes, nor did the employment probabilities of Eastern Europeans or Latin Americans, although their earnings did at least for a time.

We also estimated (1) and (2) without local unemployment rates (not reported here) in order to examine the extent of the bias produced by classical model. This model produced lower initial earnings-difference (almost 0.10 log points less) and weaker assimilation rates (TYAs up to 5 years longer).

4.3 Cohort effects

An important question in the immigration literature is whether there are unobserved differences in the productivity of immigrants across cohorts. Although we have found assimilation, it could be due to the immigrants getting work easier in times of low unemployment, or because earlier arrival-cohorts were more productive or both. Since our model and data allow identification of cohort effects, we tested these possibilities (Table 5 and 6 below).

Relative to the employment-probabilities of the pre-1970 cohort (Table 5) later cohort-effects were all negative for all regions of origin, and increasingly so over time in almost every case. That decline did not show up in the earnings of all immigrant groups, however (Table 6): The cohort-effects on earnings for Nordics were positive from the start, and for Western and Eastern Europeans as well as Latin Americans they turned positive after 1984. All other things equal, the final Nordic, Western and Eastern European, and Latin American cohorts did better than the first earning 0.12-0.53 log-points more, whereas the last arrival-cohorts of Middle Easterners, Asians and Africans earned 0.3-0.43 log-points less than the pre-1970 cohort. Somewhat Longva and Raaum (2003) found increasingly positive cohort-effects on earnings for OECD immigrants to Norway, increasingly negative for non-OECD immigrants. Possibly the changing country-composition of the Nordic and Western groups over time caused their cohort-effect to chance, as highly educated Danes and Norwegians increasingly took the place of Finns in Nordic immigration, while British and Germans took the place of Greeks, Portuguese, and Spanish among the Westerners.

Table 5 *about here*

Table 6 *about here*

We also calculated the relative earnings differences of immigrants by arrival cohorts.[11] Recent cohorts of Latin Americans and Eastern Europeans had higher initial earnings than pre- 1970 arrivals, and assimilated faster. Our model predicts that an average Latin American who arrived after 1995 would be fully assimilated in 13-14 years, and Eastern Europeans in 7-8 years. No cohort of Middle Easterners, Asians or Africans would be able to reach earnings-parity with an average native Swede.

Barth at al (2004) found that if unemployment was rising, the classical model overestimated the labour-market success of early cohorts and underestimated the success of recent arrivals because of the mechanical correlation between cohorts and calendar time in the data. Thus the classical model can understate earnings-growth across cohorts. We tried both models and found this only for the Middle Eastern, Asian, African and Latin American immigrants. For the others the classical model overstated the assimilation of earlier cohorts but did not understate the assimilation of later ones. For Nordics and Western Europeans we also found no statistically significant differences in the cohort-effect.

4.4 Effects of the educational attainments on assimilation

Table 7 and 8 show the marginal effects of education on employment-probabilities and earnings obtained from the jointly estimated earnings and employment equations. Com-

[11] The relative employment probabilities and earnings, and total years for assimilation (TYA) by arrival cohort can be provided by the authors.

pleting high school or a university degree was positive for all groups of immigrants, as expected. But having a university degree improved employment probabilities much less for Middle Eastern and African immigrants than for the others. Western Europeans, Nordics, native Swedes and Eastern Europeans improved their employment probabilities the most with a university degree.

Table 7 *about here*

Table 8 *about here*

The results on earnings showed somewhat different pattern. As Åslund and Rooth (2003) also found, Nordics, native Swedes and Eastern Europeans gained the most from a university degree, whereas Western Europeans gained less than all except Africans.

The panels in figure 5 (below) show the simulated age-employment probability and age-earnings profiles by education compared to native Swedes (dashed curves) with similar educational level[12], calculated using the means of the other variables for each educational level. The initial age is chosen as 20 except for the university-educated, for whom age 25 was used (also for university-educated native-Swedes).

In every case probability of being employed and earnings increased with education. However, while more highly-educated immigrants approached probability of employment of native Swedes, the earnings-difference increased with education. For example, lesser-educated Latin Americans reached earnings-parity with similarly educated Swede in 19 or 24 years after arrival but highly-educated ones did not, through their probability of being employed was closer to Swedes. The Swedish labour-market thus seems to absorb the highly-educated immigrants better but discounts their education, perhaps due to discrimination, or their education may not be as good. The data available does not indicate where the immigrants obtained their education, so we could not test whether Swedish education was more highly valued than country-of-origin education, though that seems quite likely.

Figure 5 *about here*

5 Discussion and conclusions

We analyzed the economic assimilation of male immigrants in Sweden, using the register-based Longitudinal Individual Data set (LINDA) for 1990-2000. We controlled for sample-selection bias by estimating employment- and earnings-equations simultaneously. We controlled unobserved heterogeneity by using a random-effects model with Mundlak's

[12] The result by country of origin classification is also available from the authors.

formulation. We compared the classical model with period-effects assumed equal, to a wage-curve model using local unemployment rates as proxy for period-effects.

We found that the classical model yielded biased results compared to the wage-curve model. Assuming equal period-effects understated initial earnings-differences (by about 0.10 log-points) and marginal assimilation-rates (by up to 5 years). Including local unemployment-rates changed the simulated employment probabilities and earnings between native Swedes and immigrants and among immigrants from different regions or countries. High local unemployment rate reduced the relative employment probabilities and earnings and much more for Middle Eastern, African and Asian immigrants than for the others. These three groups were also less likely to be employed and earned less in Sweden at any unemployment rate. Among Middle Easterners, immigrants from Iran and Turkey were able to achieve earnings-parity with native Swedes, but immigrants from Iraq did much worse. Other groups which achieved earnings-parity were Eastern Europeans (19 years) and Latin Americans (30 years). Nordic and Western European immigrants did the best. The impact of local unemployment on their employment probabilities and earnings was very weak, similar to that for native Swedes.

The declining cohort effect hypothesis is not rejected except Middle Easterners, Asians and Africans. The relative earnings and employment probabilities of these immigrant groups were declined much higher after the 1985-1989 cohorts compared to the others. This result indicated that the effect of downward trend in economy-wide conditions that occurred in the 1990s was reflected on the employment probabilities and earnings of these three immigrant groups due to their high negative unemployment elasticities.

More education resulted in higher employment-probabilities and earnings, but lesser-educated immigrants earned more compared to native Swedes than did highly-educated ones. This could indicate that university education in immigrants' country of origin was discounted more in Sweden than were lower levels of education, but we could not test this hypothesis.

In general, results presented a pessimistic portrait about the economic success of immigrants to Sweden. However, the assimilation exists, although it is weak, and the length of earnings convergence almost covers individuals' working life. The Immigrants from Middle East, Asia and Africa experienced large welfare disparity and when their declining quality is considered, earnings of the recent cohorts of these immigrants will be far from being assimilated in the future.

References

[1] Aguilar, R., and B. Gustafsson (1991), The Earnings Assimilation of Immigrants, *Labour* **5**: 37-58.

[2] Aguilar, R., and B. Gustafsson (1994), Immigrants in Sweden's Labour Market During the 1980s, *Scandinavian Journal of Social Welfare* **3**: 139-147.

[3] Antelius, J., and A. Björklund (2000), How Reliable are Register Data for Dtudies of the Return on Schooling? An Examination of Swedish data, *Scandinavian Journal of Educational Research* **44**: 341-355.

[4] Åslund, O., and O. Rooth Dan (2007), Do When and Where Matter? Initial labour market conditions and immigrant earnings, *The economic Journal*, **117**: 422-448

[5] Baker, M., and D. Benjamin (1994), The Performance of Immigrants in the Canadian Labour Market, *Journal of Labor Economics,* **12**: 369-405.

[6] Barth, E., B. Bratsberg, and O. Raaum (2002a), Local Unemployment and the Earnings Assimilation of Immigrants in Norway, Department of Economics, University of Oslo, Memorandum, 19/2002.

[7] Barth, E., B. Bratsberg, and O. Raaum (2002b), Local Unemployment and the Wages of Immigrants: Evidence from the current population surveys, Department of Economics, University of Oslo,Memorandum, 20/2005

[8] Barth, E., B. Bratsberg, and O. Raaum (2004), Identifying Earnings Assimilation of Immigrants Under Changing Macroeconomic Conditions, *Scandinavian Journal of Economics* **106**: 1-22.

[9] Bell, B. D. (1997), The Performance of Immigrants in the United Kingdom : Evidence from the GHS, *Economic Journal* **107**, 333-344.

[10] Blanchflower, D.G., and A.J. Oswald (1994), The Wage Curve: MIT Press.

[11] Borjas, G.J. (1985), Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants, *Journal of Labor Economics* **3**: 463-489.

[12] Borjas, G.J. (1987), Self-Selection and the Earnings of Immigrants, *American Economic Review* **77**: 531-553.

[13] Borjas, G.J. (1995), Assimilation, Changes in Cohort Quality: What happened to immigrant earnings in the 1980s, *Journal of Labor Economics* **13**: 201-245.

[14] Card D. (1995), The Wage Curve: A review, *Journal of Economic Literature* **33**: 785-799.

[15] Chiswick, B.R. (1978), The Effect of Americanization on the Earnings of Foreign-born Men, *The Journal of Political Economy* **86**: 897-921.

[16] Chiswick, B.R., Y. Cohen, and T. Zach (1997), The Labor Market Status of Immigrants: Effects of the unemployment rate at arrival and duration of residence, *Industrial and Labor Relations Review* **50**: 289-303.

[17] Chamberlain, G. (1984), Panel Data, in *Handbook of Econometrics*, Vol. II, edited by Z. Griliches and M. Intriligator. Amsterdam: North Holland.

[18] Duleep, H.O., and M.C. Regets (1997), The Elusive Concept of Immigrant Quality: Evidence from 1970-1990, The Urban Institute, Washington DC, PRIP-UI-41 Working paper.

[19] Duleep, H.O., and M.C. Regets (1999), Immigrants and Human Capital Investment, *American Economic Review* **89**: 186-191.

[20] Edin, P.A., R.J. LaLonde, and O. Åslund (2000), Emigration of Immigrants and Measures of Immigrant Assimilation: Evidence from Sweden, *Swedish Economic Policy Review* **7**: 163-204.

[21] Edin, P.A., and P. Frederiksson (2001), LINDA: Longitudinal Individual Data for Sweden, Department of Economics, Uppsala University, Working Paper 2001: 6.

[22] Ekberg, J. (1999), Immigration and the Public Sector : Income effects for the native population in Sweden. *Journal of Population Economics* **12**: 411-430.

[23] Glenn, Norval D. (1976), Cohort Analysis Futile Quest: Statistical attempts to separate age, period and cohort effects, *American Sociological Review* **41**: 900-904.

[24] Glenn, Norval D. (1981), The Utility and Logic of Cohort Analysis, *Journal of Applied Behavioural Science* **2**: 247-257.

[25] Grant, M.L. (1999), Evidence of New Immigrant Assimilation in Canada, *The Canadian Journal of Economics* **32**: 930-955.

[26] Hammarstatd, M., (2001), Disposable Income Differences Between Immigrants and Notives in Swerden, *International Journal of Soical Welfare*. **10**: 117-126.

[27] Hansen, J., and M. Lofstrom (2001), The Dynamics of Immigrant Welfare and Labor Market Behavior. Working Paper. IZA DP No. 360.

[28] Husted, L., H.S. Nielsen, M. Rosholm, and N. Smith (2001), Employment and Wage Assimilation of Male First Generation Immigrants in Denmark, *International Journal of Manpower* **22**: 39-68.

[29] Gustafsson, B., Zheng, J. (2006). Earnings of Immigrants in Sweden. *International Migration* **44**: 79-117

[30] Klinthäll, M. (2003), Return Migration from Sweden 1968-1996: A Longitudinal Analysis, Stockholm: Almqvist & Wiksell International.

[31] Kyriazidou, E. (1997), Estimation of a Panel-Data Sample Selection Model, *Econometrica* **65**: 1335-1364.

[32] Lalonde, R.J., and R.H. Topel (1991), Immigrants in the American labor Market: Quality, assimilation, and distributional effects, *American Economic Review* **81**: 297-302.

[33] Lalonde, R.J., and R.H. Topel (1992), The Assimilation of Immigrants in the U.S. Labor Market, NBER Working Paper 3573, 67-92.

[34] Longva, P., and O. Raaum (2002), Unemployment and Earnings Assimilation of Immigrants, *Labour* **16**: 469-489.

[35] Longva, P., and O. Raaum (2003), Earnings Assimilation of Immigrants in Norway: A reappraisal, *Journal of Population Economics* **16**: 177-193.

[36] McDonald, J.T., and C. Worswick (1997), Unemployment Incidence of Immigrant Men in Canada, *Canadian Public Policy* **23**: 353-373.

[37] Mason, K. (1973), Some Methodological Issues in Cohort Analysis of Archival Data, *American Sociological Review* **38**: 242-258

[38] Matyas, L., and P. Sevestre (1995), The Econometrics of Panel Data, A Handbook of Theory with Applications, Kluwer Academic Publishers, Netherlands.

[39] Mundlak, Y. (1978), On the Pooling of Time Series and Cross Section Data, *Econometrica* **46**: 69-85.

[40] Schmidt, C. (1997), Immigrant Performance in Germany: Labor earnings of ethnic German migrants and foreign guest-workers, *The Quarterly Review of Economics and Finance* **35**: 379-397.

[41] Scott, K. (1999), The Immigrant Experience. Changing employment and income patterns in Sweden, 1970-1993. *Lund Studies in Economic History no*: 9

[42] Vella, F. (1998), Estimating Models with Sample Selection Bias: A Survey. *The Journal of Human Resources* **33**:127-169.

[43] Vella, F. and M. Verbeek (1999), Two-step Estimation of Panel Data Models with Censored Endogenous Variables and Selection Bias, *Journal of Econometrics* **90**: 239-63.

[44] Verbeek, M., and T. Nijman (1992), Testing for Selectivity-Bias in Panel Data Models, *International Economic Review* **33**: 681-703.

[45] Zabel, J.E. (1992), Estimating Fixed and Random-Effects Models with Selectivity, *Economics Letters* **40**: 269-272.

Figure 1. Registered unemployment-rates in Sweden, 1976-2004.

Table 1. *Mean values of variables for native Swedes and immigrants by region of origin,1990-2000*

	Native Swedes	Nordic Countries	Western Europe	Eastern Europe	Middle East	Asia	Africa	Latin America
Log earnings	10.78 (3.73)	8.99 (5.14)	8.06 (5.51)	7.83 (5.71)	5.67 (5.58)	7.54 (5.36)	6.27 (5.53)	7.84 (5.16)
Employment	0.82 (0.37)	0.68 (0.47)	0.59 (0.49)	0.49 (0.50)	0.37 (0.48)	0.51 (0.50)	0.40 (0.49)	0.56 (0.49)
Local unemployment rate	2.81 (1.18)	2.66 (1.01)	2.83 (1.26)	2.85 (1.11)	3.35 (1.55)	3.21 (1.48)	3.15 (1.34)	3.01 (1.41)
Age	38.7 (10.8)	40.7 (10.8)	39.2 (10.96)	38.9 (11.2)	35.6 (9.46)	33.3 (10.5)	33.1 (9.15)	35.4 (10.8)
Years since immigration		19.0 (9.40)	14.8 (9.76)	12.2 (9.64)	9.77 (6.49)	12.6 (7.62)	8.59 (6.32)	12.1 (6.80)
Married/cohabiting	0.40 (0.49)	0.39 (0.49)	0.47 (0.50)	0.59 (0.49)	0.55 (0.50)	0.47 (0.50)	0.44 (0.50)	0.38 (0.48)
Number of children at home	1.78 (1.16)	1.61 (1.12)	1.66 (1.12)	1.81 (1.20)	1.97 (1.47)	1.70 (1.26)	1.58 (1.54)	1.69 (1.21)
Stockholm residence	0.22 (0.43)	0.35 (0.44)	0.39 (0.47)	0.22 (0.34)	0.37 (0.45)	0.30 (0.42)	0.40 (0.48)	0.43 (0.51)
Capital (non-labour) income	0.74 (2.26)	0.49 (1.83)	0.56 (1.99)	0.45 (1.76)	0.54 (1.91)	0.62 (2.03)	0.27 (1.35)	0.30 (1.44)
Highest education level								
Lower–secondary	0.23 (0.37)	0.31 (0.44)	0.32 (0.46)	0.23 (0.39)	0.45 (0.48)	0.39 (0.47)	0.32 (0.45)	0.40 (0.47)
Upper–secondary	0.51 (0.49)	0.43 (0.50)	0.36 (0.47)	0.51 (0.50)	0.39 (0.49)	0.37 (0.48)	0.46 (0.50)	0.47 (0.49)
University degree	0.26 (0.43)	0.26 (0.42)	0.32 (0.46)	0.26 (0.43)	0.26 (0.43)	0.24 (0.43)	0.22 (0.41)	0.23 (0.42)
Arrival Cohort :								
<1970		0.22 (0.44)	0.10 (0.23)	0.10 (0.29)	0.03 (0.17)	0.03 (0.19)	0.03 (0.20)	0.04 (0.25)
1970–74		0.23 (0.42)	0.17 (0.37)	0.14 (0.35)	0.04 (0.18)	0.10 (0.31)	0.04 (0.21)	0.05 (0.22)
1975–79		0.21 (0.40)	0.16 (0.36)	0.08 (0.26)	0.11 (0.31)	0.21 (0.41)	0.07 (0.26)	0.21 (0.40)
1980–84		0.09 (0.28)	0.13 (0.33)	0.10 (0.30)	0.12 (0.32)	0.18 (0.39)	0.08 (0.27)	0.18 (0.38)
1985–89		0.13 (0.33)	0.18 (0.38)	0.14 (0.34)	0.35 (0.48)	0.19 (0.39)	0.30 (0.45)	0.33 (0.47)
1990–94		0.09 (0.29)	0.17 (0.37)	0.38 (0.48)	0.29 (0.45)	0.24 (0.43)	0.42 (0.50)	0.15 (0.36)
1995–2000		0.03 (0.17)	0.09 (0.17)	0.06 (0.24)	0.06 (0.24)	0.05 (0.22)	0.06 (0.23)	0.04 (0.20)
Sample size	540651	131647	67641	107124	121914	28381	28432	36547

(Standard deviations in parentheses)

Table 2. Local unemployment-elasticities, by region of origin,1990-2000

	Native Swedes	Nordic countries	Western Europe	Eastern Europe	Middle East	Asia	Africa	Latin America
Employment	– 0.004	– 0.003	– 0.016	– 0.034	–0.056	–0.091	–0.089	–0.057
	(0.011)	(0.003)	(0.004)	(0.030)	(0.035)	(0.046)	(0.035)	(0.039)
Earnings	– 0.007	– 0.036	– 0.017	– 0.115	– 0.234	– 0.168	– 0.141	– 0.145
	(0.001)	(0.006)	(0.001)	(0.014)	(0.027)	(0.018)	(0.019)	(0.017)

Note: Marginal effects of log local unemployment-rate in the employment and earnings equations, respectively. (Standard errors in parentheses)

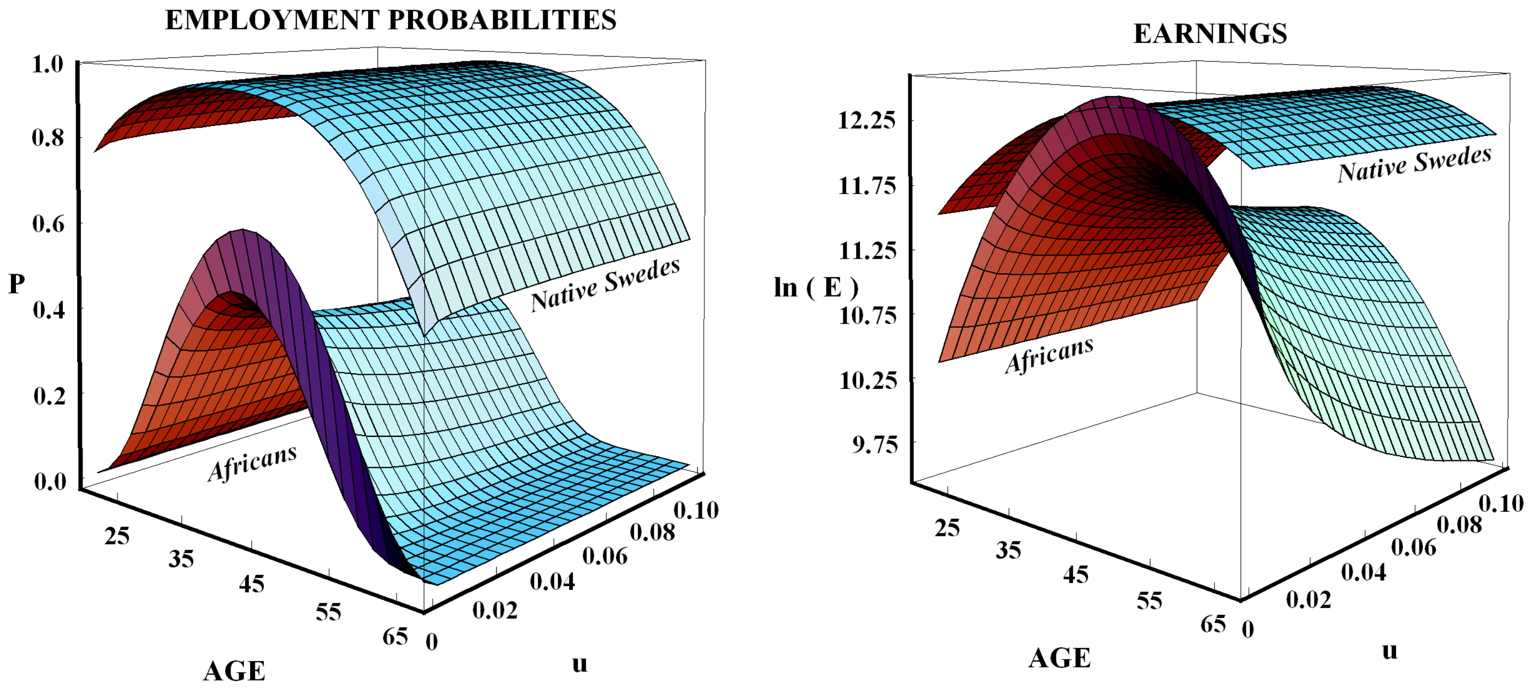


Figure 2. Employment-probabilities and earnings as joint functions of age and unemployment rates for native Swedes and Africans, 1990-2000.

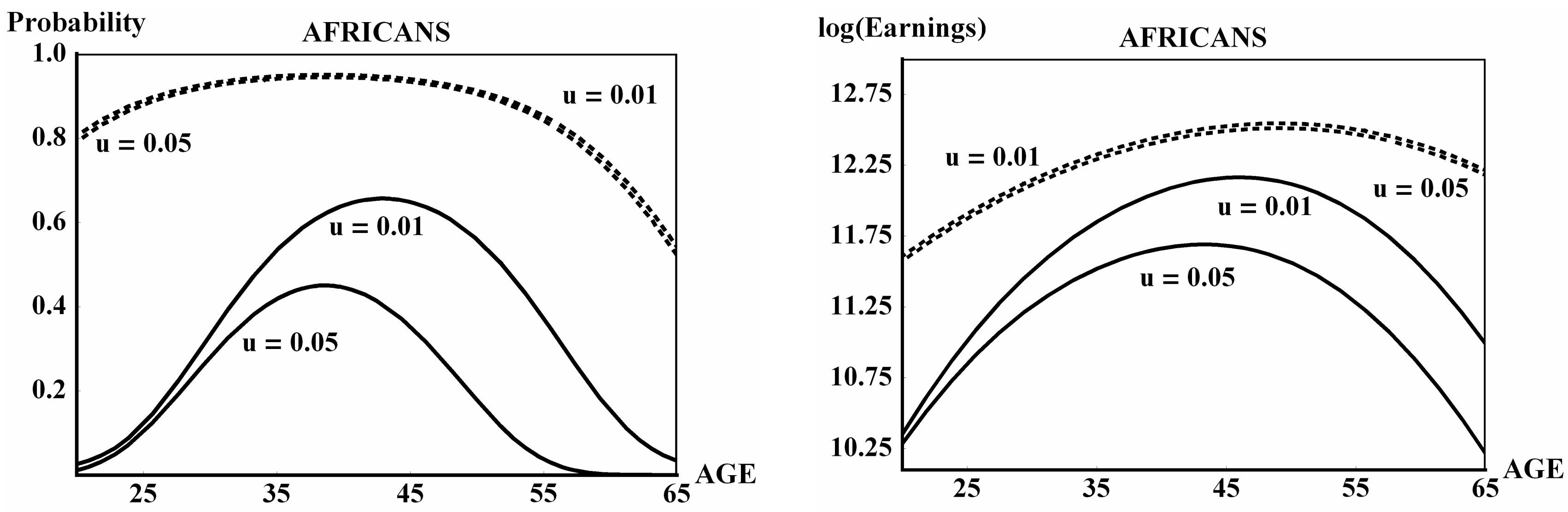


Figure 3. The effect of local unemployment rate on employment-probabilities and earnings, for Africans and (dashed curves) for native Swedes, obtained by vertical cuts of the surfaces in Figure 2 at unemployment = 0.01 and 0.05.

Table 3. Relative earnings and years-to-assimilation of immigrants, by region and country of origin, 1990-2000

	YSM									
	Initial	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	TYA
Nordic Countries	– 0.136	– 0.158	– 0.154	– 0.131	– 0.069	**0.042**	**0.094**	**0.189**	**0.311**	**22.5** (FA)
Western Europe	– 0.179	– 0.102	– 0.027	**0.045**	**0.110**	**0.169**	**0.218**	**0.259**	**0.295**	**11.8** (FA)
Eastern Europe	– 0.875	– 0.473	– 0.215	– 0.070	**0.009**	**0.031**	– 0.043	– 0.256	– 0.612	**18.4** (FA)
Middle East	– 0.812	– 0.639	– 0.518	– 0.441	– 0.404	– 0.417	– 0.494	– 0.642	– 0.858	21.4 (PA)
Asia	– 0.845	– 0.627	– 0.461	– 0.342	– 0.261	– 0.217	– 0.213	– 0.259	– 0.356	31.8 (PA)
Africa	– 0.871	– 0.611	– 0.451	– 0.371	– 0.352	– 0.395	– 0.520	– 0.748	– 1.082	19.2 (PA)
Latin America	– 0.600	– 0.442	– 0.313	– 0.209	– 0.120	– 0.046	**0.008**	**0.033**	**0.027**	**29.1** (FA)
Norway	**0.005**	**–** 0.039	– 0.060	– 0.062	– 0.048	– 0.020	**0.026**	**0.092**	**0.188**	NA
Finland	– 0.034	– 0.055	– 0.043	**0.003**	**0.061**	**0.144**	**0.240**	**0.348**	**0.470**	**14.8** (FA)
Chile	– 0.374	– 0.311	– 0.250	– 0.188	– 0.123	– 0.057	**0.002**	**0.049**	**0.083**	**26.6** (FA)
Yugoslavia	– 0.795	– 0.517	– 0.317	– 0.125	**0.042**	**0.026**	– 0.031	– 0.158	– 0.356	**17.1** (FA)
Iraq	– 1.023	– 0.664	– 0.532	– 0.573	– 0.803	– 1.286	– 2.031	– 2.571	– 2.896	8.38 (PA)
Iran	– 0.702	– 0.472	– 0.294	– 0.160	– 0.063	**0.006**	**0.032**	– 0.044	– 0.148	**24.3** (FA)
Turkey	– 0.591	– 0.510	– 0.429	– 0.345	– 0.213	– 0.100	– 0.041	**0.024**	**0.055**	**33.5** (FA)

Note: TYA is total years for assimilation and YSM is year since migration. FA and PA denote full assimilation or partial assimilation.

NA is “not applicable”.

Table 4. Relative employment-probabilities and years-to-assimilation of immigrants by region and country of origin, 1990-2000

	YSM									
	Initial	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	TYA
Nordic Countries	**0.072**	**0.028**	**0.002**	–0. 011	–0.017	–0.018	–0.019	–0.022	–0.033	NA
Western Europe	–0.194	–0.078	–0.033	–0.019	–0.013	–0.006	**0.004**	**0.014**	–0.001	**28.8** (FA)
Eastern Europe	–0.792	–0.695	–0.342	–0.155	–0.137	–0.255	–0.582	–0.617	–0.628	17.2 (PA)
Middle East	–0.712	–0.682	–0.613	–0.546	–0.603	–0.720	–0.786	–0.746	–0.628	12.1 (PA)
Asia	–0.778	–0.741	–0.574	–0.441	–0.411	–0.487	–0.647	–0.647	–0.774	18.7 (PA)
Africa	–0.773	–0.719	–0.551	–0.439	–0.449	–0.471	–0.558	–0.740	–0.821	14.4 (PA)
Latin America	–0.666	–0.561	–0.427	–0.346	–0.333	–0.388	–0.506	–0.643	–0.674	17.3 (PA)
Norway	**0.075**	**0.048**	**0.029**	**0.017**	**0.008**	–0.001	–0.014	–0.027	–0.038	NA
Finland	**0.066**	**0.029**	**0.004**	–0.012	–0.017	–0.025	–0.034	–0.075	–0.179	NA
Chile	–0.482	–0.301	–0.303	–0.257	–0.301	–0.385	–0.525	–0.664	–0.683	14.8 (PA)
Yugoslavia	–0.771	–0.644	–0.315	–0.121	–0.117	–0.220	–0.473	–0.557	–0.593	15.1 (PA)
Iraq	–0.791	–0.772	–0.636	–0.686	–0.882	–0.936	–0.908	–0.847	–0.728	9.27 (PA)
Iran	–0.712	–0.665	–0.512	–0.407	–0.509	–0.529	–0.627	–0.732	–0.783	13.6 (PA)
Turkey	–0.686	–0.621	–0.544	–0.429	–0.594	–0.621	–0.734	–0.738	–0.792	12.9 (PA)

Note: See the note on Table 3.

Figure 4. Comparison of predicted age-earnings and age-employment probability profiles of native Swedes (dashed curves) and immigrants by region of origin, 1990-2000, using median local unemployment rates: Nordics=2.89; Western Europeans=2.88; Eastern Europeans=2.81; Middle Easterners=3.17; Asians=3.02; Africans=2.99; Latin Americans=3.07 and native Swedes=2.88.

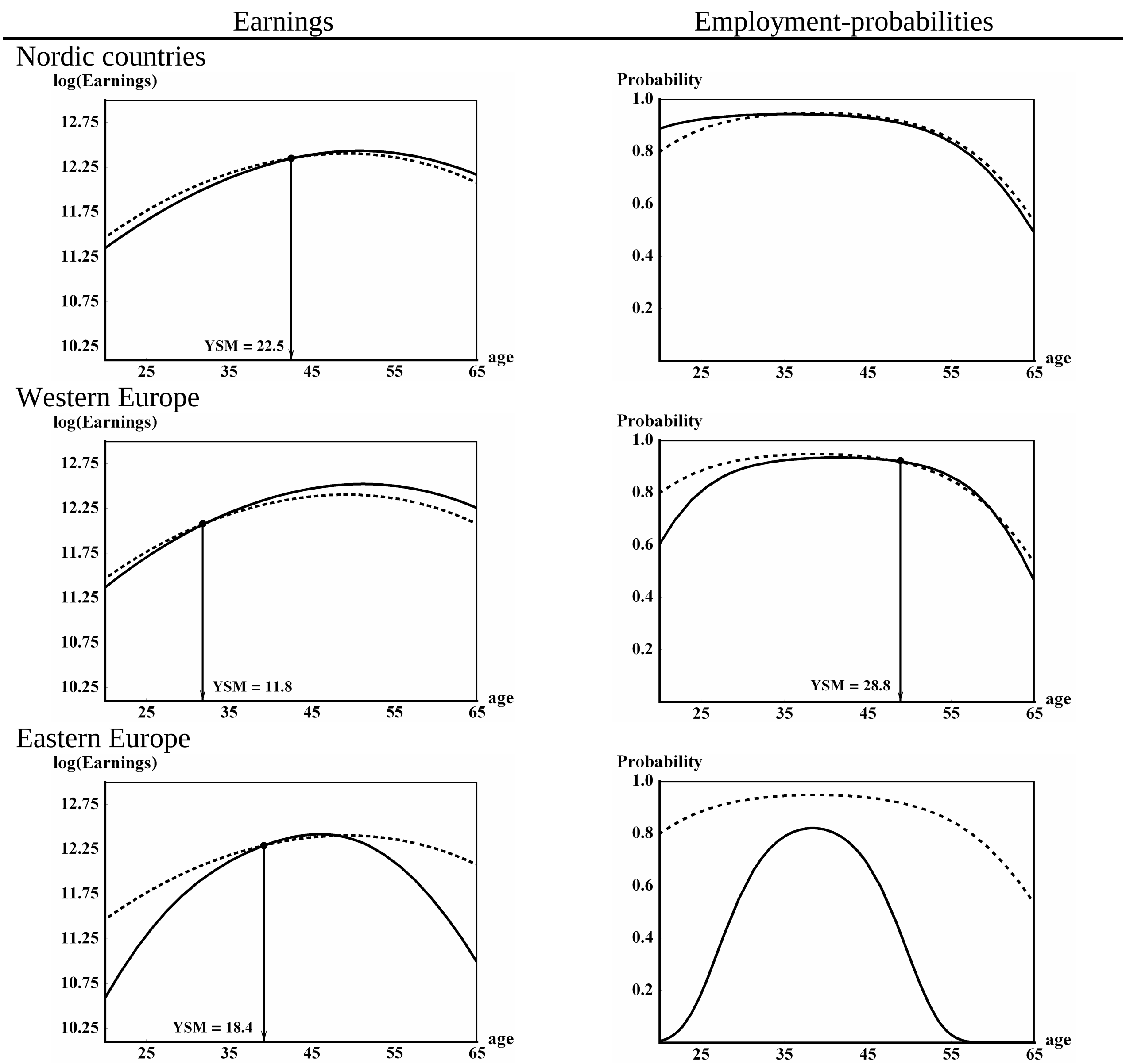


Figure 4. *Continued*

Earnings | Employment-probabilities

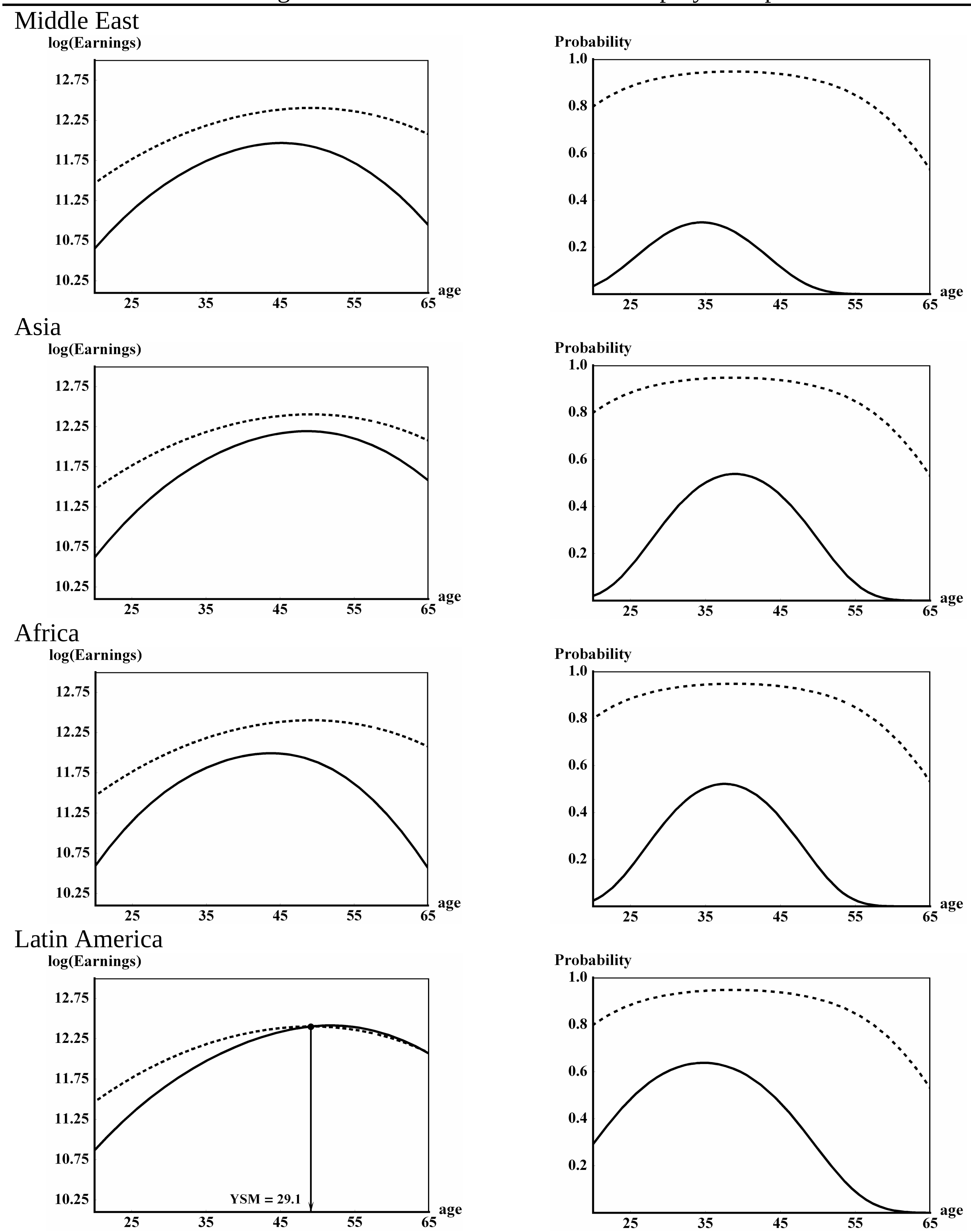


Table 5. Estimated cohort effects on employment probabilities, by region of origin, 1990-2000

Arrival cohort	Nordic countries	Western Europe	Eastern Europe	Middle East	Asia	Africa	Latin America
1970-74 (5 years)	– 0.233	– 0.171	– 0.410	– 0.305	– 0.205	– 0.503	0.008
	(0.018)	(0.036)	(0.036)	(0.064)	(0.085)	(0.072)	(0.072)
1975-79 (5 years)	– 0.403	– 0.406	– 0.617	– 0.395	– 0.285	– 0.627	– 0.116
	(0.022)	(0.042)	(0.045)	(0.065)	(0.086)	(0.071)	(0.069)
1980-84 (5 years)	– 0.545	– 0.463	– 0.558	– 0.483	– 0.296	– 0.697	– 0.276
	(0.027)	(0.046)	(0.047)	(0.070)	(0.090)	(0.075)	(0.072)
1985-89 (5 years)	– 0.647	– 0.718	–0.423	–0.541	–0.396	–0.759	–0.277
	(0.029)	(0.050)	(0.048)	(0.071)	(0.092)	(0.075)	(0.073)
1990-94 (5 years)	– 0.8176	– 0.983	– 0.602	– 0.718	– 0.618	– 1.034	– 0.573
	(0.033)	(0.055)	(0.049)	(0.071)	(0.092)	(0.075)	(0.074)
1995-2000 (6 years)	–0.937	–0.849	–0.500	–0.719	–0.690	–0.962	–0.487
	(0.042)	(0.058)	(0.055)	(0.073)	(0.096)	(0.078)	(0.076)

Note: The omitted reference-cohort is pre-1970 arrivals. Cohort effects are the marginal effects from the employment equations.

(Standard errors in parentheses)

Table 6. Estimated cohort effects on earnings, by region of origin, 1990-2000

Arrival Cohort	Nordic Countries	Western Europe	Eastern Europe	Middle East	Asia	Africa	Latin America
1970-74 (5 years)	0.015	–0.042	– 0.230	– 0.211	– 0.184	– 0.435	– 0.064
	(0.003)	(0.009)	(0.011)	(0.028)	(0.033)	(0.026)	(0.023)
1975-79 (5 years)	0.039	– 0.056	– 0.246	– 0.295	– 0.155	– 0.515	– 0.062
	(0.004)	(0.010)	(0.015)	(0.029)	(0.034)	(0.028)	(0.023)
1980-84 (5 years)	0.167	0.010	– 0.049	– 0.278	– 0.248	– 0.440	– 0.107
	(0.005)	(0.011)	(0.017)	(0.031)	(0.037)	(0.028)	(0.024)
1985-89 (5 years)	0.284	0.117	0.163	– 0.258	– 0.337	– 0.401	0.050
	(0.006)	(0.012)	(0.019)	(0.032)	(0.039)	(0.030)	(0.025)
1990-94 (5 years)	0.380	0.282	0.114	– 0.425	– 0.211	– 0.616	0.067
	(0.007)	(0.013)	(0.020)	(0.032)	(0.040)	(0.030)	(0.025)
1995-2000 (6 years)	0.525	0.477	0.274	– 0.305	– 0.347	– 0.428	0.121
	(0.009)	(0.015)	(0.022)	(0.033)	(0.043)	(0.031)	(0.025)

Note: The omitted reference-cohort is pre-1970 arrivals. Cohort effects are the total (marginal) effects of the earnings equations.

(Standard errors in parentheses)

Table 7. *Marginal effects of education on employment probabilities, by region of origin*

Native Swedes	Nordic Countries	Western Europe	Eastern Europe	Middle Eastern	Asia	Africa	Latin America
Upper-secondary							
0.231	0.157	0.298	0.191	0.064	0.175	0.118	0.185
(0.007)	(0.011)	(0.018)	(0.017)	(0.014)	(0.017)	(0.014)	(0.015)
University							
0.320	0.379	0.448	0.247	0.133	0.228	0.152	0.216
(0.008)	(0.016)	(0.020)	(0.020)	(0.016)	(0.022)	(0.018)	(0.019)

Note: Omitted reference-level is less than high-school graduation. (Standard errors in parentheses)

Table 8. *Marginal effects of education on the earnings*

Native Swedes	Nordic Countries	Western Europe	Eastern Europe	Middle Eastern	Asia	Africa	Latin America
Upper-secondary							
0.023	0.025	0.084	0.101	0.077	0.089	0.099	0.098
(0.007)	(0.002)	(0.005)	(0.001)	(0.007)	(0.007)	(0.007)	(0.006)
University							
0.357	0.379	0.244	0.340	0.296	0.304	0.179	0.246
(0.001)	(0.003)	(0.005)	(0.001)	(0.008)	(0.007)	(0.008)	(0.007)

Note: Omitted reference-level is less than high-school graduation. (Standard errors in parentheses)

Figure 5. Comparison of predicted age-earnings and age-employment probability profiles of native Swedes (dashed curves) and immigrants by education and region of origin, 1990-2000.

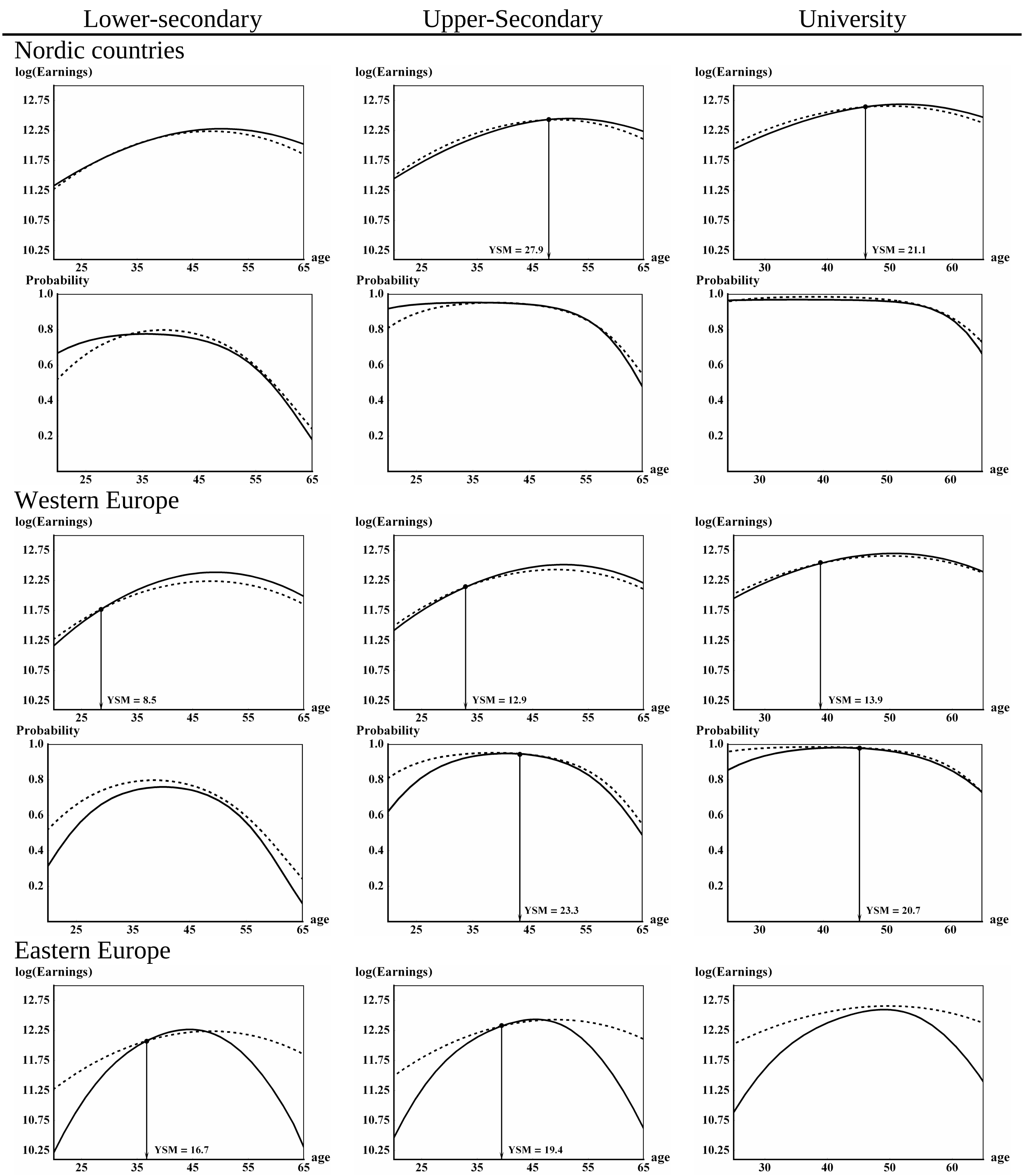


Figure 5. *Continued*

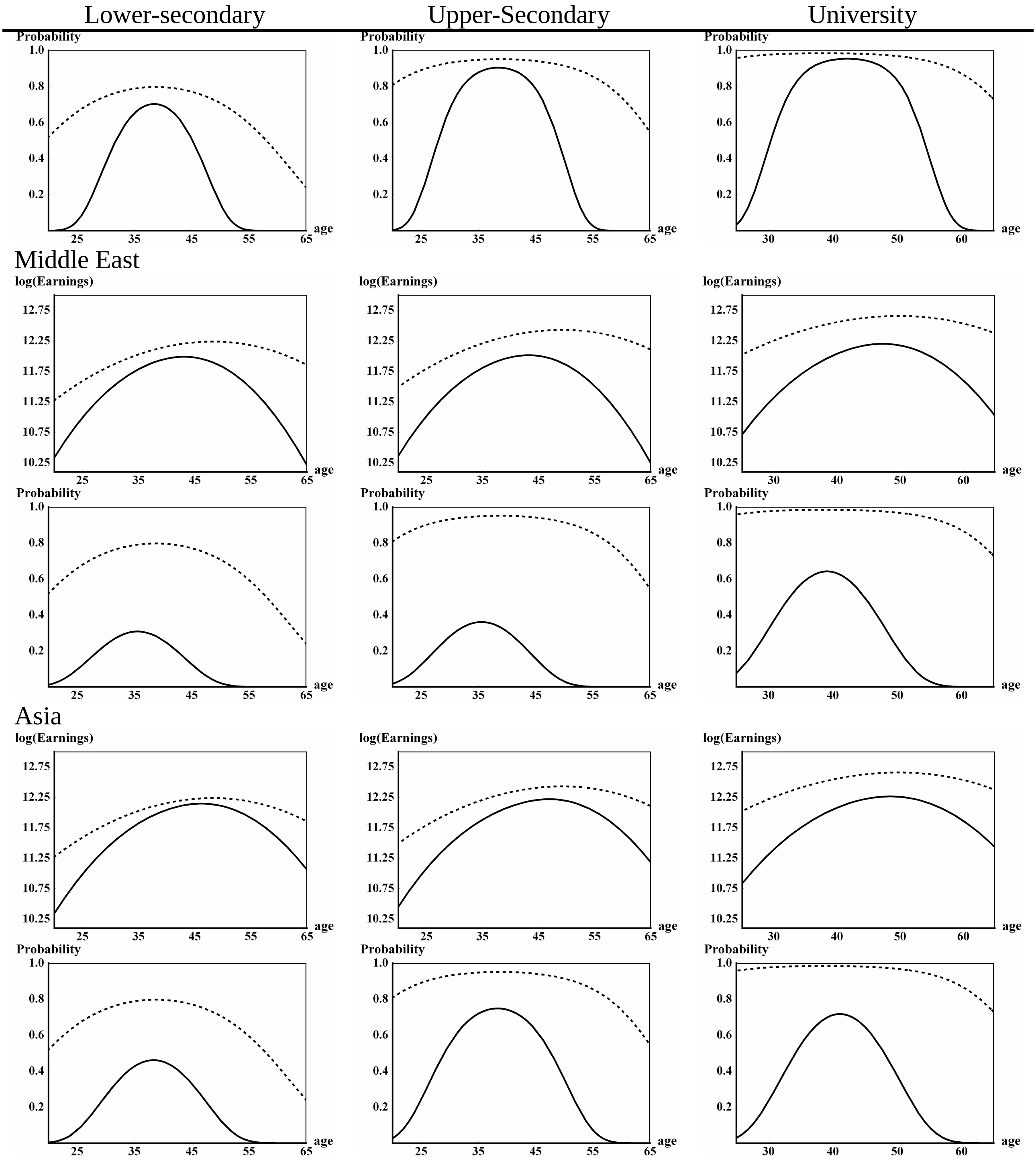
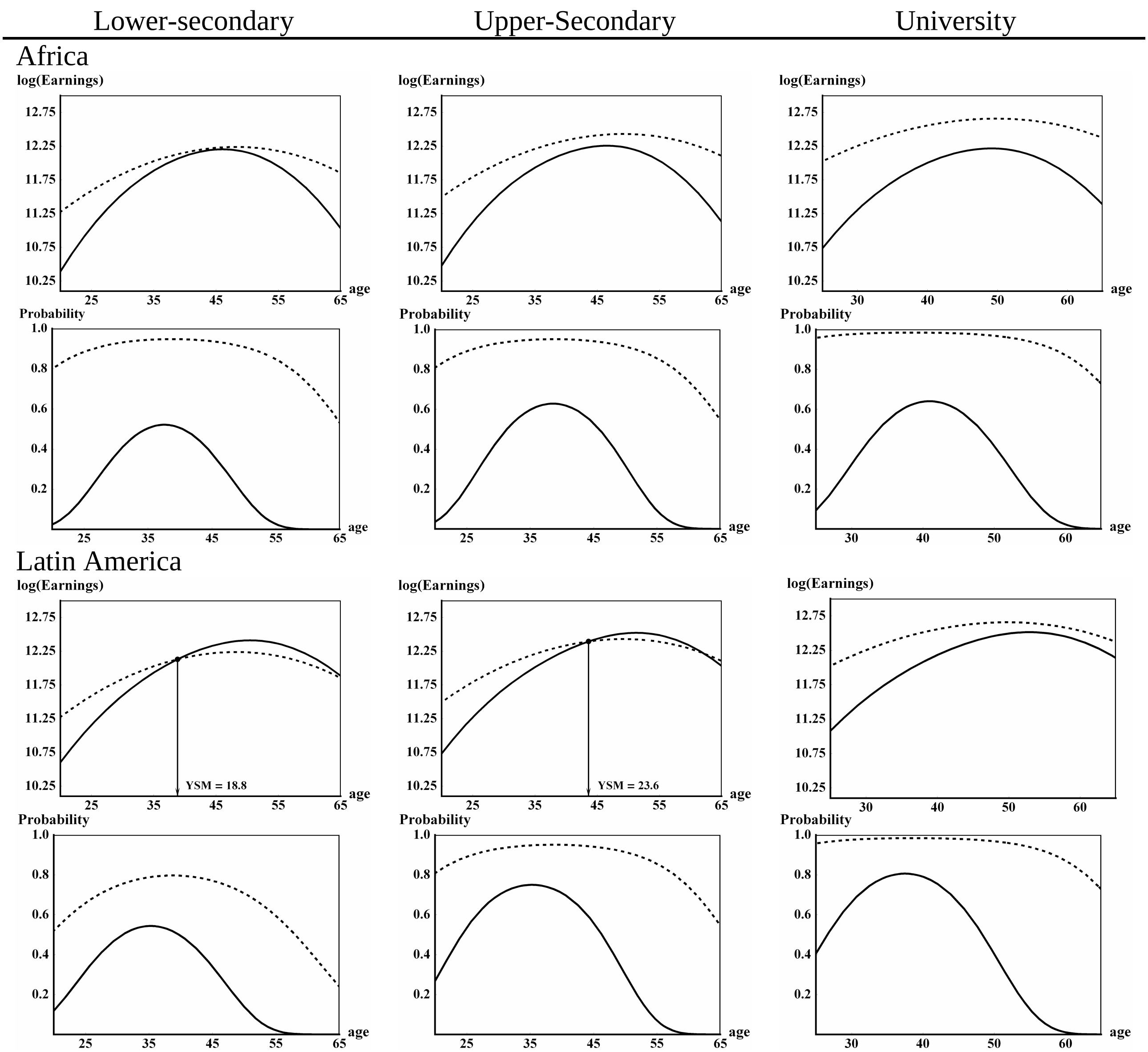


Figure 5. *Continued*



Monte Carlo Investigation of the Initial Values Problem in Censored Dynamic Random-Effects Panel Data Models*

Alpaslan Akay†

Department of Economics, Göteborg University

December 11, 2007

Abstract

Three designs of Monte Carlo experiments are used to investigate the initial-value problem in censored dynamic random-effects (Tobit type 1) models. We compared three widely used solution methods: naive method based on exogenous initial values assumption; Heckman's approximation; and the simple method of Wooldridge. The results suggest that the initial values problem is a serious issue: using a method which misspecifies the conditional distribution of initial values can cause misleading results on the magnitude of true (structural) and spurious state-dependence. The naive exogenous method is substantially biased for panels of short duration. Heckman's approximation works well. The simple method of Wooldridge works better than naive exogenous method in short panels, but it is not as good as Heckman's approximation. It is also observed that these methods performs equally well for panels of long duration.

Keywords: *Initial value problem, Dynamic Tobit model, Monte Carlo experiment, Heckman's approximation, Simple method of Wooldridge*

J.E.L Classification: C23, C25.

*I thank Lennart Flood, Konstantin Tatsiramos, Roger Wahlberg, Elias Tsakas, Peter Martinsson, and seminar participants in Göteborg for their valuable comments.

†Department of Economics, Göteborg University, Box 600 SE 405 30 Göteborg, Sweden. Tel: +46-(31) 773 5304 Email: Alpaslan.Akay@Economics.gu.se

1 Introduction

Censored dynamic panel data models have been widely analyzed by many authors (Honore, 1993; Arellano and Bover, 1997; Arellano, Bover and Labeaga, 1999; Honore and Hu, 2001; Hu, 2002). Given the goal of disentangling the *true* (*structural*) *state-dependence* from *spurious state-dependence*, one of the crucial issues is the initial values problem (Heckman, 1981; Blundell and Smith, 1991; An and Liu, 1997; Blundell and Bond, 1998; Lee, 1999; Arellano and Honore, 2001; Honore, 2002; Hsiao, 2003; Arellano and Carrasco, 2003; Honore and Hu, 2004; Arellano and Hahn, 2005; Honore and Tamer, 2006). The aim of this paper is to compare some widely used solution methods of the initial values problem in censored dynamic random-effects panel data models using various designs of Monte Carlo experiments (MCE).

The initial values problem can appear if the history of the stochastic process underlying the model is not fully observed. If the process is operated before the sample data is observed and if the initial (*sample*) values have been affected by the unobserved past, then the initial values problem can emerge since the initial values have possibly been created by the evolution of the strictly exogenous variables in interaction with unobserved individual-effects. The solution of the problem is to specify a distribution of initial values which is conditioned on strictly exogenous variables and unobserved individual-effects. Ad hoc treatments of this problem can produce bias and inconsistency in the estimators of the censored dynamic random-effects model as it would also cause in similar probit, logit or Poisson models (Heckman, 1981; Honore, 2002; Hsiao, 2003; Honore and Tamer, 2006).

Besides the initial values problem, the random-effect approach has some other limitations. It requires an assumption about the conditional distribution of unobserved individual-effects. To avoid these problems a fixed-effects approach can be used, which can be attractive as a way to ensure that the conditional distribution of unobserved individual-effects does not play a role in the estimation of the parameters. However, it can also be seriously biased since it suffers from the *incidental parameters problem* (Neyman and Scott, 1948; Greene, 2004). Alternatively, some other estimators based on semiparametric methods or combinations of these methods with the fixed-effects approach (such as censored least absolute deviation estimator suggested by Hu (2002) or the fixed-effects approach developed by Honore (1993)) can be used for estimating a censored dynamic panel data model (see also Honore and Hu, 2001). However, these estimators are still subject to the incidental parameters problem and in these estimators time-invariant exogenous variables are swept away, which can also be a serious problem in the practice. Thus, the random-effects approach is still attractive, and if it is preferred, a proper solution for the initial values problem is necessary.

The aim of this paper is to compare some widely used solution methods of the initial values problem in censored dynamic random-effects panel data models. To do this, various designs of MCE are provided. We designed cases in which a solution for the initial values problem is necessary, and three solution methods are investigated: The first is the naive approach in which the initial values are considered as *exogeneous* variables, independent from unobserved individual-effects and strictly exogenous variables. The other two consider the initial values as *endogenous* variables. Thus, the second is the Heckman's (1981) method, which uses a reduced-form approximation for the conditional distribution of initial values based on available pre-sample information. The third method is the simple method of Wooldridge (2005), which uses an auxiliary distribution of unobserved individual-effects conditioned on initial values and strictly exogenous variables.

The results suggest that the initial values problem is a serious issue which can lead to substantial bias if the conditional distribution of initial values is misspecified. The naive exogenous method can highly overstate (understate) the size of the true state-dependence (spurious state-dependence), if it is wrong. It is found that Heckman's reduced-form approximation works well for all durations of panels. The simple method of Wooldridge works much better than naive exogenous method, and it is as successful as Heckman's approximation with moderately long panels. It is also found that these methods tend to perform equally well for panels of long durations.

The paper is organized as follows; the next section will give the model, description of the initial values problem and three solution methods. Section 3 presents our Monte Carlo designs and results. Section 4 concludes.

2 The model and three solution methods of the initial values problem

Consider the following censored dynamic random-effects model with one lag of *censored* dependent variable:[1]

$$y_{i0} = \max(0, x'_{i0}\beta + \epsilon_{i0}) \tag{1}$$

$$y_{it} = \max(0, x'_{it}\beta + \gamma y_{i,t-1} + \epsilon_{it}) \tag{2}$$

[1] The other alternative is to consider that the lagged values of the dependent variable is also latent. Considering the lagged dependent variable as *observed* or latent lead to different implications in both economic and estimation terms. See Honore (1993), Hu (2002) and Hsiao (2003) for useful discussions.

where $\epsilon_{it} = \alpha_i + u_{it}$ is the composite error terms; x_{it} is a vector of *strictly* exogenous variables in a sense that they are independent from all past, current and future values of the disturbance $u_{it} \sim iidN\left(0, \sigma_u^2\right)$; α_i is time-persistent unobserved individual-effects (unobserved heterogeneity) with a conditional probability distribution $f\left(\alpha_i | x_{it}\right)$. In this paper, we assume that the distribution of the random-effects is $\alpha_i \sim iidN\left(0, \sigma_\alpha^2\right)$, and they are orthogonal to exogenous variables following the standard random-effects assumption. Throughout the paper, the number of individuals N $(i = 1, ..., N)$ is considered to be large relative to the number of periods T $(t = 1, ..., T)$. Covariance structure of the model is assumed as

$$E[\epsilon_{it}\epsilon_{i,t-s} | \{x\}_{t=1}^T] = \begin{Bmatrix} \sigma_\epsilon^2 & s = 0 \\ \rho\sigma_\epsilon^2 & s \neq 0 \end{Bmatrix} \tag{3}$$

The composite variance is written as $\sigma_\epsilon^2 = \sigma_\alpha^2 + \sigma_u^2$ and ρ is the fraction of the variation explained by the unobserved individual-effects. The likelihood at time t for an individual i is given by

$$f_{it}\left(y_{it} | y_{i,t-1}, x_{it}, \alpha_i, \theta\right) = \begin{Bmatrix} 1 - \Phi\left[(x_{it}'\beta + \gamma y_{i,t-1} + \sigma_\alpha \alpha_i)/\sigma_u\right] & y_{it} = 0 \\ (1/\sigma_u)\phi\left[(y_{it} - x_{it}'\beta - \gamma y_{i,t-1} - \sigma_\alpha \alpha_i)/\sigma_u\right] & y_{it} > 0 \end{Bmatrix} \tag{4}$$

where Φ denotes the distribution function and ϕ denotes the density function of standard normal random variable; and $\theta = \begin{bmatrix} \beta & \gamma & \sigma_u \end{bmatrix}$. The full log-likelihood function is given as

$$\ln \mathcal{L} = \sum_{i=1}^{N} \ln \left[\int_{-\infty}^{\infty} \left[\begin{array}{c} f_0\left(y_{i0} | \{x_{it}\}_{t=0}^T, \alpha_i; \theta\right) \times \\ \prod_{t=1}^{T} f_{it[y_{it}=0]} \times \prod_{t=1}^{T} f_{it[y_{it}>0]} \end{array} \right] f(\alpha_i) d\alpha_i \right] \tag{5}$$

where $f_0\left(y_{i0} | \{x_{it}\}_{t=0}^T, \alpha_i; \theta\right) = \left\{f_{0[y_{it}=0]}, f_{0[y_{it}>0]}\right\}$ is the probability distribution of initial values which is conditioned on strictly exogenous variables and the unobserved individual-effects.

There are two alternatives; either *logical* starting point of the stochastic process underlying the model (2) and the observed sample data is the same or the sample data are observed after the process is operated many periods.[2] For the first case, initial values y_{i0} may be known constants and therefore there is no reason to specify a probability distribution for initial values. Thus, $f_0\left(y_{i0} | \{x_{it}\}_{t=0}^T, \alpha_i; \theta\right)$ can be taken out from the likelihood function (Heckman, 1981; Honore, 2002; Hsiao, 2003). However, if observed

[2] Considering the complex associations between variables in economics it is not easy to determine an objective starting point for a process. For example, let us consider the relative earnings of immigrants in a host country. We can start to observe them upon arrival and *logically* the starting point of the earnings generating process can be assumed as started upon arrival. However, this assumption will ignore earnings experiences and accumulated human-capital acquired in county of origin which can also be considered as a part of the process.

sample data start after the process has been operated through many periods, the initial values (the first period in the observed sample data, $t = 1$) cannot be constant since they have possibly been created by the evolution of exogenous variables interacting with unobserved individual-effects. Thus, in this case a probability distribution of initial values ($f_{i1}\left(y_{i1}|\{x_{it}\}_{t=1}^{T}, \alpha_i; \theta\right)$) must be specified.

In general, researchers can follow two alternative ways to solve the initial values problem in practice. The first is to naively *forget* the problem and assume that the initial values have not been affected by unobserved past, even if it may not be true. It means that the initial values are *exogenous* variables, independent from unobserved individual-effects. Thus the conditional distribution of the initial values would be equal to their marginal distributions $f_{i1}(y_{i1})$ and it can be taken outside the maximization procedure of the likelihood function. If the data have not been observed at the beginning of the process, and if the disturbances that generate the process is serially correlated (which is inevitable in the presence of unobserved individual-effects), then this assumption is too strong and causes serious consequences such as bias and inconsistency in the estimators (Heckman, 1981; Hyslop, 1998; Honore, 2002).[3]

The second and more realistic approach is to assume *endogenous* initial values and specify the conditional distribution. However, it is not a easy task to find a closed-form expression for this distribution.[4] Heckman (1981) suggested a reduced-form approximation for the conditional distribution of initial values, based on available pre-sample information. Heckman's approximation can provide flexible specifications for the relationship between initial values, unobserved individual-effects and exogenous variables. Consider the following *reduced-form* equation for initial values:

$$y_{i1} = \max(0, z'_{i1}\pi + \epsilon_{i1}) \tag{6}$$

$$\epsilon_{i1} = \lambda\alpha_i + u_{i1} \tag{7}$$

where z_{i1} is a vector of available strictly exogenous instruments which will constitute the pre-sample information. This vector can also contain the first observations of exogenous variables in the observed sample; π and λ are the nuisance parameters to be estimated; ϵ_{i1}

[3] It is assumed that the actual disturbance process is serially uncorrelated (such as first order autocorrelation $AR(1)$) and the dynamic feature of the model is obtained by including a lagged dependent variable. However, it does not mean that the disturbances are serially uncorrelated. It is possible only if the variance of the unobserved individual-effects is zero, meaning that the model has no panel data characteristics.

[4] One possibility is to assume that the conditional distribution of initial values to be at the steady state. However, it is still difficult to find a closed-form expression for the distribution even for the simplest case where there is no explanatory variable. This assumption is also very strong if age-trended variables are driving the process (Heckman, 1981; Hyslop, 1998; Hsiao, 2003).

is correlated with α_i but it is uncorrelated with u_{it} $(t \geq 1)$.The random-effects assumption implies that α_i is uncorrelated with u_{i1}.Thus, the approximated conditional distribution of initial values is specified as follows:

$$f_{i1}\left(y_{i1}|z_{i1}, \alpha_i; \pi, \lambda\right) = \begin{Bmatrix} 1 - \Phi\left[(z_{i1}'\pi + \lambda\sigma_\alpha\alpha_i)/\sigma_u\right] & y_{i1} = 0 \\ (1/\sigma_u)\phi\left[(y_{i1} - z_{i1}'\pi - \lambda\sigma_\alpha\alpha_i)/\sigma_u\right] & y_{i1} > 0 \end{Bmatrix} \tag{8}$$

with $Var[\epsilon_{i1}] = \lambda^2\sigma_\alpha^2 + \sigma_u^2$ and the correlation between ϵ_{i1} and unobserved individual-effects $(\rho_{\epsilon_{i1}\alpha_i})$ is

$$\rho_{\epsilon_{i1}\alpha_i} = Corr(\epsilon_{i1}, \alpha_i) = \frac{\lambda\sigma_\alpha}{\sqrt{\lambda^2\sigma_\alpha^2 + \sigma_u^2}} = \frac{\psi}{\sqrt{\psi^2 + 1}} \tag{9}$$

where $\psi = \lambda\sigma_\alpha/\sigma_u$. The parameters of the structural system (2) and the approximate reduced-form conditional probability (8) can be simultaneously estimated without imposing any restriction (Heckman, 1981; Hsiao, 2003).

Another solution method is suggested by Wooldridge (2005) which is a simple alternative to Heckman's reduced-form approximation. This method considers the distribution of unobserved individual-effects to be conditioned on initial values and exogenous variables. Specifying the distribution on these variables can lead to very tractable functional forms, and consistent estimators in censored dynamic random-effects models as well as in similar probit, logit and Poisson models (Honore, 2002; Wooldridge, 2005).

This method suggests specifying $f\left(\alpha_i | \{x_{it}\}_{t=1}^T, y_{i1}\right)$ instead of $f_{i1}(.)$ using a similar strategy to Chamberlain's (1984) correlated-effects model. It is based on the following auxiliary distribution of unobserved individual-effects.

$$\alpha_i = \xi_0 + \xi_1 y_{i1} + \xi_2 \overline{x}_i + \eta_i \tag{10}$$

where $\alpha_i | y_{i1}, \overline{x}_i \sim N\left[\xi_0 + \xi_1 y_{i1} + \xi_2 \overline{x}_i, \sigma_\eta^2\right]$ and η_i is a new unobserved individual-effects which is assumed as $\eta_i \sim iidN\left[0, \sigma_\eta^2\right]$; y_{i1} is the initial sample values; $\overline{x}_i$ is the within-means of time-variant exogenous variables defined as $\overline{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$. Thus, we obtain a conditional likelihood which is based on the joint distribution of the observations conditional on initial values. This likelihood function will be like those in standard static random-effect censored model and the parameters can be easily estimated using a commercial random-effects software.

The likelihood function (5) of the censored dynamic random-effects model which is adopted here, involves only a single integral, which can be effectively implemented using Gaussian-Hermite Quadrature (Butler and Muffitt, 1982). This method is much less time consuming and efficient in comparison with the other alternative based on simulation with a proper simulator, such as frequency (natural) by direct Monte Carlo sampling from normal distribution and GHK. (Gourieroux and Monfort, 1993; Hajivassiliou and Ruud,1994). In this paper, we therefore prefer to use Gaussian-Hermite Quadrature in all likelihood computations.

3 Monte Carlo experiments and the results

In order to compare the finite sample performance of the solution methods several designs of MCE are considered that differ on the length of the panel, number of individuals, the relative sizes of the key parameters and on the data generating process for the explanatory variables.[5] We apply the following strategy: We first analyze the bias for the case in which the *initial values are known* constants in order to check the possible bias when the initial values problem is not exist. Second, we design cases in which the initial values problem is severe and analyze *naive exogenous initial values method* as a worst scenario. Third, we use the same data sets to analyze and to compare the performance of *Heckman's reduced-form approximation* and *simple method of Wooldridge.*

The data generating process based on the censored dynamic random-effects model is specified as follows.

$$y_{i0} = \max(0, \frac{\beta x_{i0}}{1-\gamma} + \frac{\alpha_i}{1-\gamma} + \frac{u_{i0}}{\sqrt{1-\gamma^2}}) \tag{11}$$

$$y_{it} = \max(0, \beta x_{it} + \gamma y_{i,t-1} + \alpha_i + u_{it}) \tag{12}$$

where $i = 1, ..., N$ and $t = 1, ..., T$; $\alpha_i \sim iidN\,[0, \sigma_\alpha^2]$; and $u_{it} \sim iidN\,[0, \sigma_u^2]$. The design adopted for the initial values y_{i0} aims first to include correlation between initial values and unobserved individual-effects, and second, to create mean stationarity in the stochastic process. All the results presented here are based on $L = 200$ conditioning data sets. We produced a new set of panel data for each experiment and the same data set is also used for each solution methods. The number of individuals is set to $N = 200$. The behavior of bias is also analyzed for large number of individuals by using $N = 300$, 500, 750 and 1000. The durations of the panel data sets are set to $T = 3, 5, 8, 15, 20$. Number of quadrature points (nodes and weights) used in the optimization procedure of the likelihood function is set to 30.[6]

[5] Our MCE is designed in Fortran software, and the optimization for the likelihood functions is performed using $ZXMIN$, which is very fast and robust. The routines written for the experiments can be provided by the author upon request.

[6] We used different number of quadrature nodes and weights in order to check stability of estimated parameters. It is observed that 30 quadrature points produce very stable results.

3.1 MCE_1 : Benchmark design. A normal explanatory variable

The benchmark design consists of one strictly exogenous explanatory variable which is obtained by using independent and identically distributed standard normal random variates,

$$x_{it} \sim N[0,1] \tag{13}$$

True values of the parameters β and σ_u^2 are set to 1; two values for the true state-dependence $\gamma = -0.5$ and $\gamma = 0.5$ are used. The variance of unobserved individual-effects is first set to $\sigma_\alpha^2 = 1$ and then increased to $\sigma_\alpha^2 = 3$, in order to analyze the size of the variance of unobserved-effects on the estimated parameters. The design is produced, in average, $45 - 55\%$ censored observations.

The results of MCE_1 are summarized in Table 1a, 1b, 1c and 1d. Tables report results only for the key parameters: $\widehat{\beta}$, $\widehat{\gamma}$, $\widehat{\sigma}_\alpha^2$ and $\widehat{\sigma}_u^2$. In addition to the *mean bias* and *root mean square error* ($RMSE$), the *median bias* and *median absolute error* (MAE) are also reported since the estimators of the type considered here often do not have finite theoretical moments. The median bias and MAE are also less sensitive to outliers compared to other two measures. A negative sign on both mean and median bias shows an underestimation and a positive sign shows an overestimation.

Table 1a about here

We focus first on the case in which initial values are *known* (Table 1a) in a sense that the sample data and the process start at the same time and also initial values are nonstochastic ($y_{i0} = 0$). Thus, there is no initial values problem and the bias is very small even with panels of short durations. The mean and median bias are very close to each other meaning that the bias has a symmetric distribution. The variation around the true values is reduced as T increases. A larger true value for the variance of unobserved individual-effects ($\sigma_\alpha = \sqrt{3}$) causes a slight increase in the bias and variation. Last row of Table 1a presents results by number of individuals (N) for a constant number of time periods ($T = 5$). The bias seems not to be affected by the number of individuals in the panel set.

Table 1b about here

As a second step, the process is operated through 25 periods before the sample data are collected in order to create a initial values problem.[7] Table 1b presents the results for the

[7] We operate the system through 25 periods before the sample data is observed. For example, when $T = 3$, the sample data contain the $(y_{i26}, y_{i27}, y_{i28})$ and we use it as (y_{i1}, y_{i2}, y_{i3}). Where y_{i1} are the initial sample values.

naive method based on exogenous initial values assumption. In this case, this assumption is wrong and, as expected, it causes large bias in γ and σ_α. γ is highly overestimated while σ_α is highly underestimated. The bias is $40-50\%$ when $T=3$ for these two parameters. The bias is also remarkable reduced by the duration of panel (especially for $T>10$). A large value of σ_α increased the bias substantially (70% for γ and more than 100% for σ_α). The other two parameters (β and σ_u^2) are not largely biased in almost every case.

Table 1c and Table 1d present results for Heckman's reduced-form approximation and simple method of Wooldridge, respectively. Heckman's approximation method performs very well for all durations of the panels. γ and σ_α are almost $3-5\%$ biased when $T=3$, and a large value of σ_α causes the bias to be larger ($5-10\%$). The simple method of Wooldridge also performs well but not as well as Heckman's approximation. The Wooldridge method also tends to overestimate γ and underestimate σ_α for small samples as naive exogenous method. The bias produced by this method is about $15-25\%$ for $T=3$. For a duration which is greater than $T=5$, the size of the bias produced by the simple method of Wooldridge tends to be equal to the Heckman's approximation. Additionally, all methods perform equally well for the panels which are longer than $T=10-15$.

Table 1c about here

Table 1d about here

3.2 MCE_2 : A non-normal explanatory variable

As pointed out by Honore and Kyriazidou (2000), normally distributed explanatory variables can make the bias appear smaller than it is for other distributions of the explanatory variables, which can largely affect the results in Monte Carlo studies. We, therefore, modify MCE_1 by changing the distribution of the explanatory variable to one degrees of freedom chi-square distributed random variable $\chi^2(1)$, which has a skewed distribution. We standardize this random variable to transform it to the same mean and variance with the exogenous variable given above.[8]

$$x_{it} \sim \frac{\chi^2_{(1)} - 1}{\sqrt{2}} \tag{14}$$

The data-generating process for dependent variable (11-12) is the same as for the

[8] Note that $Z = \left(\chi^2_{(k)} - k\right)/\sqrt{2k}$, where k is the degrees of freedom. Z is the standardized χ^2 random variable.

benchmark case and the only difference is explanatory variable used in the estimation. True values of the parameters are set to: $\beta = 1$, $\gamma = 0.5$, $\alpha_i \sim iidN\left[0, \sigma_\alpha^2 = 1\right]$ and $u_i \sim iidN\left[0, \sigma_u^2 = 1\right]$. The process is operated through 25 periods before the samples are observed with durations of $T = 3, 5, 8, 15, 20$, and the average number of observations that are censored is almost the same as the benchmark design.

Table 2 about here

The results of MCE_2 are summarized in Table 2. A comparison between the results in Table 1a-1d and the corresponding results in Table 2 suggests that the results in benchmark design MCE_1 are very robust. The methods do not produce significantly larger bias with non-normal explanatory variables. The bias has symmetric distribution with a decreasing variance. The performance order between the methods is clear: The smallest bias is obtained by Heckman's reduce-form approximation and it is followed by the simple method of Wooldridge for short panels. The initial values problem tended to be not important source of bias when the duration of the panel is increased.

3.3 MCE_3 : An autocorrelated explanatory variable

MCE_3 is based on a relatively complicated data generating process for explanatory variable which contains higher degree of intra-group variations. In this design, there is only one strictly exogenous variable x_{it} based on following first order autoregressive process

$$x_{it} = \rho x_{it-1} + \psi_{it} \tag{15}$$

where ψ_{it} is a standard normal random variable $\psi_{it} \sim N[0, 1]$, $\rho = 0.5$ and $\psi_{i1} = x_{i1}$. True values of the parameters are set to: $\beta = 1.0$, $\gamma = 0.5$, $\alpha_i \sim iidN\left[0, \sigma_\alpha^2 = 1\right]$ and $u_i \sim iidN\left[0, \sigma_u^2 = 1\right]$. The data generating process for dependent variable is kept the same as in (11-12) and the process is operated through 25 periods before the samples are observed with the durations $T = 3, 5, 8, 15, 20$. The number of the censored observations is almost the same as those produced in first two MCE.

Table 3 about here

The results of the MCE_3 are reported in Table 3. Introducing more intra-group variation to explanatory variable does not change the results found above. The magnitude of the bias and the performance order among the solution methods are the same as those obtained in other two MCE.

Figure 1 shows the Q-Q plots based on the quantiles of normal distribution, by solution methods. We present only for the true state-dependence and variance of unobserved individual-effects. These figures show whether the asymptotic distribution of the estimators used here can be approximated by normal distribution for our MCE samples. We plot the empirical quantiles of the estimated Monte Carlo parameters in MCE_3 against those of normal distribution, where $T = 10$ and number of MCE replication is $L = 200$.

Figure 1 about here

The Q-Q plots support the normality approximation. The empirical quantiles of estimated Monte Carlo parameters in MCE_3 lie mostly in straight lines for all solution methods.

4 Discussion and conclusions

The performance of some widely used solution methods of initial values problem in censored dynamic random-effects models is analyzed using several designs of Monte Carlo experiments. We first presented results for the case in which the initial values are known constants implying that there is no initial values problem. Second, we designed cases in which the initial values problem is severe, and the naive method based on exogenous initial values is analyzed to simulate the effect of a mistreatment for the problem. Third, the performance of the Heckman's (1981) reduced-form approximation and simple method of Wooldridge (2005) are analyzed and compared using the same conditioning data.

The initial values problem can lead to misleading results on the magnitude of true and spurious state-dependence. The naive exogenous initial values method can produce substantial bias especially for the panels of short duration. It causes true state-dependence to be highly overestimated while the variance of unobserved individual-effects is highly underestimated. Considering the durations of the micro-panel data sets encountered in the practice, which generally have thousands of individuals and small number of periods, the conditional distribution of initial values must be specified. Among the solution methods based on specifying the conditional distribution, Heckman's reduced-form approximation is the best choice for the small samples, but for moderate samples there is no clear performance order between Heckman's and Wooldridge's methods with respect to bias that they produce. The message is that the simple method of Wooldridge can be used instead of Heckman's approximation for the panels of moderate duration (such as, time periods $T = 5 - 10$ time periods). Another intuitive message is that all methods which are compared here tend to perform equally well for panels of long duration (such as, time periods $T > 10 - 15$)

From an empirical point of view, Heckman's approximation constitutes a computationally challenging task especially with an *unbalanced* panel data set. As explained in Honore (2002), ad hoc treatments of the initial values problem are in particular unappealing with unbalanced panel data sets, which are the ones generally used in empirical applications. As seen in the Monte Carlo studies above, the simple method of Wooldridge is attractive especially with panels of moderate durations and also it can be easily applied using a standard random-effect software with either balanced or unbalanced panel data sets.

References

[1] An, M.Y., and M. Liu (2000), Using Indirect Inference to Solve the Initial Conditions Problem, *Review of Economics and Statistics*, **4**: 656-667

[2] Arellano, M., O. Bover, and J. Labeaga (1997), Autoregressive Models with Sample Selectivity for Panel Data, Working Paper No. 9706, CEMFI.

[3] Arellano, M., and B. Honore (2001), Panel Data Models. Some Recent Developments, *Handbook of Econometrics*, 5, Elsevier Science, Amsterdam.

[4] Arellano, M. and O. Bover (1997), Estimating Dynamic Limited Dependent Variable Models From Panel Data, *Investigaciones Economicas*, **21**: 141-65.

[5] Arellano, M. and R. Carrasco (2003), Binary Choice Panel Data Models with Predetermined Variables, *Journal of Econometrics*, **115**: 125-157

[6] Arellano, M. and J. Hahn (2006), Understanding Bias in Nonlinear Panel Models: Some Recent Developments. In: R. Blundell, W. Newey, and T. Persson (eds.): Advances in Economics and Econometrics, Ninth World Congress, Cambridge University Press, *forthcoming.*

[7] Blundell, R.W. and R.J. Smith (1991), Initial Conditions and Efficient Estimation in Dynamic Panel Data Models, *Annales d'Economie et de Statistique*, **20/21**: 109-123.

[8] Bulundell, R., and S. Bond (1998), Initial conditions and Moment Conditions in Dynamic Panel Data Models, *Journal of Econometrics*, **87**: 115-143

[9] Butler, J.S., and R. Moffitt (1982), A Computationally Efficient Quadrature Procedure for the One Factor Multinomial Probit Model, *Econometrica*, **50**: 761-764.

[10] Chamberlain, G. (1984), Panel Data, in *Handbook of Econometrics*, Vol. II, edited by Zvi Griliches and Michael Intriligator. Amsterdam: North Holland.

[11] Heckman, J. (1981), The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time - Discrete Data Stochastic Process, in Structural Analysis of Discrete Panel Data with Econometric Applications, ed. by C. Manski and D. McFadden, Cambridge: MIT Press.

[12] Hajivassiliou, V., and P. Ruud (1994), Classical Estimation Methods for LDV Models using Simulation, in R. Engle & D. McFadden, eds. *Handbook of Econometrics*, IV, 2384-2441.

[13] Honore, B. (1993), Orthogonality-Conditions for Tobit Model with Fixed Effect and Lagged Dependent Variables, *Journal of Econometrics,* **59**: 35-61

[14] Honore, B., and E. Kyriazidou (2000), Panel Data Discrete Choice Models with Lagged Dependent Variables, *Econometrica,* **68**: 839-874

[15] Honore, B., and L. Hu (2001), Estimation of Cross Sectional and Panel Data Censored Regression Models with Endogeneity, unpublished manuscript, Princeton University.

[16] Honore, B. (2002), Nonlinear Models with Panel Data, *Portuguese Economic Journal*, **1**: 163–179.

[17] Honore, B., and E. Tamer (2006), Bounds on Parameters in Panel Dynamic Discrete Choice Models, *Econometrica*, **74**: 611-629

[18] Honore, B., and L. Hu (2004), Estimation of Cross Sectional and Panel Data Censored Regression Models with Endogeneity, *Journal of Econometrics*, **122**(2): 293–316,

[19] Hsiao, C. (2003), Analysis of Panel Data, 2nd ed. Cambridge University Press, Cambridge.

[20] Hu, L. (2002), Estimation of a censored dynamic panel-data model, *Econometrica*, **70**: 2499-2517

[21] Hyslop, D. R. (1999), State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women, *Econometrica*, **67**, 1255–1294.

[22] Gourieroux, C., and A. Monfort (1993), Simulation-based Inference: A Survey with Special Reference to Panel Data Models, *Journal of Econometrics*, **59**: 5-33.

[23] Greene, W. (2004), Fixed effects and bias due to the incidental parameters problem in the Tobit model, *Econometric Reviews*, **23**:125-147

[24] Keane, M. P. (1994), A Computationally Practical Simulation Estimator for Panel Data, *Econometrica*, **62**: 95-116

[25] Lee, L.F. (1999), Estimation of dynamic and ARCH Tobit models, *Journal of Econometrics*, **92**: 355-390

[26] McFadden, D., Ruud, P. (1994). Estimation by Simulation. *Review of Economics and Statistics*, **76**: 591-608.

[27] Mundlak, Y. (1978), On the Pooling of Time Series and Cross Section Data, *Econometrica*, **46**: 69-85

[28] Nerlove, M. (1971), Further evidence on the estimation of dynamic economic relations from a time series of cross sections, *Econometrica*, **39**: 359-383

[29] Neyman, J. and E. Scott (1948), Consistent Estimates Based on Partially Consistent Observations, *Econometrica*, **16**: 1-32.

[30] Powell, J. (1984), Least Absolute Deviations Estimation for the Censored Regression Model, *Journal of Econometrics*, **25**: 303-25.

[31] Wooldridge, J.M. (2005), Simple solutions to the initial conditions problem in dynamic, nonlinear panel-data models with unobserved heterogeneity, *Journal of Applied Econometrics*, **20**: 39-54

Table 1a. Results of MCE_1: A normal explanatory variable. *Initial values are known*

T	N	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
		Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE
3		-0.001	0.121	-0.012	0.079	0.010	0.151	0.023	0.112	-0.012	0.264	-0.011	0.130	0.008	0.124	-0.012	0.082
5		0.005	0.070	0.005	0.045	0.008	0.062	0.013	0.043	-0.010	0.162	-0.013	0.090	0.011	0.055	0.008	0.053
8		0.002	0.045	0.003	0.036	0.007	0.042	0.007	0.032	0.004	0.125	0.011	0.094	0.005	0.035	0.005	0.027
15		0.005	0.035	0.007	0.022	0.005	0.033	0.004	0.019	0.007	0.099	0.004	0.098	0.002	0.025	0.001	0.019
20		0.003	0.031	0.004	0.021	0.004	0.026	0.004	0.016	0.008	0.085	0.003	0.064	-0.001	0.021	-0.003	0.017
		$\beta=1$				$\gamma=-0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
3		-0.008	0.124	0.022	0.087	0.011	0.152	0.016	0.137	-0.016	0.244	-0.012	0.105	-0.005	0.118	-0.009	0.075
5		-0.004	0.075	0.008	0.046	0.010	0.079	0.011	0.065	0.014	0.133	0.019	0.096	-0.006	0.057	-0.003	0.036
8		0.005	0.062	0.007	0.044	0.005	0.057	0.008	0.042	0.013	0.127	0.014	0.082	0.003	0.042	0.001	0.029
15		0.002	0.048	0.006	0.030	0.004	0.035	0.009	0.027	0.005	0.095	0.007	0.059	0.001	0.026	0.000	0.022
20		0.006	0.033	-0.005	0.022	0.005	0.027	-0.002	0.019	0.002	0.092	0.005	0.043	0.002	0.024	0.002	0.016
		$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=\sqrt{3}$				$\sigma_u=1$			
3		-0.016	0.139	-0.014	0.089	0.021	0.162	0.017	0.139	-0.024	0.266	-0.021	0.206	0.006	0.102	0.017	0.087
5		-0.007	0.074	-0.008	0.047	0.016	0.078	0.013	0.077	-0.019	0.143	-0.014	0.148	0.007	0.062	0.009	0.036
8		0.001	0.056	-0.004	0.037	0.008	0.054	0.011	0.054	0.010	0.104	0.016	0.104	-0.001	0.039	0.005	0.026
15		0.005	0.035	0.003	0.027	0.005	0.046	0.008	0.028	0.014	0.102	0.018	0.066	0.004	0.026	0.004	0.019
20		0.003	0.032	0.001	0.022	0.005	0.031	0.004	0.020	0.009	0.099	0.015	0.045	0.003	0.025	0.003	0.015
T	N	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
5	300	0.005	0.045	-0.003	0.028	0.011	0.060	0.012	0.042	-0.009	0.122	-0.004	0.093	0.012	0.042	0.008	0.031
5	500	0.004	0.031	0.005	0.018	0.010	0.056	0.013	0.038	-0.001	0.114	-0.009	0.087	0.011	0.033	0.010	0.027
5	750	0.003	0.030	0.004	0.019	0.011	0.056	0.011	0.038	0.002	0.103	0.003	0.086	0.013	0.027	0.009	0.023
5	1000	0.003	0.027	0.003	0.013	0.009	0.052	0.010	0.037	0.007	0.097	0.007	0.081	0.012	0.025	0.007	0.020

Note: Monte Carlo design is based on a standard normal explanatory variable $x_{it} \sim N[0,1]$; Initial values are all constant (censored $y_{i0}=0$); $\beta=1$; $\gamma=(0.5,-0.5)$; $\sigma_\alpha=(1,\sqrt{3})$; $\sigma_u=1$; All results are based on $L=200$ Monte Carlo replications; number of individuals is $N=200$, if else is not stated; number of nodes in Gaussian-Hermite Quadrature is 30; RMSE is the root mean square error; and MAE is the mean absolute error.

Table 1b. Results of MCE_1: A normal explanatory variable. *Naïve exogenous initial values method (when it is wrong)*

T	N	$\beta=1$ Mean Bias	RMSE	Median Bias	MAE	$\gamma=0.5$ Mean Bias	RMSE	Median Bias	MAE	$\sigma_\alpha=1$ Mean Bias	RMSE	Median Bias	MAE	$\sigma_u=1$ Mean Bias	RMSE	Median Bias	MAE
3		-0.041	0.125	-0.038	0.083	0.242	0.265	0.245	0.245	-0.461	0.419	-0.445	0.445	0.057	0.115	0.059	0.067
5		-0.023	0.076	-0.018	0.057	0.099	0.146	0.098	0.098	-0.174	0.177	-0.165	0.165	0.024	0.053	0.028	0.040
8		-0.012	0.061	-0.015	0.052	0.038	0.081	0.038	0.058	-0.081	0.134	-0.082	0.093	0.011	0.039	0.010	0.029
15		0.004	0.040	0.005	0.025	0.014	0.034	0.016	0.021	-0.031	0.101	-0.025	0.048	0.008	0.023	0.006	0.016
20		0.001	0.025	0.002	0.024	0.011	0.027	0.009	0.019	-0.015	0.094	-0.013	0.042	0.002	0.020	0.005	0.015
		$\beta=1$				$\gamma=-0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
3		-0.031	0.118	-0.041	0.089	0.220	0.216	0.234	0.234	-0.499	0.438	-0.471	0.471	0.046	0.128	0.042	0.095
5		-0.014	0.082	-0.019	0.056	0.108	0.101	0.108	0.108	-0.180	0.227	-0.176	0.176	0.031	0.070	0.030	0.046
8		0.008	0.055	0.011	0.033	0.036	0.057	0.039	0.040	-0.066	0.123	-0.063	0.083	0.012	0.045	0.017	0.025
15		0.005	0.039	0.004	0.021	0.015	0.043	0.018	0.022	-0.020	0.115	-0.021	0.056	0.005	0.024	-0.004	0.021
20		-0.001	0.035	-0.002	0.020	0.008	0.036	0.011	0.023	-0.012	0.104	-0.010	0.043	-0.001	0.022	0.001	0.017
		$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=\sqrt{3}$				$\sigma_u=1$			
3		-0.053	0.151	-0.066	0.117	0.351	0.388	0.360	0.360	-1.154	1.112	-1.101	1.001	0.052	0.161	0.055	0.103
5		-0.027	0.081	-0.025	0.061	0.211	0.252	0.222	0.222	-0.589	0.567	-0.556	0.556	0.035	0.098	0.039	0.079
8		-0.014	0.050	-0.013	0.035	0.072	0.096	0.081	0.083	-0.161	0.255	-0.125	0.224	0.024	0.055	0.025	0.042
15		0.008	0.045	0.007	0.024	0.032	0.047	0.034	0.032	-0.065	0.140	-0.061	0.103	0.011	0.030	0.011	0.031
20		0.003	0.034	-0.004	0.023	0.021	0.036	0.019	0.026	-0.033	0.115	-0.028	0.075	0.013	0.027	0.011	0.024
T	N	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
5	300	-0.015	0.046	-0.017	0.023	0.092	0.136	0.093	0.093	-0.153	0.158	-0.156	0.156	0.022	0.047	0.026	0.034
5	500	-0.011	0.037	-0.010	0.024	0.091	0.130	0.092	0.092	-0.154	0.155	-0.152	0.152	0.025	0.045	0.026	0.032
5	750	-0.008	0.028	-0.007	0.022	0.091	0.129	0.093	0.093	-0.153	0.160	-0.151	0.151	0.021	0.044	0.024	0.032
5	1000	-0.005	0.022	-0.003	0.015	0.090	0.125	0.091	0.091	-0.151	0.161	-0.151	0.151	0.021	0.044	0.023	0.031

Note: Monte Carlo design is based on a standard normal explanatory variable $x_{it} \sim N[0,1]$; $y_{i0} = \max(0, x_{i0}/(1-\gamma) + \alpha_i/(1-\gamma) + u_{i0}/\sqrt{1-\gamma^2})$, $y_{it} = \max(0, \beta x_{it} + \gamma y_{i,t-1} + \alpha_i + u_{it})$ is operated through T = 25 periods before the samples are observed; $\beta = 1$; $\gamma = (0.5, -0.5)$; $\sigma_\alpha = (1, \sqrt{3})$; $\sigma_u = 1$; All results are based on $L = 200$ Monte Carlo replications; number of individuals is $N = 200$, if else is not stated; number of nodes in Gaussian-Hermite Quadrature is 30; RMSE is the root mean square error; and MAE is the mean absolute error.

Table 1c. Results of MCE_1: A normal explanatory variable. *Heckman's approximation*

T	N	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
		Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE
3		-0.018	0.097	-0.012	0.048	0.016	0.081	0.012	0.054	-0.052	0.217	-0.070	0.128	0.035	0.093	0.041	0.072
5		-0.015	0.065	-0.014	0.041	0.011	0.059	0.011	0.041	-0.028	0.137	-0.027	0.090	0.026	0.057	0.031	0.053
8		-0.010	0.062	-0.008	0.036	0.012	0.050	0.010	0.030	-0.019	0.105	-0.017	0.070	0.015	0.041	0.029	0.032
15		-0.008	0.032	-0.011	0.023	0.011	0.035	0.010	0.026	-0.005	0.095	-0.008	0.068	0.013	0.030	0.016	0.028
20		-0.005	0.030	-0.006	0.019	0.008	0.029	0.007	0.024	-0.001	0.091	-0.003	0.060	0.012	0.025	0.014	0.019
		$\beta=1$				$\gamma=-0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
3		-0.013	0.115	-0.012	0.055	0.015	0.101	0.013	0.081	-0.055	0.205	-0.062	0.138	0.016	0.081	0.015	0.066
5		-0.004	0.081	-0.005	0.045	0.014	0.092	0.015	0.062	-0.027	0.142	-0.027	0.091	0.012	0.070	0.011	0.047
8		0.008	0.064	0.009	0.042	0.012	0.068	0.008	0.055	-0.015	0.099	-0.021	0.080	0.010	0.051	0.012	0.031
15		0.003	0.041	0.011	0.036	0.008	0.054	0.006	0.030	-0.012	0.097	-0.008	0.075	0.011	0.033	0.010	0.022
20		-0.006	0.033	-0.008	0.022	0.009	0.036	0.008	0.026	-0.005	0.089	-0.004	0.064	0.006	0.027	0.008	0.019
		$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=\sqrt{3}$				$\sigma_u=1$			
3		-0.028	0.106	-0.025	0.082	0.031	0.091	0.030	0.088	-0.082	0.291	-0.097	0.242	0.049	0.104	0.051	0.081
5		-0.017	0.078	-0.023	0.057	0.016	0.066	0.017	0.071	-0.038	0.156	-0.041	0.145	0.031	0.078	0.042	0.055
8		0.022	0.062	0.015	0.045	0.018	0.061	0.013	0.049	-0.012	0.112	-0.020	0.085	0.023	0.061	0.030	0.038
15		-0.015	0.034	-0.012	0.024	0.017	0.046	0.015	0.038	-0.012	0.107	-0.014	0.082	0.012	0.039	0.026	0.025
20		0.010	0.031	0.009	0.021	0.012	0.037	0.010	0.027	-0.011	0.098	-0.007	0.071	0.007	0.027	0.012	0.019
T	*N*	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
5	300	-0.013	0.052	-0.014	0.031	0.008	0.042	0.008	0.026	-0.018	0.124	-0.029	0.081	0.024	0.052	0.030	0.043
5	500	-0.013	0.046	-0.013	0.027	-0.005	0.039	0.004	0.023	-0.015	0.112	-0.017	0.078	0.024	0.050	0.029	0.041
5	750	-0.012	0.045	-0.014	0.029	0.004	0.031	0.007	0.025	-0.016	0.101	-0.016	0.075	0.022	0.048	0.030	0.045
5	1000	-0.011	0.038	-0.012	0.022	0.004	0.026	-0.003	0.018	-0.014	0.102	-0.016	0.074	0.020	0.046	0.031	0.047

Note: Monte Carlo design is based on a standard normal explanatory variable $x_{it} \sim N[0,1]$; $y_{i0} = \max(0, x_{i0}/(1-\gamma) + \alpha_i/(1-\gamma) + u_{i0}/\sqrt{1-\gamma^2})$, $y_{it} = \max(0, \beta x_{it} + \gamma y_{i,t-1} + \alpha_i + u_{it})$ is operated through T = 25 periods before the samples are observed; $\beta = 1$; $\gamma = (0.5, -0.5)$; $\sigma_\alpha = (1, \sqrt{3})$; $\sigma_u = 1$; All results are based on $L = 200$ Monte Carlo replications; number of individuals is $N = 200$, if else is not stated; number of nodes in Gaussian-Hermite Quadrature is 30; RMSE is the root mean square error; and MAE is the mean absolute error.

Table 1d. Results of MCE_1: A normal explanatory variable. *Simple method of Wooldridge*

T	N	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
		Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE
3		0.045	0.104	0.051	0.082	0.098	0.188	0.111	0.139	-0.145	0.262	-0.152	0.185	0.039	0.103	0.038	0.071
5		0.014	0.086	0.017	0.071	0.022	0.074	0.023	0.051	-0.062	0.198	-0.051	0.117	0.011	0.065	0.012	0.044
8		0.011	0.052	0.012	0.052	0.001	0.030	0.002	0.023	-0.010	0.103	-0.010	0.082	0.004	0.041	0.009	0.027
15		-0.008	0.036	-0.005	0.023	-0.006	0.027	-0.006	0.021	-0.003	0.098	-0.005	0.074	-0.005	0.026	0.000	0.019
20		-0.006	0.030	-0.004	0.021	-0.002	0.021	-0.003	0.019	0.001	0.094	0.002	0.063	0.002	0.023	0.003	0.018
		$\beta=1$				$\gamma=-0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
3		0.031	0.123	0.043	0.118	0.096	0.166	0.099	0.136	-0.156	0.245	-0.153	0.179	0.024	0.145	0.028	0.083
5		0.013	0.085	0.021	0.073	0.025	0.079	0.029	0.057	-0.055	0.183	-0.061	0.121	0.008	0.075	0.011	0.051
8		0.010	0.067	0.009	0.056	0.010	0.036	0.014	0.029	-0.017	0.112	-0.029	0.094	0.004	0.046	0.013	0.033
15		0.011	0.042	0.008	0.032	-0.004	0.032	-0.003	0.025	-0.011	0.095	-0.017	0.082	0.003	0.032	0.008	0.021
20		0.005	0.029	-0.002	0.024	-0.007	0.026	-0.005	0.021	-0.005	0.093	-0.011	0.066	0.002	0.022	0.007	0.017
		$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=\sqrt{3}$				$\sigma_u=1$			
3		0.041	0.156	0.055	0.147	0.116	0.191	0.133	0.153	-0.336	0.326	-0.314	0.319	0.021	0.150	0.033	0.092
5		0.015	0.087	0.020	0.089	0.026	0.082	-0.021	0.077	-0.138	0.245	-0.144	0.178	0.010	0.081	0.017	0.061
8		0.010	0.058	0.017	0.065	0.021	0.036	-0.024	0.057	-0.067	0.158	-0.055	0.125	-0.010	0.053	-0.011	0.037
15		-0.009	0.046	-0.011	0.040	-0.002	0.035	-0.012	0.033	-0.031	0.121	-0.028	0.084	-0.007	0.036	-0.011	0.029
20		-0.008	0.025	-0.010	0.022	-0.004	0.024	-0.012	0.024	-0.011	0.101	-0.010	0.067	-0.004	0.023	-0.009	0.023
T	N	$\beta=1$				$\gamma=0.5$				$\sigma_\alpha=1$				$\sigma_u=1$			
5	300	0.017	0.068	0.012	0.056	0.021	0.067	0.020	0.046	-0.051	0.175	-0.053	0.089	0.010	0.047	0.010	0.033
5	500	0.015	0.054	0.011	0.042	0.020	0.052	0.019	0.042	-0.049	0.167	-0.051	0.086	0.010	0.048	0.011	0.031
5	750	0.015	0.048	0.013	0.038	0.018	0.040	0.018	0.040	-0.050	0.152	-0.048	0.075	0.011	0.036	0.011	0.030
5	1000	0.013	0.047	0.013	0.027	0.019	0.039	0.020	0.041	-0.042	0.135	-0.044	0.072	0.009	0.029	0.008	0.027

Note: Monte Carlo design is based on a standard normal explanatory variable $x_{it} \sim N[0,1]$; $y_{i0} = \max(0, x_{i0}/(1-\gamma) + \alpha_i/(1-\gamma) + u_{i0}/\sqrt{1-\gamma^2})$, $y_{it} = \max(0, \beta x_{it} + \gamma y_{i,t-1} + \alpha_i + u_{it})$ is operated through T = 25 periods before the samples are observed; $\beta=1$; $\gamma=(0.5,-0.5)$; $\sigma_\alpha=(1,\sqrt{3})$; $\sigma_u=1$; All results are based on $L=200$ Monte Carlo replications; number of individuals is $N=200$, if else is not stated; number of nodes in Gaussian-Hermite Quadrature is 30; RMSE is the root mean square error; and MAE is the mean absolute error.

Table 2. Results of MCE_2: A non-normal explanatory variable (*chi-squared distribution with one degrees of freedom*).

	$\beta = 1$				$\gamma = 0.5$				$\sigma_\alpha = 1$				$\sigma_u = 1$			
T	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE	Mean Bias	RMSE	Median Bias	MAE
Known initial values																
3	0.005	0.096	0.013	0.054	-0.003	0.086	-0.005	0.043	-0.010	0.120	-0.005	0.071	0.004	0.121	0.005	0.072
5	0.006	0.057	0.006	0.035	-0.001	0.046	0.001	0.030	-0.004	0.073	-0.007	0.055	0.002	0.074	-0.006	0.041
8	0.007	0.042	0.004	0.024	0.004	0.025	0.004	0.018	-0.003	0.072	-0.006	0.050	0.003	0.045	-0.001	0.029
15	0.005	0.034	0.003	0.024	0.001	0.018	0.001	0.014	-0.009	0.063	-0.003	0.036	0.002	0.029	0.003	0.017
20	0.001	0.021	0.001	0.023	0.000	0.015	-0.001	0.010	-0.007	0.060	-0.006	0.035	0.001	0.020	0.002	0.016
Naïve exogenous initial values method (when it is wrong)																
3	-0.016	0.088	-0.017	0.056	0.219	0.218	0.211	0.211	-0.542	0.612	-0.412	0.412	0.042	0.116	0.042	0.076
5	0.013	0.066	0.015	0.039	0.102	0.107	0.119	0.119	-0.158	0.178	-0.156	0.156	0.015	0.064	0.015	0.043
8	0.007	0.045	0.009	0.031	0.046	0.043	0.044	0.045	-0.066	0.093	-0.060	0.065	0.011	0.047	0.004	0.028
15	0.006	0.032	0.008	0.015	0.011	0.018	0.008	0.014	-0.023	0.062	-0.018	0.041	0.009	0.029	0.003	0.020
20	0.004	0.024	0.006	0.014	0.005	0.016	0.007	0.010	-0.011	0.055	-0.010	0.038	0.007	0.025	0.005	0.017
Heckman's approximation																
3	-0.011	0.095	-0.010	0.065	-0.001	0.081	0.002	0.048	-0.058	0.217	-0.070	0.128	0.022	0.096	0.020	0.074
5	0.010	0.065	0.008	0.042	0.005	0.053	0.003	0.030	-0.028	0.137	-0.027	0.090	0.018	0.045	0.015	0.056
8	0.008	0.042	0.005	0.026	0.001	0.034	0.001	0.021	-0.019	0.105	-0.017	0.072	0.011	0.044	0.014	0.035
15	-0.005	0.030	-0.004	0.022	0.000	0.028	-0.003	0.018	-0.005	0.071	-0.008	0.058	0.008	0.036	0.010	0.022
20	-0.002	0.022	-0.002	0.015	0.000	0.014	0.001	0.012	-0.001	0.062	-0.003	0.040	0.004	0.028	0.008	0.020
Simple method of Wooldridge																
3	0.011	0.186	0.014	0.067	0.098	0.147	0.110	0.139	-0.175	0.252	-0.172	0.163	0.020	0.108	0.038	0.075
5	0.010	0.085	0.015	0.048	0.029	0.074	0.030	0.051	-0.061	0.198	-0.057	0.107	0.010	0.065	0.012	0.046
8	0.009	0.045	0.010	0.029	0.001	0.030	0.002	0.021	-0.010	0.103	-0.010	0.062	0.008	0.037	0.010	0.025
15	0.008	0.028	0.007	0.017	-0.006	0.025	-0.006	0.016	-0.003	0.069	-0.005	0.043	0.003	0.026	0.006	0.026
20	-0.004	0.023	-0.005	0.015	-0.002	0.015	-0.003	0.012	-0.001	0.053	0.002	0.039	0.002	0.025	0.007	0.023

Note: Monte Carlo design is based on a standardized one degrees of freedom chi-squared explanatory variable $x_{it} \sim \chi^2_{(1)} - 1\big/2$; for the case initial values are known $y_{i0} = 0$; for other cases the process $y_{i0} = \max(0, x_{i0}/(1-\gamma) + \alpha_i/(1-\gamma) + u_{i0}/\sqrt{1-\gamma^2})$, $y_{it} = \max(0, \beta x_{it} + \gamma y_{i,t-1} + \alpha_i + u_{it})$ is operated through T = 25 periods before the samples are observed; $(\beta, \gamma, \sigma_\alpha, \sigma_u) = (1, 0.5, 1, 1)$. All results are based on $L = 200$ Monte Carlo replications; number of individuals is $N = 200$; number of nodes in Gaussian-Hermite Quadrature is 30; RMSE is the root mean square error; and MAE is the mean absolute error.

Table 3. Results of MCE_3: An autocorrelated explanatory variable

T	$\beta=1$ Mean Bias	RMSE	Median Bias	MAE	$\gamma=0.5$ Mean Bias	RMSE	Median Bias	MAE	$\sigma_\alpha=1$ Mean Bias	RMSE	Median Bias	MAE	$\sigma_u=1$ Mean Bias	RMSE	Median Bias	MAE
Known initial values																
3	0.009	0.050	-0.002	0.046	-0.015	0.140	-0.017	0.096	-0.024	0.200	-0.018	0.114	0.012	0.149	0.019	0.097
5	0.004	0.048	0.006	0.040	-0.003	0.065	0.002	0.047	-0.015	0.125	-0.014	0.072	0.008	0.075	0.010	0.070
8	0.004	0.047	0.004	0.034	-0.005	0.041	0.001	0.030	-0.009	0.095	-0.008	0.063	0.005	0.053	0.008	0.041
15	0.006	0.035	0.003	0.029	-0.000	0.023	0.001	0.015	-0.015	0.089	-0.015	0.061	0.003	0.034	0.006	0.031
20	0.005	0.020	0.003	0.014	-0.001	0.021	0.000	0.014	-0.010	0.088	-0.016	0.060	0.004	0.029	0.002	0.018
Naïve exogenous initial values method (when it is wrong)																
3	-0.046	0.056	-0.034	0.041	0.207	0.214	0.208	0.208	-0.487	0.587	-0.482	0.482	0.053	0.228	0.047	0.199
5	-0.017	0.038	-0.016	0.026	0.088	0.104	0.093	0.093	-0.154	0.207	-0.167	0.172	0.033	0.129	0.027	0.082
8	-0.003	0.033	-0.003	0.012	0.032	0.049	0.034	0.037	-0.068	0.119	-0.062	0.079	0.012	0.075	0.016	0.041
15	0.003	0.015	0.004	0.012	0.005	0.028	0.004	0.022	-0.022	0.093	-0.024	0.066	0.004	0.036	0.005	0.029
20	0.002	0.011	0.006	0.010	0.002	0.021	0.002	0.014	-0.010	0.092	-0.012	0.058	0.006	0.034	0.007	0.020
Heckman's approximation																
3	0.004	0.043	0.005	0.024	0.001	0.088	-0.002	0.063	-0.043	0.219	-0.052	0.150	0.014	0.113	0.011	0.077
5	0.007	0.024	0.008	0.018	0.004	0.049	0.003	0.033	-0.030	0.136	-0.023	0.081	0.011	0.067	0.005	0.051
8	0.004	0.021	0.003	0.016	0.005	0.038	0.002	0.024	-0.015	0.111	-0.014	0.072	0.005	0.046	0.009	0.042
15	0.003	0.020	0.002	0.013	0.001	0.025	0.002	0.019	-0.011	0.095	-0.012	0.066	0.004	0.035	0.007	0.029
20	0.002	0.014	0.002	0.012	0.001	0.021	0.000	0.015	-0.009	0.089	-0.010	0.061	0.007	0.033	0.009	0.026
Simple method of Wooldridge																
3	-0.022	0.053	0.011	0.054	0.064	0.181	0.056	0.108	-0.083	0.290	-0.091	0.191	0.011	0.145	0.017	0.117
5	0.011	0.044	0.010	0.042	0.026	0.076	0.024	0.046	-0.027	0.148	-0.028	0.093	0.013	0.088	0.014	0.062
8	0.009	0.041	0.010	0.021	-0.001	0.042	-0.003	0.028	-0.017	0.109	-0.011	0.074	0.008	0.062	0.009	0.054
15	0.004	0.022	0.007	0.017	0.003	0.029	-0.011	0.019	-0.016	0.088	-0.010	0.062	0.007	0.054	-0.001	0.027
20	0.005	0.020	0.006	0.014	0.000	0.022	-0.001	0.016	-0.011	0.087	-0.009	0.059	-0.003	0.042	0.006	0.022

Note: Monte Carlo design is based on an autocorrelated explanatory variable $x_{it}=\rho\, x_{i,t-1}+\psi_{it}$, $\psi_{it}\sim N[0,1]$, $\rho=0.5$ and $x_{i0}=\psi_{i1}$; for the case initial values are known $y_{i0}=0$; for other cases the process $y_{i0}=\max(0, x_{i0}/(1-\gamma)+\alpha_i/(1-\gamma)+u_{i0}/\sqrt{1-\gamma^2})$, $y_{it}=\max(0,\beta x_{it}+\gamma y_{i,t-1}+\alpha_i+u_{it})$ is operated through T = 25 periods before the samples are observed; $(\beta,\gamma,\sigma_\alpha,\sigma_u)=(1,0.5,1,1)$. All results are based on $L=200$ Monte Carlo replications; number of individuals is $N=200$; number of nodes in Gaussian-Hermite Quadrature is 30; RMSE is the root mean square error; and MAE is the mean absolute error.

Figure 1. Q-Q plots based on the quantiles of normal distribution by solution methods for true state-dependence and the variance of unobserved individual-effects. $L = 200$ estimated Monte Carlo parameters based on $T = 10$ and the design; $x_{it} = \rho x_{it-1} + \psi_{it}$, $\psi_{it} \sim N\,[0, 1]$, $\rho = 0.5$ and $x_{i0} = \psi_{i1}$; $y_{i0} = \max(0, \beta x_{i0}/(1-\gamma) + \alpha_i/(1-\gamma) + u_{i0}/\sqrt{1-\gamma^2})$; $y_{it} = \max(0, \beta x_{it} + \gamma y_{i,t-1} + \alpha_i + u_{it})$; $(\beta, \gamma, \sigma_\alpha, \sigma_u) = (1, 0.5, 1, 1)$; and number of individuals is $N = 200$.

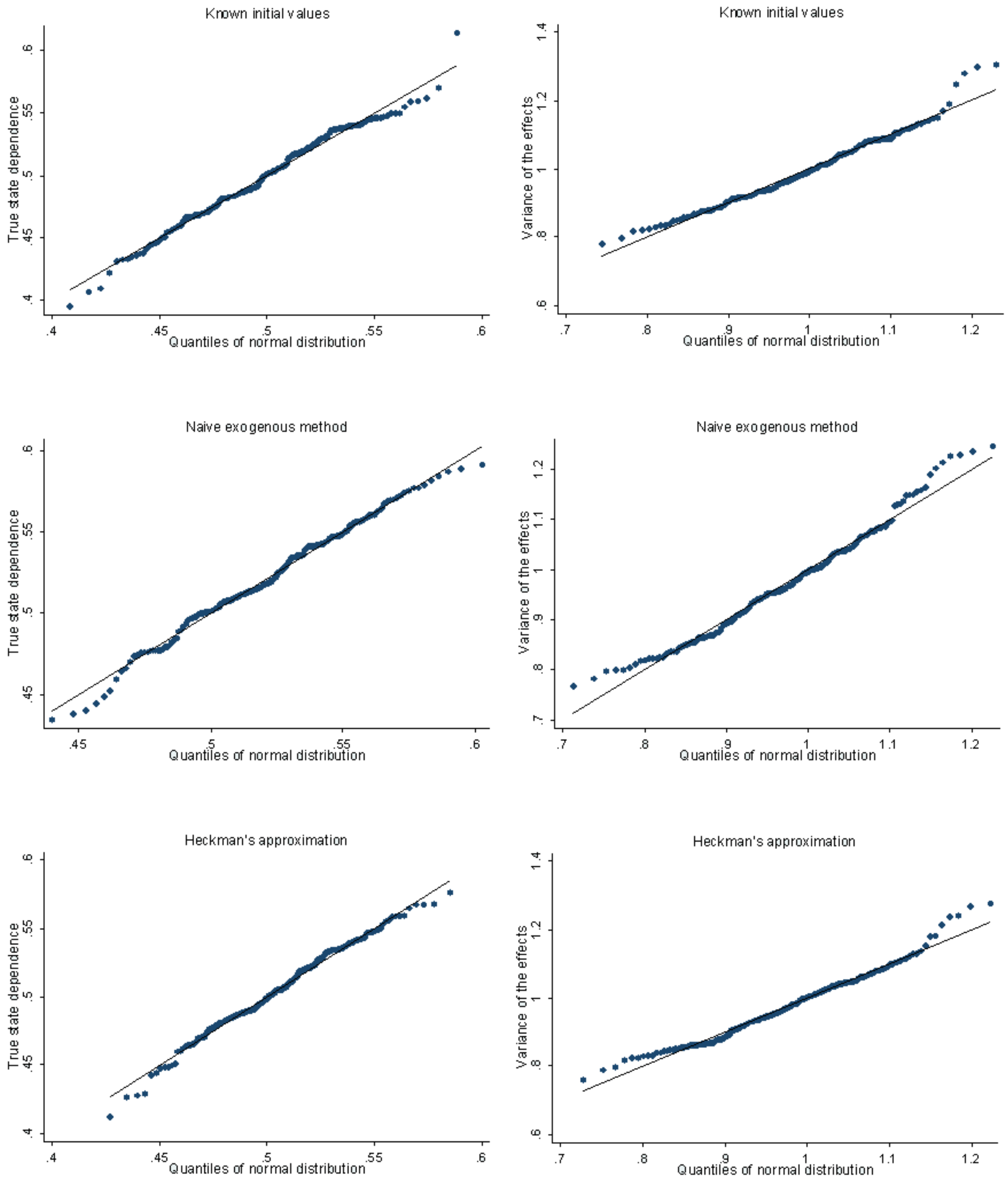
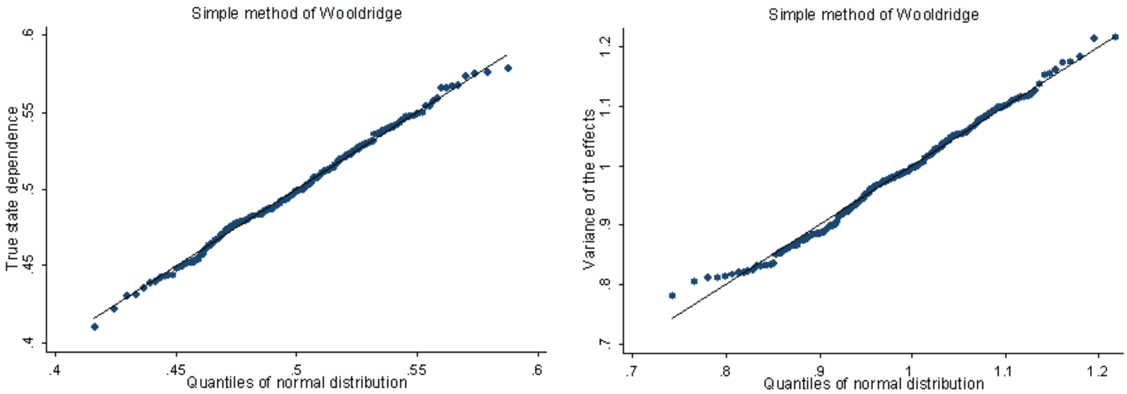


Figure 1. *Continued*



Dynamics of Employment- and Earnings-Assimilation of First-Generation Immigrant Men in Sweden,1990-2000*

Alpaslan Akay†

Department of Economics, Göteborg University

December 15, 2007

Abstract

The employment- and earnings-assimilation of first-generation immigrant men in Sweden was estimated using a dynamic random-effects sample-selection model with eleven waves of unbalanced panel-data during 1990-2000. Endogenous initial values were controlled for using the simple Wooldridge method. Local market unemployment-rates were used as a proxy in order to control for the effect of changing macroeconomic conditions. Significant structural (true) state-dependence was found both on the employment-probabilities and on the earnings of both immigrants and native Swedes. The size of structural state-dependence differed between immigrants and Swedes. Failure to control for the structural state-dependence could have caused bias not only in the assimilation measures but also in the cohort-effects. For example, standard (classic) assimilation model seriously overestimates short-run marginal assimilation-rates and underestimates long-run marginal assimilation-rates. The model controlling for structural state-dependence shows that the earnings of all immigrants in Sweden (except Iraqies) eventually converge to those of native Swedes, but only Nordics and Westerners are able to reach the employment-probability of native Swedes.

Keywords: *Dynamic random-effects sample-selection model, employment and earnings assimilation, initial values problem, wage-curve method.*

J.E.L Classification: C33, J15, J61.

*I would like to thank Lennart Flood, Konstantin Tatsiramos, Måns Söderbom, Roger Whalberg, Peter Martinsson, Elias Tsakas and the seminar participants in Göteborg University.

†Department of Economics, Göteborg University, Box 600 SE 405 30 Göteborg, Sweden. Tel: +46-(31) 773 5304 Email: Alpaslan.Akay@Economics.gu.se

1 Introduction

In recent decades many studies have assessed the economic assimilation of immigrants, e.g., for North America: Chiswick, 1978; Borjas, 1985 and 1995; LaLonde and Topel, 1991 and 1992; Baker and Benjamin, 1994; and Duleep and Regets, 1999; for Europe: Aguilar and Gustafson, 1991 and 1994; Ekberg, 1999; Scott, 1999; Edin et al., 2000; Bauer and Zimmermann, 1997; Longva and Raaum, 2002 and 2003; Aslund and Rooth, 2003; Barth et al., 2002a, 2002b, and 2004; and Gustafson and Zheng, 2006. The focus of these studies has been to determine to what extent immigrants attain employment- and earnings-parity with native-born residents as years since immigration increase. The crucial issue is finding an unbiased way to measure how long employment- and earnings-assimilation takes, as an input to immigration policy debates.

Immigrants arrive in a new country with a particular skill-endowment and confront there a new set of skill-requirements. The rate at which their skills converge to those required in their new home determines their rate of earnings-assimilation. Among Western countries Sweden has particularly many immigrants and their assimilation is one of the main policy-issues for the government. Recent studies show that there has been a decline in the amount of human capital (education, training, skills, and relevant working experience) of newly-arrived immigrants.[1] The poor outcomes of recent immigrants has increased the interest whether immigrants can assimilate into Swedish labour market.

The first objective here is to empirically analyze the dynamics of the economic assimilation of immigrants in Sweden. The labour-force participation decisions and the development of earnings were analyzed simultaneously using a high-quality register-based longitudinal individual data-set (LINDA) during 1990-2000. The second objective here is to compare the classical (static) assimilation model, which has been widely applied in previous studies, with the dynamic model used here.

Employment- and earnings-outcomes can be understood as the result of the investment program in human capital by individual workers (Ashenfelter, 1978). But employers and other conditions of the labour-market can distort the program and the outcomes. For example, employers might use past unemployment as a signal of low productivity, while of course unemployment can also lead to skill-losses. These factors can create *persistence* of the employment-status and earnings of both immigrants and natives. Ignoring these dynamic aspects of human-capital accumulation can lead to biased estimates of immigrants' economic assimilation.

[1] See Hammarstedt (2001) and Gustafson and Zheng (2006), for comprehensive reviews of assimilation in Sweden.

Earlier studies on the economic assimilation of immigrants have either been based on a single cross-section of immigrants and natives, or (better) based on a succession of cross-sections, using the *synthetic-panel* (*or quasi-panel*) *approach* (Borjas, 1985, 1987 and 1995; Longva and Raaum, 2001; Barth et al., 2004). The synthetic panel approach has been standard for assimilation-studies, but even it cannot overcome the problems dealt with in this paper; it cannot accommodate unobserved individual-specific characteristics, sample-selection bias, nor genuine dynamic behavior. Analyzing the dynamics behind the employment and earnings of immigrants together with selection-bias and unobserved individual characteristics requires a genuine *panel data method* including *lagged* employment-status and earnings, as was done here. One can then distinguish *structural* (*or true*) *state-dependence* -which is the persistence of an individual's experience based only on their past experience-, from *spurious state-dependence*, based on time-invariant unobserved individual-specific characteristics.

Another often neglected source of possible bias is the equality-restriction on period-effects (assumed representative of overall macroeconomic conditions), which has also been widely assumed in previous studies. However, if the employability and earnings of immigrants respond differently from natives' to a trend or temporary shock in economy-wide conditions then a assimilation model which uses equal-period-effects restriction can produce biased estimates of years-since-migration and cohort-effects. In studying immigrants' and natives' earnings in Norway, Barth et al., (2004) used local unemployment rates to at least partially eliminate this bias.

To address these potential biases, a dynamic random-effects sample-selection model was used in which both observed and unobserved individual-characteristics were controlled in order to analyze the dynamics of the employment and earnings of the immigrants simultaneously. The equal-period-effects restriction was imposed, but a *wage-curve model* was used based on local unemployment-rates, as was suggested by Barth et al., (2004).

In the analysis, immigrants were categorized by seven regions and seven specific countries of origin, since they were not homogenous. The results suggest that immigrants and natives experienced different levels of both structural and spurious state-dependence and also responded differently to varying macroeconomic conditions, different even across immigrant groups. The classic (static) assimilation model predicts higher marginal assimilation-rates during immigrants' first years after arrival, but in fact the rates quickly turned to negative, as both the employment probabilities and earnings of immigrants diverged widely (with some exceptions) from those of native Swedes. Thus, the classic (static) assimilation model seems to *overstate* short-run employment probabilities and earnings, and *understate* the long-run. The model used here predicts much less earnings-disadvantage upon arrival, low short-run assimilation-rates and higher long-run assimilation-rates.

The classic (static) assimilation model predicted that immigrants from Middle East, Asia and Africa were not able to reach earnings-parity with comparable native Swedes. However, with the dynamic model, it was found that all regions and countries of origin (except Iraq) were able to reach the parity, although it usually took longer than one individual's working life. A similar result was found by classic (static) and dynamic models in employment probabilities. Immigrants from no region or country of origin were able to reach the employment probabilities of native Swedes, except for those from Nordic Countries and the rest of Western Europe.

The next section discusses the hypotheses. Section 3 then presents the dynamic random-effects sample-selection model and discusses issues which can create bias in the measures of assimilation. Section 4 then presents data, and Section 5 the empirical results. Section 6 summarizes and draws conclusions.

2 Hypotheses

Economic assimilation studies focus on whether there is a difference in the economic performance of otherwise identical individuals who differ solely in terms of being an immigrant or a native; and if there is, how this difference changes for an immigrant with time spent in the host-country.

The difference in performance of immigrants and natives has been considered as a function of, first, the differences between the human-capital endowments of the immigrants and those of otherwise identical natives, and, second, the transferability of country-of-origin human-capital to the one required in host country. In other words, immigrants arrive with some human capital but they lack host-country-specific human capital; and they acquire the necessary knowledge to be as productive employees as natives are. Their productivity not only increases but they also become able to better communicate it to potential employers. Therefore, as years since migration increase, immigrants' employment-probabilities and earnings levels tend to catch up with those of otherwise identical natives (Chizwick, 1978; Borjas, 1987 and 1985; Price, 2001). This is the classic assimilation hypothesis that we mainly test here.

However, the development of host-country-specific human capital and the resulting economic performance of immigrants may be much more complicated, involving both structural and spurious state-dependence. Structural state-dependence is the persistence of an individual's experience (state) only because of their past experience. Spurious state-dependence, on the other hand, is caused by time-persistent unobserved individual characteristics, which, in this case, can influence the economic performance of individuals.

There can be many sources of structural state-dependence in the employment-probabilities and earnings of immigrants, so that persistence can start upon arrival or in any later period. Initial market-conditions and the resulting performance of the immigrants in the arrival period can be important in determining their future performance. For instance, high unemployment upon arrival can *scar* the economical performance of the immigrants in the future. If they are unable to get work initially or in a later period, they may not be able to develop host-country-specific human capital, and may continue to be offered only low paid jobs (if that) afterwards. Unemployment can also change preferences and search-costs, prices and cause skill-depreciation, all of which can reduce later employability and earnings (Heckman and Borjas, 1980). Employers often use past employment-status as a *screening device,* and consider past unemployment as a *signal* (or proxy) of unobservable low productivity (employers can believe that an individual who has been unemployed is not as productive as an identical individual who has not experienced the state of being unemployed, Hansen and Lofstrom, 2001). Thus, productivity, bargaining power and reservation-wage of those who persistently experience unemployment, would all be reduced.

To control for the effect of arrival-year macroeconomic conditions, Chiswick et al., (1997) suggested including arrival-year unemployment-rates in the analysis. The same strategy is adopted here as well. However, if the scarring effect is a result of an unemployment experience in a later period (even if the arrival-year macroeconomic conditions were good) then controlling only for arrival-year macroeconomic conditions would not be enough to identify the scarring effect that is a result of later unemployment experience. Thus, in order to capture overall scarring effects, the structural and spurious state-dependence must be controlled for in any assimilation model.

Immigrants in particular are vulnerable to possible labour-market *discrimination.* Employers may interpret signals differently from immigrants leading to differences in the scarring effect. In this case, the size of structural state-dependence in the employment and earnings may differ for immigrants and natives. Failure to control for structural state-dependence can thus lead to bias in measuring both short- and long-run assimilation-rates.

If there is statistically significant structural state-dependence in the employment and earnings of immigrants relative to natives, the wage-curve specification with local unemployment rates in the classic (static) assimilation-model may not be able to identify the true period-effects. As explained by Barth et al. (2004), the wage-curve effect (i.e., local-market unemployment elasticity) can be considered as a function of years since migration and, implicitly, the bargaining power, reservation wage, and marginal-productivity levels of immigrants and natives. Over time, economic integration of immigrants increase, the difference between the immigrants' and a comparable native's sensitivity to changing macroeconomic conditions will decrease. However, if there is structural state-dependence due to past unemployment, the sensitivity differences between immigrants and natives to changing macroeconomic conditions can also persist since structural state-dependence is also a function of bargaining power, reservation wage and others. Classic (static) assimilation model can overstates the size of local unemployment elasticities. It can lead biased assimilation measures depending on the difference between the sizes of structural state-dependence of immigrants and natives.

Immigrants can also differ in both time-invariant and time-variant unobserved individual characteristics (representing time-invariant and time-variant *preferences*) that influence their probability of employment and their earnings. If these unmeasured (because unobserved) variables are correlated over time and are not properly controlled for, then previous unemployment (or earnings) might appear to be a determinant of later unemployment (or earnings) solely because it was a proxy for those temporally correlated unobservables (Heckman and Borjas, 1980). Time-invariant unobserved characteristics could thus create a *spurious* state-dependence. Identification of the true (structural) state-dependence thus requires proper treatment of unobserved individual characteristics. Failure to control for structural state-dependence, on the other hand, could lead to overestimation of immigrants' and natives' individual-heterogeneity.

3 Econometric Specifications

3.1 Specification of the Dynamic Assimilation Model

The empirical approach used here aims to capture the dynamics of labour force participation decisions (employment) and resulting earnings simultaneously by identifying the structural state dependence for both. To do this, observed and unobserved individual characteristics must be controlled for. A full dynamic panel data random-effects sample-selection model was thus used (following Amemia, 1984, called a Tobit type 2 model), participation and resulting earnings were simultaneously determined (which is why the model called *full*).[2]

Sample-selection bias can arise either from self-selection by the individuals under investigation or from sample-selection decisions made by the analyst. Such bias can be a major problem with both cross-sectional as well as panel data (Matyas and Sevestre, 1995; Kyriazidou, 1997). It has been common in many economic analyses of panel-data to study only a balanced sub-panel without correcting for selection bias. The static version

2 There are many possible variants of this model. For example, just the "participation", the selection-equation, could contain lagged decision, or it could contain the earnings in a *partial* framework. The model here includes both and is thus called a *full*y dynamic sample-selection model.

of the model used in this paper (without lagged employment-status and earnings), has been widely analyzed by Zabel (1992), Verbeek and Nijman (1992), Matyas and Sevestre (1995), Kyriazidou (1997), Vella (1998), Rochina-Barrachina, (1999), Vella and Verbeek (1999), and a similar dynamic model was analyzed by Kyriazidou (2001).

The income-generating process of immigrants (I) with the dynamic model based on first order state-dependence (one lag of dependent variables) is given by

$$d_{it}^{I}=1\left\{\begin{array}{c}\mathbf{Z}_{it}^{I}\beta^{I}+\lambda^{I}d_{i,t-1}^{I}+\phi^{I}AGE_{it}^{I}+\delta YSM_{it}\\ +\sum_{j}\psi_{j}C^{j}+\sum_{k}\theta_{k}^{I}\Pi^{k}+\xi_{emp}^{I}\log UR_{it}^{mI}+\eta_{i}^{I}+\epsilon_{it}^{I}>0\end{array}\right\} \tag{1}$$

$$y_{it}^{I}=\left\{\begin{array}{ll}\mathbf{X}_{it}^{I}\beta^{I}+\gamma^{I}y_{i,t-1}^{I}+\phi^{I}AGE_{it}^{I}+\delta YSM_{it} & \\ +\sum_{j}\psi_{j}C^{j}+\sum_{k}\theta_{k}^{I}\Pi^{k}+\xi_{inc}^{I}\log UR_{it}^{mI}+\alpha_{i}^{I}+u_{it}^{I} & d_{it}^{I}=1\\ 0 & d_{it}^{I}=0\end{array}\right\} \tag{2}$$

where d_{it} is a binary variable indicating whether an individual is employed during the current period; η_i and α_i are the additive unobserved individual-effects (such as work ability, motivation, etc.); The vectors $(\eta_i, \alpha_i)'$ are assumed independent from the error vectors $(\epsilon_{it}, u_{it})'$. $\mathbf{Z}_{it}$ and $\mathbf{X}_{it}$ are vectors of current socio-demographic characteristics (such as educational attainment, marital status, and non-labour income); AGE denotes age; YSM is years since migration;[3] C^j denotes arrival-cohort j; Π^k denotes period-effects k; and UR_{it}^m is the local unemployment-rate in municipality m (where individual i lives in year t). In order to obtain the local unemployment elasticities on employment-probabilities (ξ_{emp}) and earnings (ξ_{inc}), this variable expressed in logarithms.

Equation (1) expresses that the current employment-status of individual i during period t is a function of previous employment-status $d_{i,t-1}$. This determines whether an individual is included in the sample on which the earnings equation (2) is based. The parameter λ captures the effect of past selection outcome $d_{i,t-1}$, i.e., structural state-dependence on employment-probabilities. In the earnings- equation (2), the logarithms of the earnings y_{it} are considered as a function of the logarithms of previous earnings ($y_{i,t-1}$) and thus γ is the parameter representing the structural state-dependence on earnings.[4] This parameter can thus be interpreted as the earnings elasticity of previous earnings on the current earnings.

[3] The model also includes the squared-age and squared-years since migration; and interactions of local unemployment-rates with both years since migration and squared-years since migration (but not shown for simplicity).

[4] Following Heckman (1981), this paper uses the term *structural* to refer to *true state-dependence* for both discrete and continuous outcomes.

The income-generating process of the native Swedes (N) is given

$$d_{it}^N = 1\left\{\begin{array}{c} \mathbf{Z}_{it}^N\beta^N + \lambda^N d_{i,t-1}^N + \phi^N AGE_{it}^N \\ +\sum_k \theta_k^N \Pi^k + \xi_{emp}^N \log UR_{it}^{mN} + \eta_i^N + \epsilon_{it}^N > 0 \end{array}\right\} \tag{3}$$

$$y_{it}^N = \left\{\begin{array}{cc} \mathbf{X}_{it}^N\beta^N + \gamma^N y_{i,t-1}^N + \phi^N AGE_{it}^N & \\ +\sum_k \theta_k^N \Pi^k + \xi_{inc}^N \log UR_{it}^{mN} + \alpha_i^N + u_{it}^N & d_{it}^N = 1 \\ 0 & d_{it}^N = 0 \end{array}\right\} \tag{4}$$

where, the variables which are not making sense such as years since migration (YSM) and cohort-effects (C) are excluded.

The model assumes that the error-terms ϵ_{it} and u_{it} are non-autocorrelated and that sample-selectivity would show up over the error-terms with the following relatively simple covariance structure

$$\Omega_{\epsilon u} = \begin{bmatrix} 1 & \rho_{\epsilon u}\sigma_u \\ \rho_{\epsilon u}\sigma_u & \sigma_u^2 \end{bmatrix}$$

where $\rho_{\epsilon u}$ is the correlation between the participation (selection) and earnings-equations; σ_u^2 is the variance of error terms in the earnings equation and the variance of the error term in participation equation has been normalized to unity due to identification.

3.2 Identification

The model above has two identification problems. First, a credible analysis of selection requires a robust instrument (an exclusion-restriction). The second problem arises because the model aims to separate years since migration, arrival-cohort, and period-effects.

Identification of selection-bias depends on the exclusion restriction or identifying instrument: At least one explanatory variable in the selection equation must be excluded from the earnings equation. In other words, some variable(s) must explain employment but not earnings. The number of variables usable for this purpose in empirical applications is very limited; it is not easy to find a defensible and robust identifying instrument. For instance, health status and language proficiency are two logical candidates but we do not have information on them. Other possible (but weak) candidates are number of children; marital status; and some components or compositions of non-labour income, in particular capital non-labour income. There are many possible types of non-labour income, including sickness payments and child care, welfare, capital income and others. The main one that can be linked with the human-capital investment and participation, and earnings is capital income. The restriction adopted here is that *temporary capital income* is assumed to only affect participation, whereas the *permanent* capital income can affect earnings, through human capital investment.

Capital income *per se* might be thought to only affect participation but not earnings. For instance, individuals with high capital income one specific year could reduce their labour supply for that year. However, capital income might affect earnings, indirectly. Individuals with high but variable capital income might choose to invest in human capital (i.e. education) as a means of buffering this variability. Individuals with permanently high capital income, or who expect to get high capital income in the future, might decide to use (or barrow against) this income to invest in human capital. Thus, depending on the amount and time-pattern, capital income could affect either just participation, or earnings; temporary changes in the amount of capital income could only be expected to affect the decision for hours worked, but only permanent (though not necessarily constant) capital income would affect earnings.

Consider the capital income y_{it}^{nl} of individual i during t, which can be split into two uncorrelated components, $\beta y_{it}^{nl} + \varphi \overline{y}_i^{nl}$, where $\overline{y}_i^{nl} = (1/T_i)\sum_1^{T_i} y_{it}^{nl}$ is the average over time. This can also be written as $\beta(y_{it}^{nl} - \overline{y}_i^{nl}) + (\beta + \varphi)\overline{y}_i^{nl}$. The first part of the expression is the difference from the within individual means, and represents *temporary shocks* on the capital income and the second part is *permanent capital income* or *level effect*. It was assumed that temporary shocks affected only current participation but not the earnings, and it was therefore excluded from the earnings equations and used as identifying restriction. Thus, by including $\overline{y}_i^{nl}$ to both employment and earnings equations the effect of permanent capital income in human capital investment was also controlled.

The available data supports this approach. The correlation between temporary capital income and the level of education was positive but quite low, only 0.0 and 0.1 for the various immigrant groups, while the correlation between permanent capital income and level of education was much higher, 0.05-0.25.

The other identification problem is that the period-effect Π in equations (1) and (2) is a linear combination of the effects of arrival-cohort and years since migration, since the calendar year at any cross-section is the sum of years since migration and the year in which the individual immigration occurred (i.e., the arrival-cohort). It is not possible to analyze the effects of years since migration, arrival-cohort, and period simultaneously. An additional restriction must be imposed, either that the period-effect, the impact of the transitory shocks in the overall macroeconomic conditions, is the same for both immigrants and native Swedes, or that the cohort-effect is the same across different arrival cohorts of immigrants. The changing pattern of immigration over time, generated by political conflicts in source-countries and changes in immigration policy in Sweden, makes constant cohort-effects unrealistic. Since the interest here is mainly to analyze the effect of the years since migration, the only reasonable way to deal with this identification problem is then to impose the restriction that period-effects are the same for immigrants and native Swedes in all periods (i.e., $\theta_k^I = \theta_k^N$).

This assumption would be credible if there was no change in macroeconomic conditions or even if it was changed, the responsiveness of immigrants and natives to these changes should be the same. Changing macroeconomic conditions might influence the price paid for skills of immigrants and natives differently. A change in relative employment-probabilities and earnings could then reflect price difference rather than differences in human capital (Borjas, 1995). Thus, if, in fact, the sensitivities of immigrants and native Swedes were different and if they were not equally affected by changing macroeconomic conditions, this restriction could lead to severe bias in estimates of the effects of arrival-cohort and years-since-migration (Barth et al., 2004).

Sweden (and other Nordic Countries) experienced a sharp economic downturn coinciding with the sample period, 1990-2000. Thus, the model which assumes equal-period effects could be biased. To attempt to control for this bias, at least partially, local market unemployment-rates were used by following the *wage-curve model* suggested in Card (1995) and Barth et al., (2002a, 2002b, and 2004). In order to include the changes in the sensitivities occuring with years spent in Sweden, the model was also augmented by interacting the years-since-migration and with local unemployment rates. The augmented wage-curve model was also restricted by equal-period-effects assumption. However, it was assumed that the period-effects could be identified (at least partially) by controlling for local unemployment rates.

3.3 The initial values problem, unobserved individual-effects and estimators

A fully parametrized random-effects approach was followed with simulated maximum likelihood-estimator. Such an approach requires correct specification of the distribution of initial values, conditioned on observed and unobserved individual-effects. It also requires correct specification of the distribution of those unobserved individual-effects themselves which are possibly correlated with the observed explanatory variables. Thus, these two issues are also related to each other.

Given the goal of disentangling structural (true) state-dependence from spurious state-dependence, the initial values are important (Blundell and Smith, 1991; Honore and Hu, 2004; Arellano and Hahn, 2005; Heckman, 1981; Hsiao, 2003; Wooldridge, 2005; Honore and Tamer, 2006). An *initial values problem* can emerge if the history of the underlying participation or earnings generating process is not fully observed, in which case it cannot be assumed that the initial observed sample-values are *exogenous* variables, given outside the process. Many immigrants (and of course native Swedes) entered the Swedish labour market much before the beginning of the study period in 1990. Thus, assuming exogenous initial values would be too strong, possibly causing biased and inconsistent estimators (Heckman, 1981). The sample initial observations must instead be considered *endogenous*, with a probability distribution conditioned on observed and unobserved individual characteristics.

But what about the distribution of the unobserved individual-effects, which are themselves possibly correlated with the observed individual characteristics (i.e. $E[\eta_i|x_{it}] \neq 0$ and $E[u_i|x_{it}] \neq 0$). For example, *work ability*, an unobserved factor influencing the employment probability and earnings, might be correlated with educational level, while *motivation* can be correlated with immigrant status. In this case, treating unobserved individual characteristics as i.i.d. errors would then also lead to biased and inconsistent estimators.

To avoid these problems a fixed-effects approach could be used instead. However, familiar *within* effects approach based on *differencing* out strategy for the unobserved individual characteristics would not work in this models. Instead one should have to construct a dummy variable for each individual and estimate a parameter for the effect of their unobserved individual characteristic. Considering the thousands of individuals in the data set, this would not be easy. Even if this computational problems were solved (with the *zig-zag* approach of Heckman and MaCurdy (1980) or with *brute-force* maximization of the likelihood function), *incidental-parameters problem* could create high bias and inconsistency (Neyman and Scott, 1948, Lancaster, 2000). The maximum-likelihood estimator inconsistently estimates parameters of individual-specific dummies, and for a small-T (T is duration of panel data) they would be seriously biased. Besides, inconsistency and bias are transmitted to other parameters in the model.

Alternatively, Kyriazidou (2001) suggests a semiparametric fixed-effects approach, in which the unobserved individual-effects are assumed to be fixed, and moment-restrictions are defined in order to construct *kernel-weighted GMM* estimators which are consistent and asymptotically normal. However, there are drawbacks to this approach as well. It would not allow average partial-effects to be calculated, and time-invariant variables would be *swept-away* (Wooldridge, 2005).

Here we prefer to deal with the initial values problem and follow random-effects approach. Therefore it was necessary to specify a conditional probability distribution for the initial values. There are two main methods for doing this: Heckman's reduced-form approximation (1981) and the simple method of Wooldridge (2005).[5]

Heckman suggested approximating the conditional-probability distribution, using avail-

[5] Another possibility is to assume that the conditional distribution of initial values is in steady-state. However, it would still be difficult to find a closed-form expression for the distribution, even for the simplest case where there were no explanatory variables (Heckman, 1981; Hsiao, 2003).

able pre-sample information, via a reduced-form equation defined for the initial sample period. This approximation allows a flexible specification of the relationships among initial sample values, observed and unobserved individual characteristics. The method is still not easy especially with unbalanced panel data (as here) with which initial values problem can be more serious (Honore, 2002).

Wooldridge (2005) introduced a simple alternative to Heckman's reduced-form approximation, in terms of both likelihood-computation and availability of commercial software. Wooldridge suggested that one can consider the unobserved individual characteristics conditional on the initial sample values and the time-varying exogenous variables. Specifying the distribution of the unobserved individual-effects on these variables can lead to very tractable functional forms in dynamic random-effects sample-selection models (as here), as well as in similar probit, censored regression, and Poisson models (Honore, 2002; Wooldridge, 2005).

Consider a fully parametric random-effects model in which the unobserved individual characteristics can be represented as a function of a constant, within means of time-variant explanatory variables and the initial sample value of relevant dependent variable. The initial values were defined for the immigrants, separately for participation- and earnings-equations, with the following auxiliary distribution of the unobserved individual characteristics

$$\eta_i^I = \pi_0 + \pi_1 d_{i1}^I + \pi_2 \overline{\mathbf{Z}}_i^I + \pi_3 AUR + \widetilde{\eta}_i^I \tag{5}$$

and

$$\alpha_i^I = \pi_0 + \pi_1 y_{i1}^I + \pi_2 \overline{\mathbf{X}}_i^I + \pi_3 AUR + \widetilde{\alpha}_i^I \tag{6}$$

where $\overline{\mathbf{Z}}_i$ and $\overline{\mathbf{X}}_i$ are vectors of within individual means of the time-variant explanatory variables (such as age, years since migration, number of children and local unemployment-rates) in participation- and earnings-equations, defined as $\overline{\mathbf{Z}}_i = (1/T_i)\sum_{t=1}^{T_i}\mathbf{Z}_{it}$ and $\overline{\mathbf{X}}_i = (1/T_i)\sum_{t=1}^{T_i}\mathbf{X}_{it}$; $\widetilde{\eta}_i$ and $\widetilde{\alpha}_i$ are new unobserved individual-effects assumed as $iidNormal\left[0, \sigma_{\widetilde{\eta}}^2\right]$ and $iidNormal\left[0, \sigma_{\widetilde{\alpha}}^2\right]$; and AUR is the arrival-year national unemployment-rate, and taken to represent initial labour-market conditions.

The auxiliary distribution for the native Swedes were

$$\eta_i^N = \kappa_0 + \kappa_1 d_{i1}^N + \kappa_2 \overline{\mathbf{Z}}_i^N + \widetilde{\eta}_i^N \tag{7}$$

and

$$\alpha_i^N = \kappa_0 + \kappa_1 y_{i1}^N + \kappa_2 \overline{\mathbf{X}}_i^N + \widetilde{\alpha}_i^N \tag{8}$$

A quasi-fixed effects approach would also be possible in which the fixed unobserved individual characteristics are specified for each individual as linear projection on the within individual means of time-varying explanatory via Mundlak's formulation (1978) or Chamberlain's (1984) *correlated-effects model.* However, the simple Wooldridge method also defines the auxiliary distribution similar to this approach. Thus, there should be no problem assuming that the distribution of the unobserved-individual effects is also fully specified with the simple Wooldridge method.

One of the aim of this paper is to estimate the employment- and earnings-assimilation. Two estimators are needed to measure, the marginal assimilation-rates and total years to assimilation based on the model used here. There are two type of approaches in the literature: Earnings assimilation can be considered to have occurred when immigrant earnings catch-up over time with the earnings of natives (following Borjas, 1985, 1987 and 1995), or it can be considered as a situation where immigrants' acquisition of country specific human capital lead to higher earnings (following Lalonde and Topel, 1992; Edin et al., 2000).

Here, the first was followed. An estimator of the *marginal assimilation rate* (MRA) was defined simply as (see Akay and Tsakas (2007) for details of the estimators)

$$\widehat{MRA_j}(t) = \frac{\partial E^I}{\partial t} - \frac{\partial E^N}{\partial t} \tag{9}$$

where E is the conditional expectation of the model either for the participation or the earnings-equation, t is a proxy for the time spent in the host country after arrival i.e., years-since-migration (YSM). Equivalently, in terms of estimated parameters,

$$\widehat{MRA_j}(t) = (\widehat{\delta}^I(t) + \widehat{\phi}^I(t_0 + t)) - \widehat{\phi}^N(t_0 + t) \tag{10}$$

where t_0 is the entry-age to the labour market.

The ultimate goal is to estimate *total years to assimilation* (TYA), the time needed to fully achieve equal employment-probability and earnings parity with otherwise identical native Swedes. TYA is thus the upper-limit of the integral which accumulates the MRA of each period, the time required in the host country before the age-employment probability or age-earnings curves of immigrants and native Swedes intersect.

4 The data

The study was based on the 1990-2000 panel of the Swedish register-based Longitudinal Individual Data-set (LINDA), which contains two distinct random samples: a population sample, which includes 3.35% of the entire population each year, and an immigrant sample, which includes almost 20% of immigrants to Sweden.[6] The sampling frame consists of everyone who lived in Sweden during a particular year, including those who were born or died, and those who immigrated or emigrated. The data is updated with current household information each year with data from the population and housing censuses and from the official Income Register, as well as a higher-education register. The Income Register data, based on filed tax returns, is contingent on the tax rules for that year (for more details on LINDA, see Edin and Frederiksson, 2001).

To avoid selection-problems due to retirement at age 65, the 33,504 immigrant men in LINDA aged 18-55 in 1990 were initially selected for the study, as well as an equal-sized control group of randomly-selected native Swedish men, matched for age and county (län) of residence.[7] An additional 20% of new immigrants, 2,000-4,000 were added each year, as well as an equal number of randomly-selected but matched native Swedes. By 2000, these unbalanced panels consisted of 65,800 immigrant men (generating 521,761 annual observations) and slightly more native Swedes.

Edin et al. (2000) point out that the measures of immigrant-assimilation can be distorted if a significant fraction of immigrants return back to their home country. This did not seem to be a problem since less than 5% disappeared from the data during the observation period. In any case it would be difficult to model return migration with this data since it is not possible to distinguish emigrants from those who died.[8]

The immigrants were categorized as being from other Nordic countries; other Western Europe (including the USA, Canada, Australia, and New Zealand), Eastern Europe, the Middle East, Asia, Africa, or Latin America.

The earnings-variable used was gross labour-income, measured in thousands of Swedish Krona (SEK) per year, inflated by the consumer price index (to 2000 prices). To eliminate those with short employment periods or part-time jobs with low pay, Antelius and Björklund (2000) were followed in considering as employed only those earning at least 36,400 SEK.[9] The employment-indicator (d_{it}) was defined as 1 if the individual was employed and 0 otherwise.

[6] Immigrants to Sweden enter the national register (and thus the sampling-frame) when they receive a residence permit. In general, immigrants may become Swedish citizen after a sufficient number of years.

[7] The self-employed were excluded from the analysis since their employment- and earnings-conditions are considerably different from wage-earners.

[8] Klinthäll (2003) found that 40% of immigrants arriving from Germany, Greece, Italy and the U.S. left Sweden within five years. His main hypothesis borrowed from the U.S. Emigration Studies, is that the least successful immigrants left. However, as pointed out by Arai (2000), even low-earning immigrants might have strong incentive to stay because of the relatively high living standard even in the lower range of the earnings-distribution compared to other countries. The difference in mean earnings between who disappeared (2,934 individuals) and those in the final sample was minimal.

[9] This criterion, also adopted in LINDA is the “basic amount” that qualifies one for the earnings-related part of the public pension-system.

The key explanatory variables were age and age-squared; years since migration and squared; marital status (cohabiting was considered married); number of children living at home; highest education level; residence in Stockholm or elsewhere; capital non-labour income; arrival-cohort; local unemployment-rate and its interactions with years since migration and squared. Local unemployment rates were calculated by dividing the number of unemployed by the population in the municipality of residence, which was assumed to be exogenous to employment and earnings, though conditional on individuals' observed and unobserved characteristics.[10]

No data on work-experience was available. In most U.S. studies, this is handled by calculating *potential work experience* as age minus years of schooling minus six. But Swedish education-data is given in terms of highest level, not years, so such a calculation would introduce severe measurement-error.

Table 1 shows the mean values for these variables, for both immigrants and native Swedes.

Table 1 *about here*

Both the earnings and employment rates (83% vs. 36-74%) and were considerably higher for native Swedes. On the other hand, more immigrants were married or cohabiting (40% vs. 38-59%). Native Swedes were generally better educated: About 77% had at least upper-secondary education, compared to 61-77% for immigrants. The earlier immigrant arrival-cohorts each had 9-12% of the total, whereas 1985-89 had 18%, and 1990-94 had almost 25%. The Iran-Iraq war and various conflicts in former Yugoslavia occurred during the latter periods. The Nordic area accounted for 25% of all immigrants, followed by the Middle East (23%), Eastern Europe (21%), and Western Europe (14%). Asia, Africa, Latin America each had 5-6%.

The immigrant population was clearly not homogenous: Employment rates and earnings were much higher for those from Nordic or Western countries. Middle-Eastern and African immigrants were far less likely to be employed, and had lower earnings if they were. Immigrants from non-Nordic Western countries probably had more education than all other groups (nearly 32% had a university degree), followed by Eastern Europeans. Despite the fact that Nordic immigrants, most of them from Finland, had less education, they had a higher employment-rate and earned more than all other groups. All this is generally in accord with previous studies on immigrants in Sweden.

[10] Because of the immigrant-placement policies implemented in 1985, immigrants' country of origin and their municipality-of-residence can be correlated (Edin et al., 2002 and 2003; Åslund and Rooth, 2003).

5 Empirical analysis

5.1 Structural state-dependence, unobserved individual-effects, and local and arrival-year unemployment elasticities

The main interest here is the size of any structural state-dependence, in any spurious state-dependence, in the impact of observation period macroeconomic shocks, and in the relationship of these three to employment-probabilities and earnings. The results obtained from the dynamic assimilation model will also be compared with those from classical (static) model. The full estimation-results are not reported here, but in general, they are in line with those of previous studies. Employment-probabilities and earnings increased with age at a decreasing rate. Having high school or even more, a university degree raised employment-probabilities and earnings of all immigrant groups. And temporary capital income -used only in the participation equation- negatively affected the employment-probabilities.[11]

Table 2 presents the estimated marginal effects on employment-probabilities and earnings for both classic (static) and dynamic assimilation model. The classic (static) model is indicated by $S+CRE+WC$, where S denotes static, CRE adds the *correlated random effects* model of Mundlak (1978) and Chamberlain (1984); and WC indicates the wage-curve model. The dynamic model of main interest is indicated by $SD(1)+WC+WIV$, where $SD(1)$ indicates first order state dependence (one period lagged values of dependent variables as explanatory variable); and WIV indicates the simple Wooldridge method of dealing with initial values problem. Note that, since the Wooldridge method includes the within means of time-variant explanatory variables, similar to CRE approach, these two, classic (static) and dynamic assimilation models, can be directly compared.

The results are separately given for the jointly estimated participation-equation (as employment-probabilities) and earnings-equation (as earnings). Table 2 reports the estimated marginal effects of structural state-dependence for the employment-probabilities $\widehat{\lambda}$ and for earnings $\widehat{\gamma}$; the variances of the unobserved individual-effects ($\widehat{\sigma}_{\widetilde{\eta}}$ or $\widehat{\sigma}_{\widetilde{\alpha}}$); local unemployment elasticities for employment-probabilities $\widehat{\xi}_{emp}$ and for earnings $\widehat{\xi}_{inc}$. Arrival-year national unemployment elasticities are shown [in brackets]. The marginal effects of initial sample period employment-status and earnings are shown (in parentheses). The third row for each region or country of origin indicates the correlation between the error terms of the participation and earnings equations ($\widehat{\rho}_{\epsilon u}$).

Table 2 about here

[11] Full estimation-results and marginal effects will be provived by the author upon request.

Structural state-dependence ($\widehat{\lambda}$) in the employment-probabilities was all positive (in the range $0.30 - 0.70$) and highly statistically significant even after controlling for the observed and unobserved individual characteristics (i.e., in the dynamic model). The size of the structural state-dependence for Eastern Europeans (0.70) and Latin Americans (0.64) was slightly higher than for native Swedes (0.62). Middle Easterners (0.45) and in particular Iraqis (0.31) were lowest. However, in general, the impact on the current employment-probabilities of having been employed in the previous period was fairly consistent between immigrants and native Swedes, and across immigrant regions or countries of origin.

Similarly, there was statistically significant structural state-dependence in the earnings ($\widehat{\gamma}$), though smaller and varying more between immigrants and native Swedes. Structural state-dependence here indicates an elasticity of the previous period earnings on the current period. Based on structural state-dependence alone, Swedes had 6 SEK in current earnings for every 100 SEK of previous earnings, which was 2 to 3 times more than that of those from Middle East, Asia, or Latin America.

The marginal effect of being employed in 1990 was not large on the later employment-probabilities of native Swedes (0.017). However, the effect of the first year was much larger on immigrants mostly from non-European countries. Their later employment-probabilities were more influenced by initial employment-status and much less influenced by their own observed and unobserved characteristics. Conditional on working, the elasticity of initial earnings on the later earnings was larger for only the Nordics and other Western Europeans ($0.027 - 0.028$) compared to native Swedes (0.016); and other immigrant groups (mostly non-European) were lower ($0.004 - 0.015$). This results is an indication that the initial values problem is much important for immigrants compared to natives.

The other question is whether there is an effect of the macroeconomic conditions in the arrival-year of the immigrants and the observation period (especially the positive trend in unemployment rates after 1990) on the employment-probabilities and earnings, and whether the effect differs between immigrants and natives, and also across immigrant groups. The local unemployment elasticities were all negative, those on earnings being more statistically significant. They were not only different between natives and immigrants but also across immigrant groups. They were very small for native Swedes ($\widehat{\xi}_{emp} = -0.005$ and $\widehat{\xi}_{inc} = -0.010$) and not much larger for immigrants from Nordic countries ($\widehat{\xi}_{emp} = -0.007$ and $\widehat{\xi}_{inc} = -0.034$) and Western Europe ($\widehat{\xi}_{emp} = -0.018$ and $\widehat{\xi}_{inc} = -0.007$), but they were much larger for all others. For example, for immigrants from the Middle East was $\widehat{\xi}_{emp} = -0.225$, and -0.343 for those from Iraq. Thus, non-European immigrants were much more affected by changing macroeconomic conditions. Another important result is that there is not much difference on the local unemployment elasticities between the classic (static) and dynamic assimilation models.

Arrival year national unemployment elasticities [in brackets] on the employment-probabilities were all negative but small indicating that higher arrival-year unemployment rates correlated with lower employment-probabilities later, and statistically significant only for Middle Eastern immigrants. They were statistically significant on earnings for all immigrants-groups, however. And as with local unemployment-rates, the effect were larger on Middle Eastern, Asian, African and Latin American immigrants ($-0.028, -0.054$).

The variance of the unobserved individual-effects can be used to measure the extent of spurious state-dependence in both employment-probabilities and earnings. There was considerable unobserved individual-effects (heterogeneity) among immigrants and also natives. The size of the variance was large in the classic (static) models for both immigrants and native Swedes, smaller in the dynamic model controlling for structural state-dependence. The variance was also smaller for earnings than for employment, perhaps because of controlling for selection-bias. It could be expected that variance across individuals selected as working would be smaller than that when some individuals are working some are not.

We also observed that selection-bias was a problem independently from static or dynamic specifications: Simultaneous estimation of participation and earnings yielded statistically significant and negatively correlated error-terms, ($\rho = -0.30$ to -0.80). There was also a link between structural state-dependence and selection-bias. The high correlation found with the classic (static) model ($\rho = -0.32$ to -0.80) is reduced in the dynamic model ($\rho = -0.30$ to -0.73), even more so in case where structural state-dependence was large (the average reduction was about 0.10).

To check the sensitivity of the results to exclusion-restrictions, the models were estimated for various combinations of exclusion-restrictions (only number of children, or number of children + marital status, or number of children + marital status + transitory capital income). The results were quite robust to these restrictions, with some change which would not alter the results substantially.

5.2 Predicting employment- and earnings-assimilation from static and dynamic models

The results thus indicate that there is substantial structural state-dependence in the employment-probabilities and earnings, varying between the immigrants and native Swedes, and also across immigrant-groups. The static model, which does not control for the structural state-dependence, is thus potentially biased. That bias can be quantified by predicting the life-cycle employment-probabilities (Table 3a) and earnings (Table 3b) of immigrants and native Swedes. Since the immigrants are not homogenous, the results are reported separately for seven regions and seven specific countries of origin.

The first column of each table gives the differences in predicted initial employment-probability or earnings of immigrants vs. native Swedes (the *entry-effect*). These values were obtained by setting labour market entry (t_0) to age 20, years since migration to zero ($t = 0$) and almost all other variables (such as marital status and education levels etc.) to mean values. Local and arrival-year national unemployment-rates are the exceptions. As shown, the employment -probabilities and the earnings of immigrants were very sensitive to labour-market conditions, so that the values used in the estimation of the assimilation-measures could lead to misleading conclusions. For these variables, it was thus here to use sample medians, which are much more robust than means.

The next eight columns show similar values during $5-$year intervals for the next 40 years. The last column shows total years to assimilation (TYA), where the notation FA indicates $full\ assimilation$, the number of years needed to reach the employment-probability or earnings of an otherwise equivalent native Swede. The notation PA means $partial\ assimilation$, the number of years needed for the differences in employment-probability or earnings to reach their minimum, if full assimilation was newer reached.

Table 3a about here

5.2.1 Dynamic employment-assimilation of immigrants, by region and country of origin

Both classic (static) and dynamic assimilation models predict that immigrants from the Nordic Countries (and in particular, from Norway and Finland) and from Western Europe reach the employment-probability of native Swedes. The static model actually predicts Nordic immigrants as having higher employment-probability than Swedes upon arrival. However, in the dynamic model, they are 5.1 to 5.9 percentage-points less likely to gain immediate employment upon arrival. But their employment-probabilities continuously improved, converging to those of native Swedes at $29-32$ years. Although the large TYA measures might be seen longer in the first look, it is observed that the difference in the employment-probabilities of Nordics and Western Europeans are very small.

There is no other immigrant-group which is able to attain employment-probability level of native Swedes. For example, the Eastern Europeans are reduced the employment-probability gap from 76.1 to 23.7 percentage points at 20 years after arrival (classic (static) model predicts the same as 79.2 to 13.7 percentage-points at 17.2 years). These results are in line with those for Sweden in previous studies (Edin et al., 2000; Aslund and Rooth, 2003; Gustafson and Zheng, 2006), and also with those for Norway (Longva and Raaum, 2002; Barth et al., 2004).

Controlling for structural state-dependence on the predicted employment probabilities mainly appears on the rates of assimilation. Thus, the classic (static) model *overestimated* the short-run assimilation-rates and *underestimates* the long-run depending on the size of the structural state-dependence. The total years to assimilation TYA was much longer for the dynamic model implying positive assimilation-rates for longer periods. Figure 1a illustrates the impact of controlling for structural state-dependence on the marginal assimilation rates on employment-probabilities. The employment-probabilities of native Swedes were almost flat when estimated with dynamic model (solid curve), much more variable with classic (static) model (dashed curve).

Figure 1a about here

Estimates from the classic (static) model are also much more curved than those from the dynamic model for each of the immigrant-groups. For example, the employment-probabilities of Latin American immigrants reached their maximum 29 years after arrival (age $20 + 29 = 49$) when estimated with the dynamic model compared to 17 years with the classic (static) model (age $20 + 17 = 37$). The penalty of age for the immigrants is not as high as the one obtained from static model. The time point in which marginal assimilation rates turned to negative was almost 12 years shorter for Latin American immigrants with classic (static) model. Employment-probabilities do not fall off as fast with age when estimated with the dynamic model, indicating that accumulated human capital in the past was transferred to later ages and it helped immigrants keeping their employment-probability higher and more closer to those of native Swedes.

5.2.2 Dynamic earnings-assimilation of immigrants, by region and country of origin

Table 3b shows the relative earnings and years-to-assimilation of immigrants compared with otherwise identical native Swedes. The classic (static) model predicts that only immigrants from the Nordic countries, Western Europe, Eastern Europe, and Latin America attain earnings parity, in line with previous studies in Sweden. However, these results are biased, as comparison with the results from the dynamic model reveal.

Table 3b about here

The over all pattern in predicted relative earnings is similar to that for employment-probabilities, but the effect of controlling for structural state-dependence is much apparent. It is observed first that the initial earnings-differences is overestimated with classic (static) model. For instance, according to the classic (static) model, Eastern European immigrants are predicted to earn 0.88 log-points less than native Swedes upon arrival, but then to experience very fast earnings growth, catching-up earnings parity of native Swedes in about 18 years. It also predicts that their human capital depreciates fast and the earnings-difference then increases again even up to 0.61 log-points at $36 - 40$ years. This pattern is the same for all immigrant groups with the classic (static) assimilation model. The dynamic model, on the other hand, predicts a smaller initial earnings-difference (0.53 log-points), followed by smooth and continuous relative earnings-growth which attain parity after 37 year.

Briefly, the predictions of the static model is not plausible. It is biased in a way that it overestimates the speed of Sweden-specific human-capital accumulation in the short-run and it does not able to predict true rate of human-capital depreciation. In fact, all immigrant-groups (except those from Iraq) eventually attained earnings parity, in periods ranging from 12 years (Western Europe) to 55 years (Middle East).

Figure 1b shows the age-earnings profiles predicted by the classic (static) and dynamic models by region of origin.

Figure 1b about here

5.3 Cohort effects

Arrival-cohort effects are mostly interpreted as unobserved differences in the productivity of immigrants, i.e., their "quality", and these cohort-effects can be identified by both classic (static) and dynamic models used here. However, many factors can influence the estimates of these effects, and here we deal with many possible sources of bias on the estimates of cohort-effects on both the employment-probabilities and earnings of immigrants.

Macroeconomic conditions prevailing at the time of arrival might influence later outcomes, e.g., though human-capital accumulation; signalling effects; and "scarring" by unemployment. Similarly, immigration policies in effect at arrival might influence what kind of competition immigrants face, and the potential for statistical discrimination (e.g., for or against political refugees and immigration for work). Changes in general attitudes towards foreigners among the population or the eligibility criteria set by the immigration policy could also have an effect. Thus, the employment- probabilities and earnings potential of immigrant cohorts might depend on a host of factors which are also linked with the sources of the structural state-dependence, besides their own quality.

Controlling for the structural state-dependence, and for local unemployment-rates at the time of observation as well as for selection into employment at that time, and arrival-year national unemployment-rates, are important for getting cleaner estimates of the cohort-effects. For example, Barth et al., (2004) found that when unemployment was rising -as in Sweden during 1990s- the classical (static) assimilation model with equal-period-effects restriction and without controlling for local unemployment-rates, overestimated the labour-market success of early cohorts, and underestimated that of later. The dynamic model estimated here will allow to look at the "true" cohort-effects uncompromised by these other factors, and to compare those results with those from classic (static) model also estimated.

Seven cohorts of immigrants from each region (pre-1970, in five-year period, 1970-1974, 1975-1979, 1980-1984, 1985-1989, 1990-1994, six-years period, 1995-2000) were estimated, relative to the omitted pre-1970. Table 4 presents the cohort-effects on both employment-probabilities and earnings, from both classic (static) and dynamic models.

Table 4 about here

The dynamic model estimated all-negative cohort-effects on employment-probabilities, generally getting sequentially larger across cohorts for each regions of origin. This suggests unobserved employability of immigrants declined steadily relative to those who arrived before 1970. This result is in line with previous studies on immigrants in Scandinavian countries.

However, the dynamic estimates controlling for the structural state-dependence were smaller than the static estimates, where the negative trend across cohorts also appeared much more starkly. Much of the effect picked up by the static model was presumably captured as structural state-dependence in the dynamic model. Thus the *sharp* decline in employability of recent immigrants found by the static model, is not supported by the dynamic model. For example, the classic (static) model estimates that immigrants from Asia after 1970 were $20 - 69$ percentage-point less likely to be employed compared to pre-1970 arrivals. The dynamic model estimates them as only $5 - 28$ percentage-points less likely to be employed.

Both static and dynamic models find that earnings capacity of immigrants who arrived after 1970 from the Nordic countries, Western Europe and Eastern Europe were generally higher across cohorts. The cohort-effect on earnings was positive from the start for Nordic immigrants, and turned positive after 1984 even in the static model for Western and Eastern Europeans as well as Latin Americans. With the exception of immigrants from Asia, and those from Middle East after 1984, the dynamic model finds better earnings relative to those arrived before 1970 than does the classic (static) model.

The cohort-effects on earnings for immigrants from the Middle East, Asia, and Africa were generally increasingly negative, with the earnings of newly arrived immigrants considerably lower than those who arrived before 1970. The decline in the earnings-capacity for these immigrant-cohorts was much higher in the dynamic model. For example, Asian immigrants arrived after 1970 earned $0.18 - 0.35$ log-points less than pre-1970 arrivals in the classic (static) model, but $0.30 - 0.80$ less in the dynamic model.

6 Discussion and Conclusions

The dynamics behind the employment-probabilities and earnings-assimilation of immigrants were studied using high-quality register-based panel data covering 1990-2000. The primary question was the extent of structural state-dependence, and whether it differed between natives and immigrants, and also across immigrant groups. The link between the structural state-dependence and the cohort-effects was also investigated. Results from a dynamic random-effects sample selection model controlling for structural state-dependence in both participation and earnings, for selection-bias, and for unobserved individual-specific characteristics, were compared with results from a static model widely used in the previous studies. Employment-probabilities and earnings were simultaneously estimated, using local unemployment-rate as proxy for the changing economy-wide conditions to deal with a possible bias due to identification restrictions on the period-effects.

The simple method of Wooldridge (2005) was used considering that initial (sample) employment status and earnings are endogenous variables correlated with observed and unobserved individual characteristics to deal with the initial values problem. Arrival-year national unemployment-rates- which could affect the later success of immigrants- was used as a part of the conditional distribution of unobserved individual characteristics to link it by initial values problem.

Substantial structural and spurious state-dependence were found both in employment-probabilities and earnings of both immigrants and native Swedes. Structural state-dependence was larger in employment-probabilities than in earnings. The structural state-dependence found in employment-probabilities was slightly different for native Swedes as for immigrants, and also across immigrant groups. However, although smaller, the structural state-dependence found in earnings differed substantially between native Swedes and immigrants, and also across immigrant groups. Native Swedes had $2 - 3$ times more structural state-dependence than immigrants. Failure to control for structural state-dependence (i.e., using the classic (static) model instead of dynamic model) was found to cause serious overestimation of variance for the unobserved individual-effect.

The results suggest that the classical (static) model does not capture the actual behavior of human-capital accumulation with years spent in the host country. It seriously overstated the short-run marginal assimilation rates and understated the long-run ones. It thus overstates human-capital accumulation in the first years after arrival, but fast and high depreciation later, thus predicting the "penalty of age" too early for immigrants.

On the other hand, the dynamic model predicts a smaller initial-earnings disadvantage, and slower human-capital accumulation in the first years after arrival, but less depreciation later. Total years to assimilation (whether partial or full) - in both employment-probability and earnings- are thus longer in the dynamic than the static model, but more stable once achieved.

Both static and dynamic models found that no immigrants except those from Nordic and other Westerners European countries were able to reach the employment-probabilities of native Swedes. While the static model found that Middle Eastern, Asian, and African immigrants were not able to reach earnings parity with native Swedes, the dynamic model found that all (except immigrants from Iraq) eventually reach parity, though (for Middle Easterners) it could take up to 55 years.

Unobserved immigrant quality -i.e., cohort-effects- were also estimated in both models. The results suggest that the classic (static) model overstates the slope of the decline over succession of cohorts in the employability of the immigrants. This sharp decline in the cohort-effects is not supported by the dynamic model, much of the effect picked up by the static model is captured as structural state-dependence in the dynamic model.

The differences between the static and dynamic results for earnings by cohort were more complicated. Earnings-capacity of immigrants from Nordic and other Western European countries, Eastern Europe, and Latin America increased across cohorts, and this rise was underestimated by classic (static) model. But the earnings-capacity of immigrants from the Middle East, Asia, and Africa declined and this was also underestimated by the static model.

Policies based on the biased results of the classical (static) model may be questioned. There is significant state-dependence on employment-probabilities and earnings of both immigrants and natives. It appears that early-intervention policies which aim to change the living standards, income inequality, and poverty can alter the long-run outcomes both in employability and earnings. All immigrant groups in Sweden (except Iraqi immigrants) were found to be able to reach earnings parity, though not parity in employment-probabilities. Thus the question for Sweden is not whether the earnings of immigrants converge or not, but how many years it takes, and what policies might help them achieve employment-parity as well.

References

[1] Aguilar, R., and B. Gustafsson (1991), The Earnings Assimilation of Immigrants, *Labour* **5**: 37-58.

[2] Aguilar, R., and B. Gustafsson (1994), Immigrants in Sweden's Labour Market during the 1980s, *Scandinavian Journal of Social Welfare* **3**: 139-147.

[3] Akay A., and E. Tsakas (2007), Asymptotic Bias Reduction for a Conditional Marginal Effects Estimator in Sample Selection Models, *Forthcoming*, *Applied Economics.*

[4] Antelius, J., and A. Björklund (2000), How Reliable are Register Data for Studies of the Return on Schooling? An examination of Swedish data, *Scandinavian Journal of Educational Research* **44**: 341-355.

[5] Arellano, M., O. Bover, and J. Labeaga (1997), Autoregressive Models with Sample Selectivity for Panel Data. CEMFI, Working Paper No. 9706.

[6] Arellano, M., and B. Honore, (2001), Panel Data Models. Some Recent Developments. *Handbook of Econometrics*, **5**, Elsevier Science, Amsterdam.

[7] Arellano, M. and O. Bover, (1997), Estimating Dynamic Limited Dependent Variable Models From Panel Data, *Investigaciones Economicas*, **21**: 141-165.

[8] Arellano, M. and J. Hahn (2006), Understanding Bias in Nonlinear Panel Models: Some recent developments, in: R. Blundell, W. Newey, and T. Persson (eds.), Advances in Economics and Econometrics, Ninth World Congress, Cambridge University Press, *forthcoming.*

[9] Ashenfelter, O. (1978), Estimating the Effect of Training Programs on Earnings, *Review of Economics and Statistics*, **60**: 47-57

[10] Åslund, O., and O. Rooth Dan (2007), Do When and Where Matter? Initial labour market conditions and immigrant earnings, *The economic Journal*, **117**: 422-448

[11] Baker, M., and D. Benjamin (1994), The Performance of Immigrants in the Canadian Labour Market, *Journal of Labor Economics,* **12**: 369-405.

[12] Barth, E., B. Bratsberg, and O. Raaum (2002a), Local Unemployment and the Earnings Assimilation of Immigrants in Norway, Department of Economics, University of Oslo, Memorandum, 19/2002.

[13] Barth, E., B. Bratsberg, and O. Raaum (2002b), Local Unemployment and the Wages of Immigrants: Evidence from the current population surveys, Department of Economics, University of Oslo,Memorandum, 20/2005

[14] Barth, E., B. Bratsberg, and O. Raaum (2004), Identifying Earnings Assimilation of Immigrants Under Changing Macroeconomic Conditions, *Scandinavian Journal of Economics* **106**: 1-22.

[15] Borjas, G.J. (1985), Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants, *Journal of Labor Economics* **3**: 463-489.

[16] Borjas, G.J. (1987), Self-Selection and the Earnings of Immigrants, *American Economic Review* **77**: 531-553.

[17] Borjas, G.J. (1995), Assimilation, Changes in Cohort Quality: What happened to immigrant earnings in the 1980s, *Journal of Labor Economics* **13**: 201-245.

[18] Blundell, R.W. and R.J. Smith (1991), Initial Conditions and Efficient Estimation in Dynamic Panel Data Models, *Annales d'Economie et de Statistique* **20/21**: 109-123.

[19] Bulundell, R., S. Bond (1998), Initial Conditions and Moment Conditions in Dynamic Panel Data Models, *Journal of Econometrics* **87**: 115-143

[20] Card D. (1995), The Wage Curve: A review, *Journal of Economic Literature* **33**: 785-799.

[21] Chiswick, B.R. (1978), The Effect of Americanization on the Earnings of Foreign-born Men, *The Journal of Political Economy* **86**: 897-921.

[22] Chiswick, B.R., Y. Cohen, and T. Zach (1997), The Labor Market Status of Immigrants: Effects of the unemployment rate at arrival and duration of residence, *Industrial and Labor Relations Review* **50**: 289-303.

[23] Chamberlain, G. (1984), Panel Data, in *Handbook of Econometrics*, Vol. II, edited by Z. Griliches and M. Intriligator. Amsterdam: North Holland.

[24] Duleep, H.O., and M.C. Regets (1997), The Elusive Concept of Immigrant Quality: Evidence from 1970-1990, The Urban Institute, Washington DC, PRIP-UI-41 Working paper.

[25] Duleep, H.O., and M.C. Regets (1999), Immigrants and Human Capital Investment, *American Economic Review* **89**: 186-191.

[26] Edin, P.A., R.J. LaLonde, and O. Åslund (2000), Emigration of Immigrants and Measures of Immigrant Assimilation: Evidence from Sweden, *Swedish Economic Policy Review* **7**: 163-204.

[27] Edin, P.A., and P. Frederiksson (2001), LINDA: Longitudinal Individual Data for Sweden, Department of Economics, Uppsala University, Working Paper 2001: 6.

[28] Ekberg, J. (1999), Immigration and the Public Sector : Income effects for the native population in Sweden. *Journal of Population Economics* **12**: 411-430.

[29] Hammarstatd, M. (2001), Disposable Income Differences Between Immigrants and Natives in Sweden. *International Journal of Social Welfare* **10**: 117-126.

[30] Hansen, J., M. Lofstrom (2001), The Dynamics of Immigrant Welfare and Labor Market Behavior, Institute for the Study of Labor (IZA) DP Working Paper No. 360.

[31] Heckman, J.J. G.J. Borjas (1980), Does Unemployment Cause Future Unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence. *Economica*, *Special Issue on Unemployment* **47**: 247-283.

[32] Heckman, J.J. T.E. MaCurdy, (1980), A Life-Cycle Model of Female Labour Supply, *Review of Economic Studies* **47**:47-74.

[33] Heckman, J.J. (1981), The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time - Discrete Data Stochastic Process, in *Structural Analysis of Discrete Panel Data with Econometric Applications*, ed. by C. Manski and D. McFadden, Cambridge: MIT Press.

[34] Honore, B. (2002), Nonlinear Models with Panel Data, *Portuguese Economic Journal*, **1**: 163–179.

[35] Honore, B., and E. Tamer (2006), Bounds on Parameters in Panel Dynamic Discrete Choice Models, *Econometrica*, **74**: 611-629.

[36] Honore, B., and L. Hu (2004), Estimation of Cross Sectional and Panel Data Censored Regression Models with Endogeneity, *Journal of Econometrics*, **122**: 293–316.

[37] Hsiao, C. (2003), Analysis of Panel Data, 2nd ed, Cambridge University Press.

[38] Gustafsson, B., J. Zheng (2006), Earnings of Immigrants in Sweden. *International Migration* **44**: 79-117.

[39] Klinthäll, M. (2003), Return Migration from Sweden 1968-1996: A longitudinal analysis, Stockholm: Almqvist & Wiksell International.

[40] Kyriazidou, E. (1997), Estimation of a Panel-Data Sample Selection Model, *Econometrica* **65**: 1335-1364.

[41] Kyriazidou, E. (2001), Estimation of Dynamic Panel Data Sample Selection Model, *Review of Economic Studies* **68**: 543-472.

[42] Lancaster, T., (2000), The Incidental Parameter Problem Since 1948, *Journal of econometrics* **95**: 391-413.

[43] Lalonde, R.J., and R.H. Topel (1991), Immigrants in the American labor Market: Quality, assimilation, and distributional effects, *American Economic Review* **81**: 297-302.

[44] Lalonde, R.J., and R.H. Topel (1992), The Assimilation of Immigrants in the U.S. Labor Market, NBER Working Paper 3573, 67-92.

[45] Longva, P., and O. Raaum (2002), Unemployment and Earnings Assimilation of Immigrants, *Labour* **16**: 469-489.

[46] Longva, P., and O. Raaum (2003), Earnings Assimilation of Immigrants in Norway: A reappraisal, *Journal of Population Economics* **16**: 177-193.

[47] Matyas, L., and P. Sevestre (1995), The Econometrics of Panel Data, A Handbook of Theory with Applications, Kluwer Academic Publishers, Netherlands.

[48] Mundlak, Y. (1978), On the Pooling of Time Series and Cross Section Data, *Econometrica* **46**: 69-85.

[49] Neyman, J. and E. Scott (1948), Consistent Estimates Based on Partially Consistent Observations, *Econometrica* **16**: 1-32.

[50] Price, S.W. (2001), The Employment Adjustment of Male Immigrants in England, *Journal of Population Economics* **14**: 193-220

[51] Rochina-Barrachina, M.E., (1999), A New Estimator for Panel Data Sample Selection Models, *Annales d'Economie et de Statistiques* **55-56**: 154-182.

[52] Scott, K. (1999), The Immigrant Experience: Changing Employment and Income patterns in Sweden, 1970-1993. *Lund Studies in Economic History no*: 9.

[53] Vella, F. (1998), Estimating Models with Sample Selection Bias: A Survey. *The Journal of Human Resources* **33**:127-169.

[54] Vella, F. and M. Verbeek (1999), Two-step Estimation of Panel Data Models with Censored Endogenous Variables and Selection Bias, *Journal of Econometrics* **90**: 239-63.

[55] Verbeek, M., and T. Nijman (1992), Testing for Selectivity-Bias in Panel Data Models, *International Economic Review* **33**: 681-703.

[56] Wooldridge, J.M. (2005), Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel-Data Models with Unobserved Heterogeneity, *Journal of Applied Econometrics* **20**: 39-54

[57] Zabel, J.E. (1992), Estimating Fixed and Random-Effects Models with Selectivity, *Economics Letters* **40**: 269-272.

Table 1. *Mean values of variables for native immigrants and Swedes, by region of origin, 1990-2000*

	Native Swedes	Nordic Countries	Western Europe	Eastern Europe	Middle East	Asia	Africa	Latin America
Log earnings	10.78 (3.73)	8.99 (5.14)	8.06 (5.51)	7.83 (5.71)	5.67 5.58)	7.54 (5.36)	6.27 (5.53)	7.84 (5.16)
Log lagged earnings	10.86 (3.60)	9.09 (5.05)	8.16 (5.44)	6.71 (5.72)	5.60 (5.57)	7.48 (5.35)	6.14 (5.52)	8.10 (5.15)
Log earnings in 1990	10.99 (3.19)	9.79 (4.43)	8.51 (5.12)	6.01 (5.73)	5.90 (5.51)	7.16 (5.28)	5.87 (5.48)	8.38 (4.89)
Employment	0.82 (0.37)	0.68 (0.47)	0.59 (0.49)	0.49 (0.50)	0.37 (0.48)	0.51 (0.50)	0.40 (0.49)	0.56 (0.49)
First lag of employment	0.83 (0.37)	0.69 (0.45)	0.60 (0.49)	0.47 (0.49)	0.36 (0.48)	0.50 (0.50)	0.39 (0.48)	0.55 (0.50)
Employment in 1990	0.83 (0.38)	0.74 (0.44)	0.61 (0.49)	0.42 (0.49)	0.38 (0.48)	0.44 (0.50)	0.36 (0.49)	0.56 (0.50)
Local unemployment rate	2.81 (1.18)	2.66 (1.01)	2.83 (1.26)	2.85 (1.11)	3.35 (1.55)	3.21 (1.48)	3.15 (1.34)	3.01 (1.41)
Age	38.7 (10.8)	40.7 (10.8)	39.2 (10.96)	38.9 (11.2)	35.6 (9.46)	33.3 (10.5)	33.1 (9.15)	35.4 (10.8)
Years since immigration		19.0 (9.40)	14.8 (9.76)	12.2 (9.64)	9.77 (6.49)	12.6 (7.62)	8.59 (6.32)	12.1 (6.80)
Married/cohabiting	0.40 (0.49)	0.39 (0.49)	0.47 (0.50)	0.59 (0.49)	0.55 (0.50)	0.47 (0.50)	0.44 (0.50)	0.38 (0.48)
Number of the children at home	1.78 (1.16)	1.61 (1.12)	1.66 (1.12)	1.81 (1.20)	1.97 (1.47)	1.70 (1.26)	1.58 (1.54)	1.69 (1.21)
Stockholm residence	0.22 (0.43)	0.35 (0.44)	0.39 (0.47)	0.22 (0.34)	0.37 (0.45)	0.30 (0.42)	0.40 (0.48)	0.43 (0.51)
Log capital (non-labor) income	0.74 (2.26)	0.49 (1.83)	0.56 (1.99)	0.45 (1.76)	0.54 (1.91)	0.62 (2.03)	0.27 (1.35)	0.30 (1.44)
Lower–secondary	0.23 (0.37)	0.31 (0.44)	0.32 (0.46)	0.23 (0.39)	0.45 (0.48)	0.39 (0.47)	0.32 (0.45)	0.40 (0.47)
Upper–secondary	0.51 (0.49)	0.43 (0.50)	0.36 (0.47)	0.51 (0.50)	0.39 (0.49)	0.37 (0.48)	0.46 (0.50)	0.47 (0.49)
University degree	0.26 (0.43)	0.26 (0.42)	0.32 (0.46)	0.26 (0.43)	0.26 (0.43)	0.24 (0.43)	0.22 (0.41)	0.23 (0.42)
Arrival Cohorts								
<1970		0.22 (0.44)	0.10 (0.23)	0.10 (0.29)	0.03 (0.17)	0.03 (0.19)	0.03 (0.20)	0.04 (0.25)
1970–74		0.23 (0.42)	0.17 (0.37)	0.14 (0.35)	0.04 (0.18)	0.10 (0.31)	0.04 (0.21)	0.05 (0.22)
1975–79		0.21 (0.40)	0.16 (0.36)	0.08 (0.26)	0.11 (0.31)	0.21 (0.41)	0.07 (0.26)	0.21 (0.40)
1980–84		0.09 (0.28)	0.13 (0.33)	0.10 0.30)	0.12 (0.32)	0.18 (0.39)	0.08 (0.27)	0.18 (0.38)
1985–89		0.13 (0.33)	0.18 (0.38)	0.14 (0.34)	0.35 (0.48)	0.19 (0.39)	0.30 (0.45)	0.33 (0.47)
1990–94		0.09 (0.29)	0.17 (0.37)	0.38 (0.48)	0.29 (0.45)	0.24 (0.43)	0.42 (0.50)	0.15 (0.36)
1995–2000		0.03 (0.17)	0.09 (0.17)	0.06 (0.24)	0.06 (0.24)	0.05 (0.22)	0.06 (0.23)	0.04 (0.20)
Sample size	540651	131647	67641	107124	121914	28381	28432	36547

Notes: (Standard deviations in parentheses)

Table 2. *Structural state dependence, unobserved individual-effects; local and arrival year unemployment-elasticities on employment-probabilities and earnings; obtained from jointly-estimated employment- and earnings-equations; by region and country of origin, 1990-2000.*

	Employment Probability					Earnings				
	S + CRE + WC		*SD*(1) + *WC* + *WIV*			*S + CRE + WC*		*SD*(1) + *WC* + *WIV*		
Region or country	$\hat{\sigma}_{\eta}$	$\hat{\xi}_{emp}$	$\hat{\lambda}$	$\hat{\sigma}_{\eta}$	$\hat{\xi}_{emp}$	$\hat{\sigma}_{\alpha}$	$\hat{\xi}_{inc}$	$\hat{\gamma}$	$\hat{\sigma}_{\alpha}$	$\hat{\xi}_{inc}$
Sweden										
	1.737	-0.004	**0.619***** (0.017)***	1.138	-0.005	0.435	-0.007***	**0.060***** (0.016***)	0.406	-0.010
ρ	-0.721			-0.380						
Nordic Countries										
	2.012	-0.003	**0.575***** (0.301)***	0.839	-0.007* [-0.002]	0.463	-0.036***	**0.044***** (0.028***)	0.411	-0.034*** [-0.001]***
ρ	-0.322			-0.322						
Norway										
	1.755	-0.018*	**0.540***** (0.312***)	0.757	-0.012* [-0.004]	0.497	-0.030***	**0.047***** (0.028***)	0.431	-0.038*** [-0.020***]
ρ	-0.464			-0.394						
Finland										
	2.044	-0.013	**0.580***** (0.459***)	0.828	-0.009 [-0.007]	0.395	-0.043***	**0.049***** (0.028***)	0.371	-0.036*** [-0.005***]
ρ	-0.399			-0.306						
Western Countries										
	1.920	-0.016***	**0.582***** (0.170***)	0.829	-0.018* [-0.004]	0.520	-0.017***	**0.046***** (0.027***)	0.487	-0.007** [-0.010***]
ρ	-0.470			-0.308						
Eastern Europe										
	1.529	-0.034	**0.698***** (0.246***)	0.156	-0.099** [-0.002]	0.381	-0.115***	**0.040***** (0.015***)	0.228	-0.102*** [-0.011***]
ρ	-0.624			-0.455						
Yugoslavia										
	1.647	-0.071*	**0.671***** (0.285***)	0.524	-0.076* [-0.004]	0.369	-0.075***	**0.036***** (0.015***)	0.367	-0.099*** [-0.026*]
ρ	-0.581			-0.510						

Table 2. *Continued*

	Employment Probability					Earnings				
	S + CRE + WC		*SD*(1) + *WC* + *WIV*			*S + CRE + WC*		*SD*(1) + *WC* + *WIV*		
Region or country	$\hat{\sigma}_\eta$	$\hat{\xi}_{emp}$	$\hat{\lambda}$	$\hat{\sigma}_\eta$	$\hat{\xi}_{emp}$	$\hat{\sigma}_\alpha$	$\hat{\xi}_{inc}$	$\hat{\gamma}$	$\hat{\sigma}_\alpha$	$\hat{\xi}_{inc}$
Middle East										
	1.179	-0.056*	**0.447*****	0.517	-0.036	0.328	-0.234***	**0.024*****	0.344	-0.225***
			(0.132***)		[-0.002*]			(0.009***)		[-0.054***]
ρ	-0.780			-0.647						
Iran										
	1.047	-0.049*	**0.418*****	0.494	-0.013	0.325	-0.071***	**0.027*****	0.308	-0.084***
			(0.081***)		[-0.001]			(0.005***)		[-0.006]
ρ	-0.721			-0.670						
Iraq										
	1.080	-0.114**	**0.313*****	0.514	-0.036**	0.284	-0.295***	**0.023*****	0.314	-0.343***
			(0.117***)		[-0.010*]			(0.004***)		[-0.095***]
ρ	-0.799			-0.732						
Turkey										
	1.363	-0.046*	**0.450*****	0.565	-0.043*	0.375	-0.187***	**0.023*****	0.164	-0.251***
			(0.240***)		[-0.017**]			(0.004***)		[-0.072***]
ρ	-0.634			-0.619						
Asia										
	1.401	-0.091**	**0.587*****	0.074	-0.056*	0.380	-0.168***	**0.032*****	0.218	-0.089***
			(0.169***)		[-0.004]			(0.010***)		[-0.054***]
ρ	-0.522			-0.566						
Africa										
	1.175	-0.089***	**0.611*****	0.907	-0.109***	0.293	-0.141***	**0.024*****	0.262	-0.170***
			(0.097)		[-0.006]			(0.007***)		[-0.029*]
ρ	-0.782			-0.688						

Table 2. *Continued*

	Employment Probability					Earnings				
	S + *CRE* + *WC*		*SD*(1) + *WC* + *WIV*			*S* + *CRE* + *WC*		*SD*(1) + *WC* + *WIV*		
Region or country	$\hat{\sigma}_\eta$	$\hat{\xi}_{emp}$	$\hat{\lambda}$	$\hat{\sigma}_\eta$	$\hat{\xi}_{emp}$	$\hat{\sigma}_\alpha$	$\hat{\xi}_{inc}$	$\hat{\gamma}$	$\hat{\sigma}_\alpha$	$\hat{\xi}_{inc}$
Latin America										
	1.221	-0.057*	**0.638***** (0.142)	0.153	-0.045* [-0.009]	0.336	-0.145***	**0.033***** (0.011***)	0.162	-0.131*** [-0.028***]
ρ	-0.728			-0.669						
Chile										
	1.197	-0.054*	**0.617***** (0.135)***	0.387	-0.044* [-0.011]	0.292	-0.166***	**0.032***** (0.005***)	0.080	-0.183*** [-0.028***]
ρ	-0.640			-0.662						

Notes: All results reported in this table are marginal effects on employment-probabilities and earnings. *S* is static; *CRE* is correlated random effects; *WC* is wage-curve model including interactions with year since migration and year since migration squared; *SD* (1) is first order state dependence; *WIV* is simple method of Wooldridge; $\hat{\lambda}$ and $\hat{\gamma}$ are estimated marginal effects of structural state-dependence on both employment-probabilities and earnings; $\hat{\sigma}_\eta$ and $\hat{\sigma}_\alpha$ are variance of unobserved individual-effects in both equations; $\hat{\xi}_{emp}$ and $\hat{\xi}_{inc}$ are local unemployment elasticities on employment-probabilities and earnings, respectively; The marginal effects of initial sample-period dependent variable (in parentheses); the figures in brackets are the marginal effects of arrival-year national unemployment elasticities. ρ is correlation between participation and earnings-equations. *, **, *** represent significance at 0.01, 0.05 and 0.10, respectively.

Table 3a. *Relative employment-probabilities and years-to-assimilation of immigrants, by region and country of origin, 1990-2000* (percentage-points)

	Years since migration									
	Initial	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	TYA
Nordic Countries										
Static	**0.072**	**0.028**	**0.002**	– 0.011	– 0.017	– 0.018	– 0.019	– 0.022	– 0.033	NA
Dynamic	– 0.051	– 0.023	– 0.023	– 0.021	– 0.018	– 0.014	– 0.008	**0.002**	**0.011**	**31.3** (FA)
Norway										
Static	**0.075**	**0.048**	**0.029**	**0.017**	**0.008**	–0.001	–0.014	–0.027	–0.038	NA
Dynamic	– 0.059	– 0.051	– 0.039	– 0.023	– 0.012	– 0.003	**0.002**	**0.006**	**0.008**	**29.0** (FA)
Finland										
Static	**0.066**	**0.029**	**0.004**	– 0.012	– 0.017	– 0.025	– 0.034	– 0.075	– 0.179	NA
Dynamic	– 0.058	– 0.051	– 0.042	– 0.033	– 0.024	– 0.017	– 0.009	**0.003**	**0.008**	**32.0** (FA)
Western Europe										
Static	– 0.194	– 0.078	– 0.033	– 0.019	– 0.013	– 0.006	**0.004**	**0.014**	– 0.001	**28.8** (FA)
Dynamic	– 0.127	– 0.065	– 0.037	– 0.027	– 0.017	– 0.008	– 0.002	**0.004**	**0.012**	**31.1** (FA)
Eastern Europe										
Static	– 0.792	– 0.695	– 0.342	– 0.155	– 0.137	– 0.255	– 0.582	– 0.617	– 0.628	17.2 (PA)
Dynamic	– 0.761	– 0.581	– 0.407	– 0.290	– 0.237	– 0.241	– 0.304	– 0.431	– 0.470	20.2 (PA)
Yugoslavia										
Static	–0.771	–0.644	–0.315	–0.121	–0.117	–0.220	–0.473	–0.557	–0.593	15.1 (PA)
Dynamic	–0.782	–0.639	–0.490	–0.377	–0.316	–0.304	–0.343	–0.432	–0.497	23.5 (PA)
Middle East										
Static	– 0.712	– 0.682	– 0.613	– 0.546	– 0.603	– 0.720	– 0.786	– 0.746	– 0.628	12.1 (PA)
Dynamic	– 0.783	– 0.703	– 0.629	– 0.579	– 0.560	– 0.575	– 0.622	– 0.693	– 0.771	20.2 (PA)
Iraq										
Static	– 0.791	– 0.772	– 0.636	– 0.686	– 0.882	– 0.936	– 0.908	– 0.847	– 0.728	9.27 (PA)
Dynamic	– 0.875	– 0.778	– 0.649	– 0.580	– 0.609	– 0.723	– 0.844	– 0.893	– 0.896	16.0 (PA)
Iran										
Static	– 0.712	– 0.665	– 0.512	– 0.407	– 0.509	– 0.529	– 0.627	– 0.732	– 0.783	13.6 (PA)
Dynamic	– 0.823	– 0.741	– 0.652	– 0.583	– 0.549	– 0.557	– 0.304	– 0.681	– 0.769	21.5 (PA)
Turkey										
Static	– 0.686	– 0.621	– 0.544	– 0.429	– 0.594	– 0.621	– 0.734	– 0.738	– 0.792	12.9 (PA)
Dynamic	– 0.706	– 0.643	– 0.595	– 0.569	– 0.566	– 0.588	– 0.631	– 0.691	– 0.757	17.8 (PA)
Asia										
Static	– 0.778	– 0.741	– 0.574	– 0.441	– 0.411	– 0.487	– 0.647	– 0.647	– 0.774	18.7 (PA)
Dynamic	– 0.714	– 0.648	– 0.585	– 0.526	– 0.468	– 0.415	– 0.367	– 0.405	– 0.460	29.1 (PA)
Africa										
Static	– 0.773	– 0.719	– 0.551	– 0.469	– 0.449	– 0.471	– 0.558	– 0.740	– 0.821	18.4 (PA)
Dynamic	– 0.752	– 0.643	– 0.537	– 0.454	– 0.406	– 0.393	– 0.416	– 0.474	– 0.563	24.2 (PA)
Latin America										
Static	– 0.666	– 0.561	– 0.427	– 0.346	– 0.333	– 0.388	– 0.506	– 0.643	– 0.674	17.3 (PA)
Dynamic	– 0.561	– 0.452	– 0.364	– 0.300	– 0.262	– 0.248	– 0.235	– 0.317	– 0.369	28.6 (PA)
Chile										
Static	– 0.482	– 0.301	– 0.303	– 0.257	– 0.301	– 0.385	– 0.525	– 0.664	– 0.683	14.8 (PA)
Dynamic	– 0.445	– 0.370	– 0.317	– 0.286	– 0.273	– 0.265	– 0.307	– 0.353	– 0.421	24.5 (PA)

Notes: The values were obtained by setting the years since migration to zero then adding five years at a time until 40; other variables are set to their mean values, except local market unemployment-rates (median was used). For each region of origin, the first row presents the static correlated random effects model with augmented wage-curve method (*S+CRE+WC*). The second row presents the results from dynamic model with augmented wage curve methodology and Wooldridge initial values (*SD(1)+WC + WIV*). Bold indicates that the employment-probabilities of an immigrant group exceed those of native Swedes. *FA* indicates full assimilation, *PA* partial assimilation. *NA* "not applicable".

Figure 1a. Comparison of predicted age-employment probabilities-profiles of native Swedes and immigrants by region of origin, 1990-2000, obtained from classic static assimilation model (*dashed curves*, *S+ CRE+WC*) and dynamic assimilation model (*solid curves*, *SD*(1)+*WC+WIV*), using median local unemployment rates: for Nordics = 2.89%; Western Europeans = 2.88%; Eastern Europeans = 2.81%; Middle Easterners = 3.17%; Asians = 3.02%; African = 2.99%; Latin Americans = 3.07% and for native Swedes = 2.88%; see also the note on Table 3a.

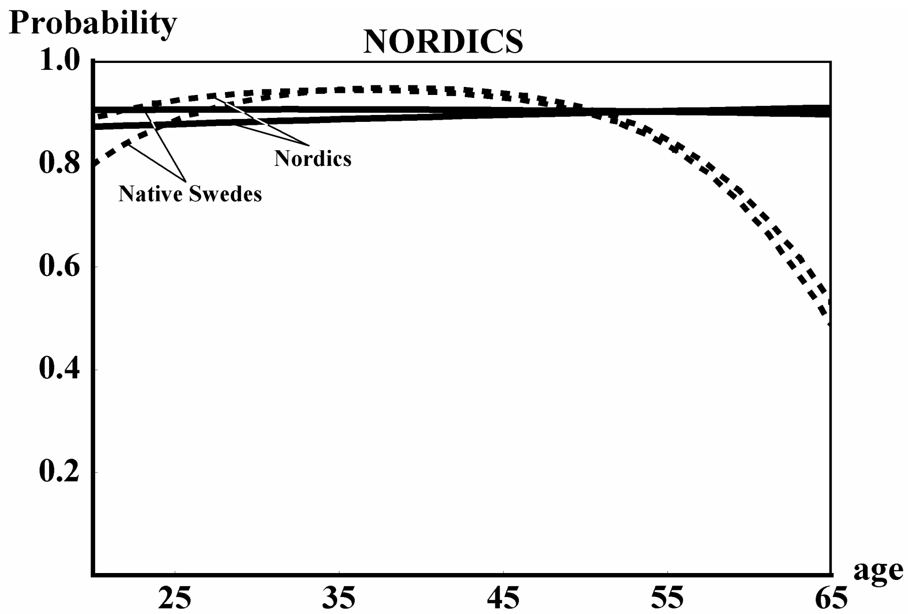
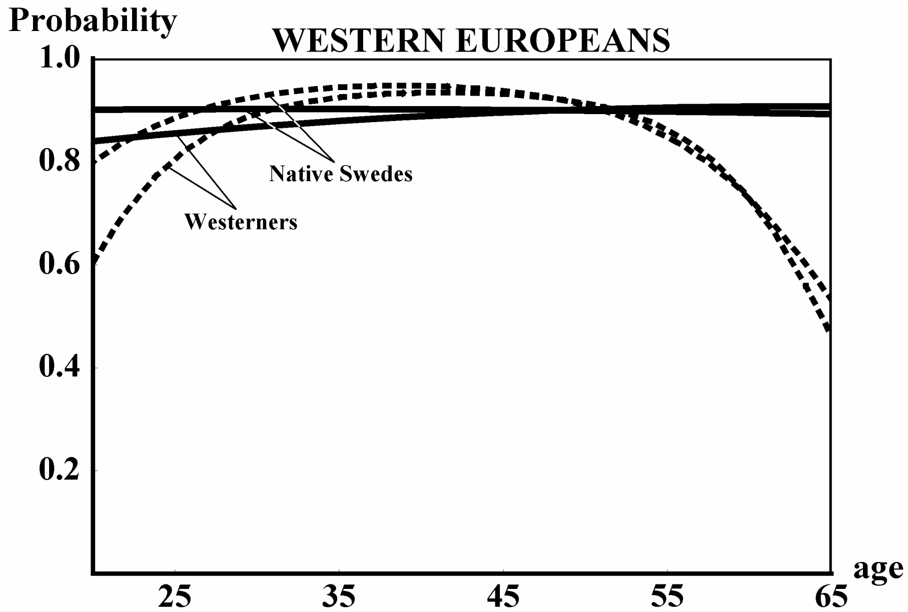


Figure 1a. *Continued*



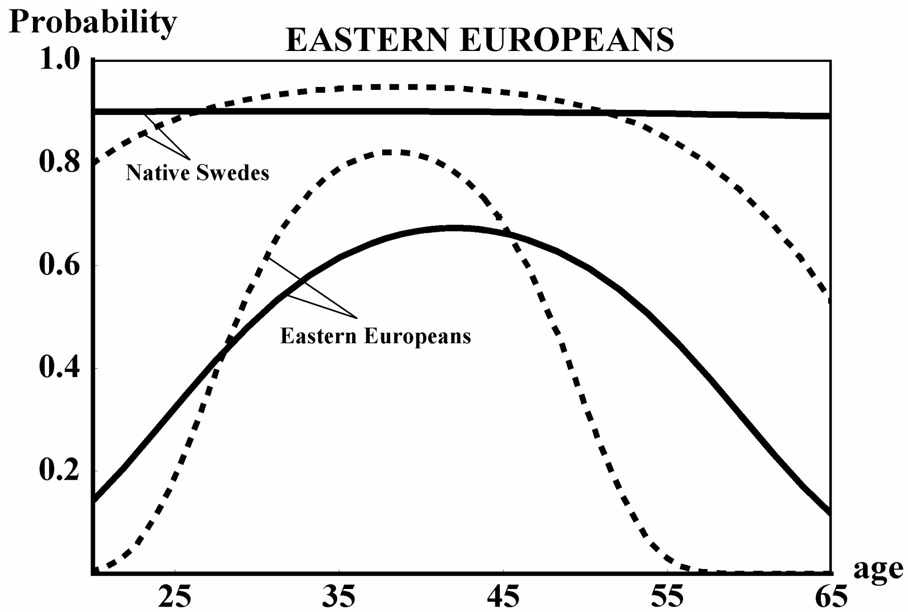
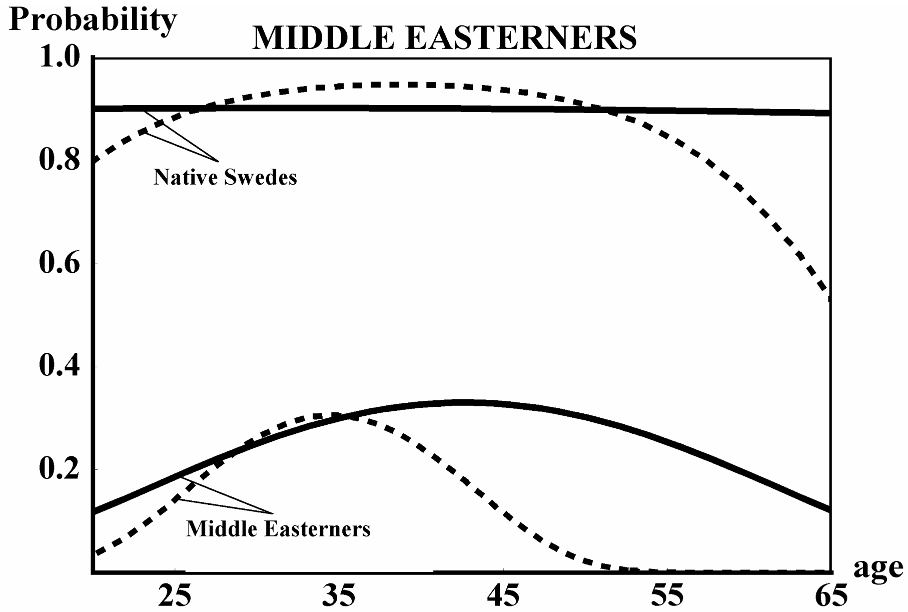


Figure 1a. *Continued*



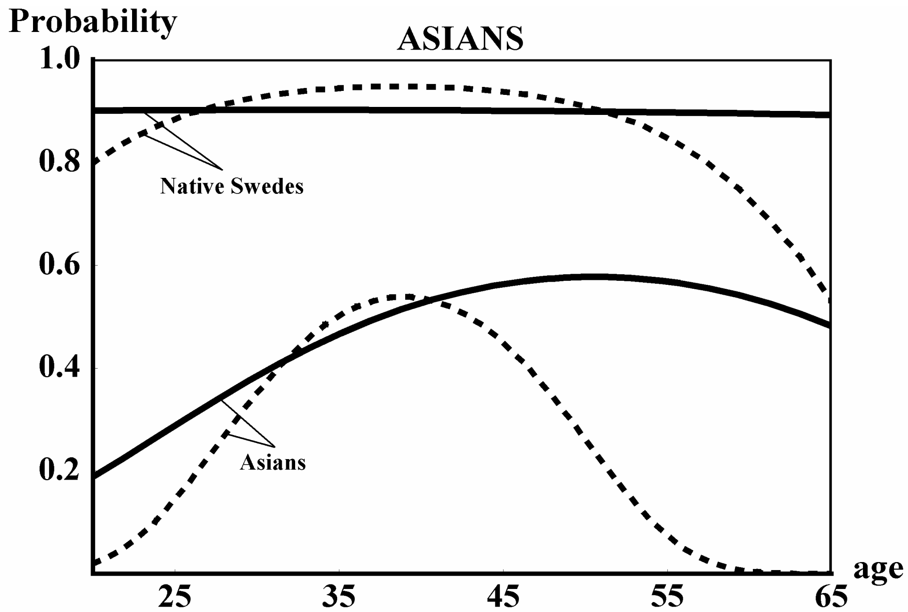
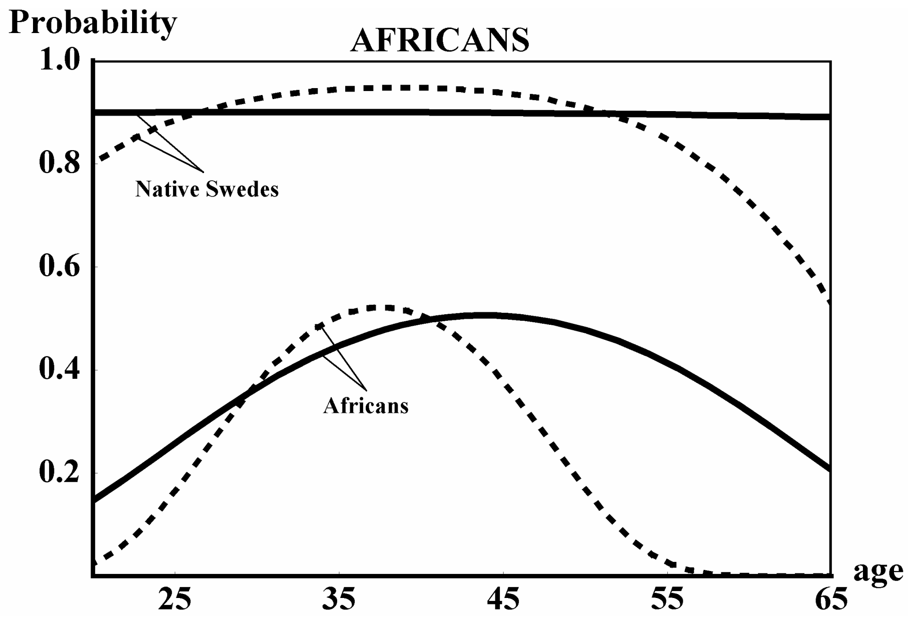


Figure 1a. *Continued*



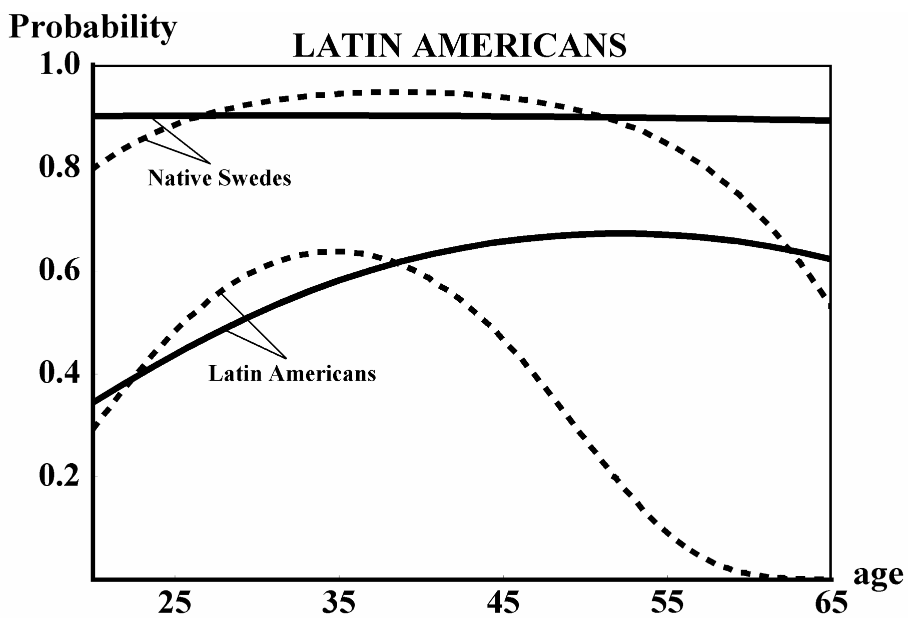


Table 3b. *Relative earnings and years-to-assimilation of immigrants, by region and country of origin, 1990-2000 (Log-points)*

	Year since migration									
	Initial	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	TYA
Nordic Countries										
Static	– 0.136	– 0.158	– 0.154	– 0.131	– 0.069	**0.042**	**0.094**	**0.189**	**0.311**	**22.5** (FA)
Dynamic	– 0.058	– 0.099	– 0.104	– 0.096	– 0.076	– 0.045	– 0.005	**0.043**	**0.100**	**30.6** (FA)
Norway										
Static	**0.005**	– 0.039	– 0.060	– 0.062	– 0.048	– 0.020	**0.026**	**0.092**	**0.188**	NA
Dynamic	– 0.049	– 0.048	– 0.044	– 0.036	– 0.023	– 0.007	**0.013**	**0.038**	**0.047**	**26.5** (FA)
Finland										
Static	– 0.034	– 0.055	– 0.043	**0.003**	**0.061**	**0.144**	**0.240**	**0.348**	**0.470**	**14.8** (FA)
Dynamic	– 0.031	– 0.043	– 0.049	– 0.037	**0.008**	0.038	0.101	0.179	0.275	**18.3** (FA)
Western Europe										
Static	– 0.179	– 0.102	– 0.027	**0.045**	**0.110**	**0.169**	**0.218**	**0.259**	**0.295**	**11.8** (FA)
Dynamic	– 0.160	– 0.090	– 0.026	**0.032**	**0.055**	**0.079**	**0.082**	**0.078**	**0.051**	**12.1** (FA)
Eastern Europe										
Static	– 0.875	– 0.473	– 0.215	– 0.070	**0.009**	**0.031**	– 0.043	– 0.256	– 0.612	**18.4** (FA)
Dynamic	– 0.532	– 0.427	– 0.339	– 0.263	– 0.194	– 0.130	– 0.071	– 0.020	**0.016**	**37.5** (FA)
Yugoslavia										
Static	– 0.795	– 0.517	– 0.317	– 0.125	**0.042**	**0.026**	– 0.031	– 0.158	– 0.356	**17.1** (FA)
Dynamic	– 0.544	– 0.473	– 0.407	– 0.344	– 0.279	– 0.212	– 0.141	– 0.076	**0.007**	**39.4** (FA)
Middle East										
Static	– 0.812	– 0.639	– 0.518	– 0.441	– 0.404	– 0.417	– 0.494	– 0.642	– 0.858	21.4 (PA)
Dynamic	– 0.746	– 0.682	– 0.618	– 0.554	– 0.486	– 0.416	– 0.242	– 0.268	– 0.195	**55.3** (FA)
Iran										
Static	– 0.702	– 0.472	– 0.294	– 0.160	– 0.063	**0.006**	**0.032**	– 0.044	– 0.148	**24.3** (FA)
Dynamic	– 0.581	– 0.484	– 0.351	– 0.238	– 0.143	– 0.043	**0.001**	**0.009**	**0.017**	**30.7** (FA)
Iraq										
Static	– 1.023	– 0.664	– 0.532	– 0.573	– 0.803	– 1.286	– 2.031	– 2.571	– 2.896	8.38 (PA)
Dynamic	– 0.833	– 0.675	– 0.572	– 0.508	– 0.479	– 0.487	– 0.544	– 0.661	– 0.846	17.4 (PA)
Turkey										
Static	– 0.591	– 0.510	– 0.429	– 0.345	– 0.213	– 0.100	– 0.041	**0.024**	**0.055**	**33.5** (FA)
Dynamic	– 0.586	– 0.607	– 0.681	– 0.680	– 0.650	– 0.549	– 0.421	– 0.262	– 0.151	**40.1** (FA)
Asia										
Static	– 0.845	– 0.627	– 0.461	– 0.342	– 0.261	– 0.217	– 0.213	– 0.259	– 0.356	31.8 (PA)
Dynamic	– 0.695	– 0.631	– 0.565	– 0.497	– 0.424	– 0.348	– 0.268	– 0.184	– 0.097	**45.2** (FA)
Africa										
Static	– 0.871	– 0.611	– 0.451	– 0.371	– 0.352	– 0.395	– 0.520	– 0.748	– 1.082	19.2 (PA)
Dynamic	– 0.642	– 0.559	– 0.494	– 0.444	– 0.404	– 0.344	– 0.292	– 0.229	– 0.160	**52.9** (FA)
Latin America										
Static	– 0.600	– 0.442	– 0.313	– 0.209	– 0.120	– 0.046	**0.008**	**0.033**	**0.027**	**29.1** (FA)
Dynamic	– 0.525	– 0.500	– 0.466	– 0.422	– 0.368	– 0.304	– 0.229	– 0.143	– 0.045	**42.2** (FA)
Chile										
Static	– 0.374	– 0.311	– 0.250	– 0.188	– 0.123	– 0.057	**0.002**	**0.049**	**0.083**	**26.6** (FA)
Dynamic	– 0.389	– 0.326	– 0.266	– 0.206	– 0.146	– 0.085	– 0.025	**0.028**	**0.043**	**31.7** (FA)

Notes: See Table 3a.

Figure 1b. Comparison of predicted age-earnings-profiles of native Swedes and immigrants by region of origin, 1990-2000, obtained from classic static assimilation model (*dashed curves*, *S+ CRE+WC*) and dynamic assimilation model (*solid curves*, *SD*(1)+*WC+WIV*), using median local unemployment rates: for Nordics = 2.89%; Western Europeans = 2.88%; Eastern Europeans = 2.81%; Middle Easterners = 3.17%; Asians = 3.02%; African = 2.99%; Latin Americans = 3.07% and for native Swedes = 2.88%; see also the note on Figure 1a.

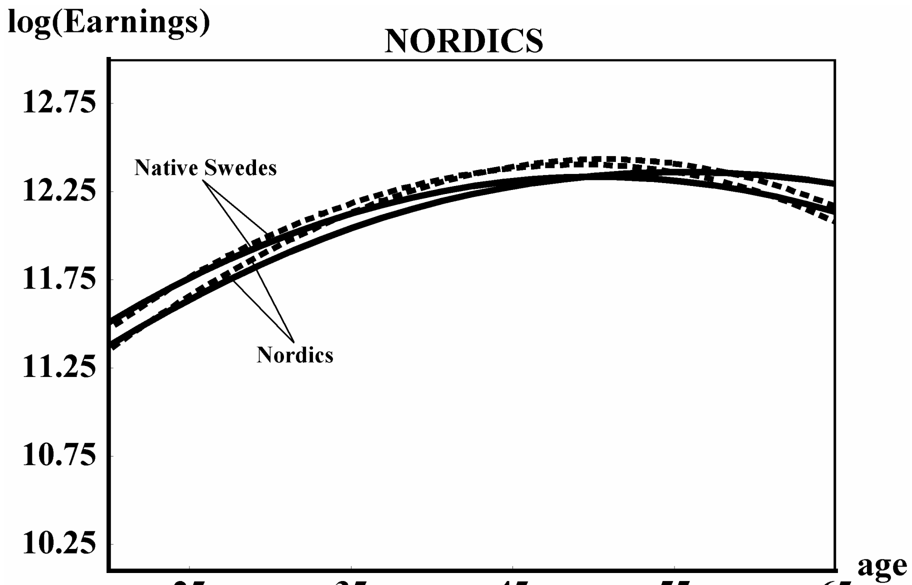
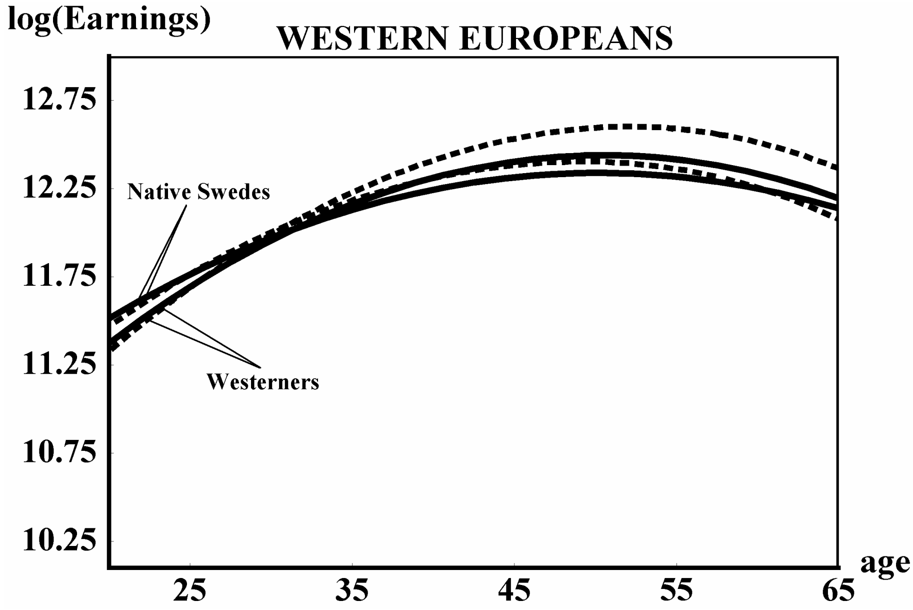


Figure 1b. *Continued*



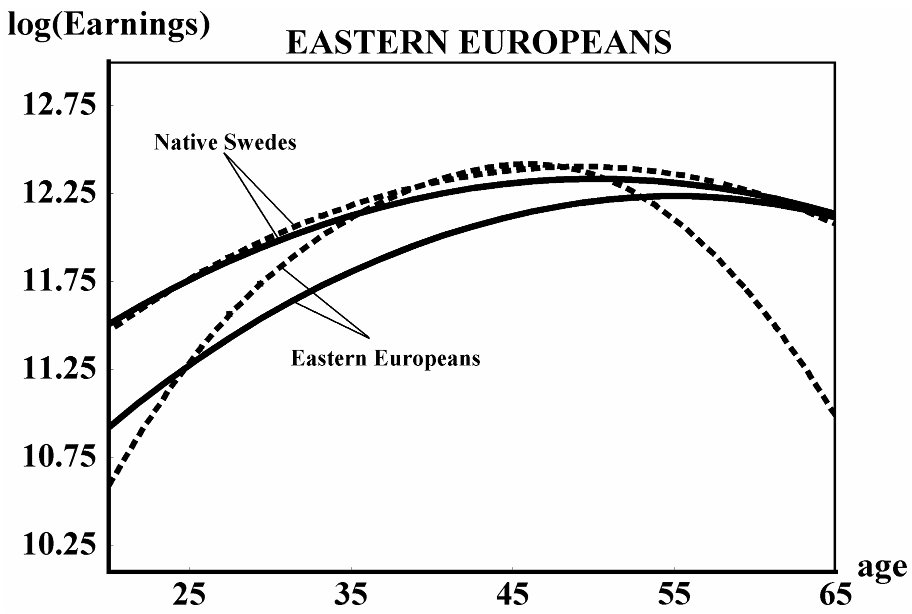
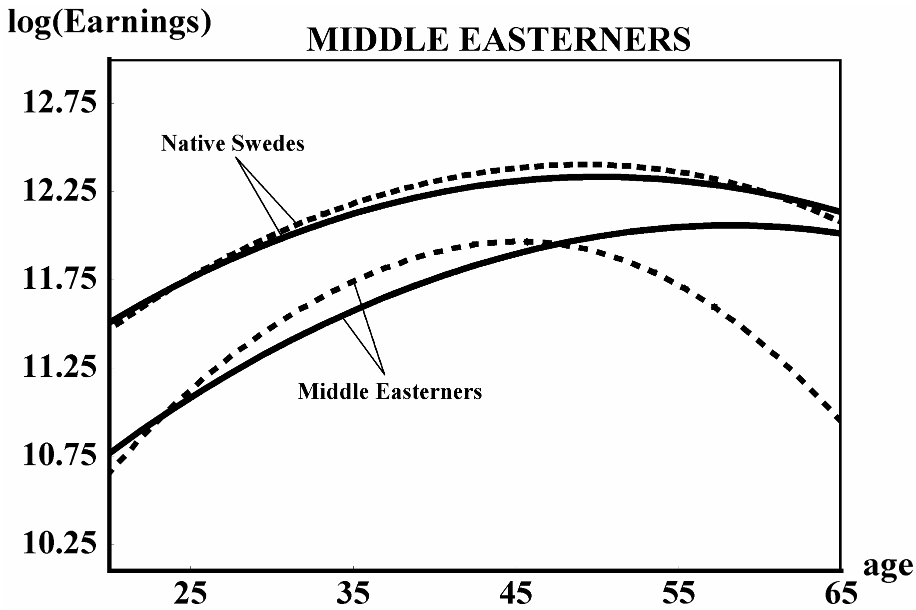


Figure 1b. *Continued*



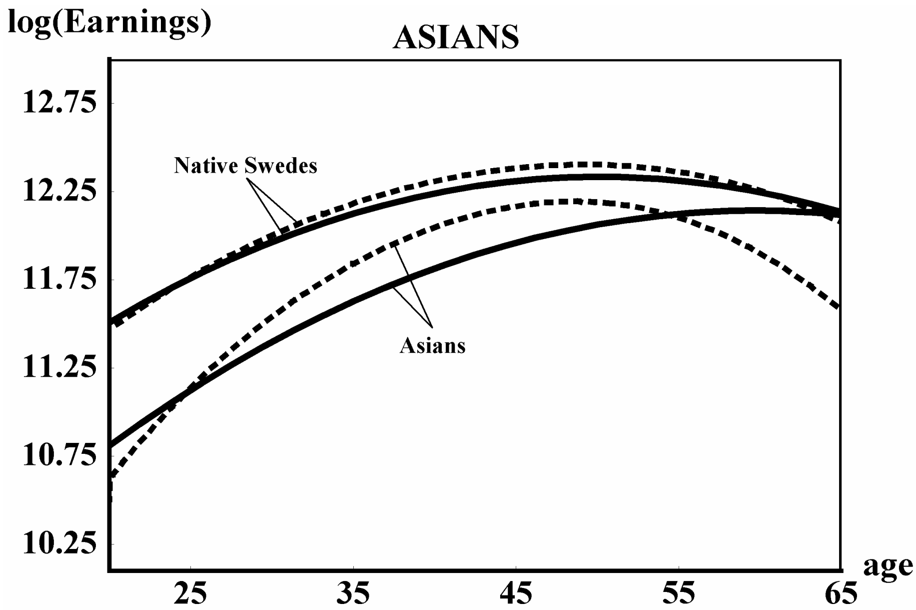
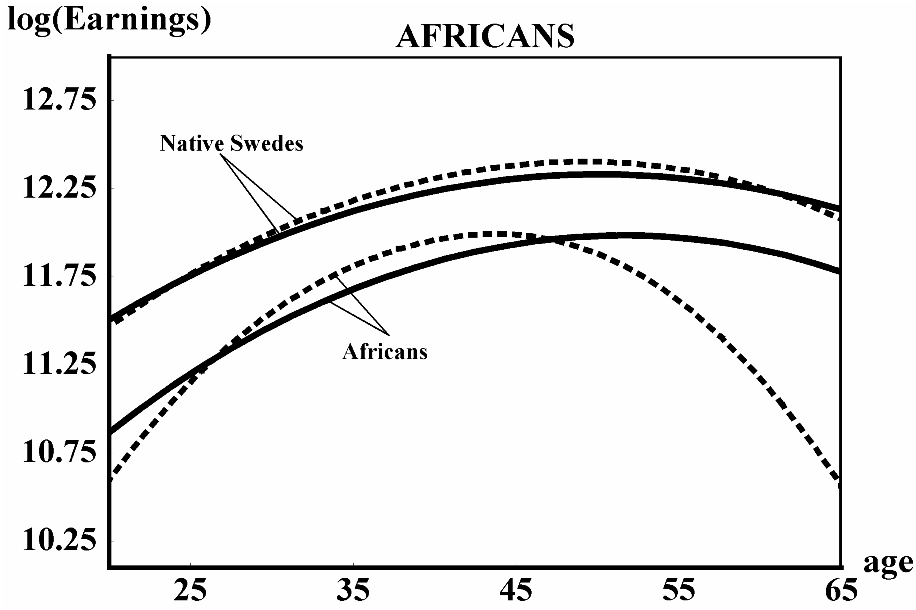


Figure 1b. *Continued*



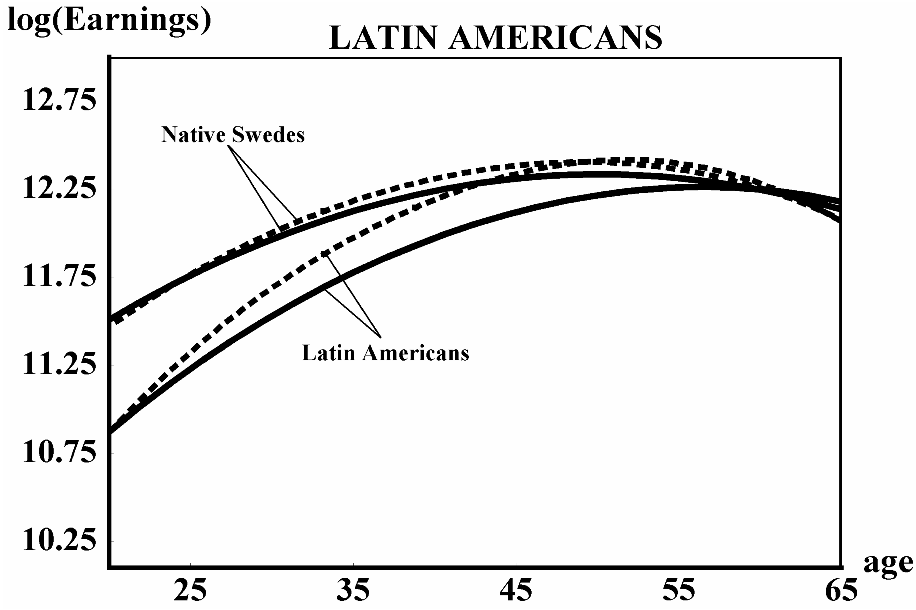


Table 4. *Estimated cohort-effects on employment-probabilities and earnings from static and dynamic models, by region of origin*

	Employment Probabilities		Earnings	
Arrival Cohort	*S+ CRE + WC*	*SD*(1) + WC+WIV	*S+ CRE + WC*	*SD*(1) + WC+ WIV
Nordic Countries				
1970-74	– 0.233 (0.018)	– 0.014 (0.016)	0.015 (0.003)	0.082 (0.003)
1975-79	– 0.403 (0.022)	– 0.014 (0.021)	0.039 (0.004)	0.164 (0.004)
1980-84	– 0.545 (0.027)	– 0.039 (0.027)	0.167 (0.005)	0.223 (0.005)
1985-89	– 0.647 (0.029)	– 0.070 (0.032)	0.284 (0.006)	0.398 (0.006)
1990-94	– 0.817 (0.099)	– 0.055 (0.037)	0.380 (0.007)	0.521 (0.007)
1995-2000	– 0.937 (0.042)	– 0.070 (0.049)	0.525 (0.009)	0.680 (0.009)
Western Countries				
1970-74	– 0.171 (0.036)	– 0.035 (0.027)	– 0.042 (0.009)	0.001 (0.006)
1975-79	– 0.406 (0.042)	– 0.037 (0.033)	– 0.056 (0.010)	0.163 (0.007)
1980-84	– 0.463 (0.046)	– 0.044 (0.038)	– 0.010 (0.011)	0.186 (0.008)
1985-89	– 0.718 (0.050)	– 0.094 (0.042)	0.117 (0.012)	0.356 (0.009)
1990-94	– 0.983 (0.055)	– 0.057 (0.045)	0.282 (0.013)	0.497 (0.010)
1995-2000	– 0.849 (0.058)	– 0.018 (0.051)	0.477 (0.015)	0.655 (0.011)
Eastern Europe				
1970-74	– 0.410 (0.036)	– 0.074 (0.018)	– 0.230 (0.011)	– 0.001 (0.005)
1975-79	– 0.617 (0.045)	– 0.068 (0.022)	– 0.246 (0.015)	0.126 (0.006)
1980-84	– 0.558 (0.047)	– 0.013 (0.030)	– 0.049 (0.017)	0.249 (0.008)
1985-89	– 0.423 (0.048)	– 0.145 (0.032)	0.163 (0.019)	0.435 (0.009)
1990-94	– 0.602 (0.049)	– 0.108 (0.033)	0.114 (0.020)	0.647 (0.009)
1995-2000	– 0.500 (0.055)	– 0.112 (0.034)	0.274 (0.022)	0.776 (0.012)
Middle East				
1970-74	– 0.305 (0.064)	– 0.037 (0.042)	– 0.211 (0.028)	– 0.014 (0.014)
1975-79	– 0.395 (0.065)	– 0.015 (0.045)	– 0.295 (0.029)	– 0.156 (0.015)
1980-84	– 0.482 (0.070)	– 0.010 (0.048)	– 0.278 (0.031)	– 0.212 (0.015)
1985-89	– 0.541 (0.071)	– 0.009 (0.047)	– 0.258 (0.032)	– 0.375 (0.016)
1990-94	– 0.718 (0.071)	– 0.036 (0.048)	– 0.425 (0.032)	– 0.538 (0.017)
1995-2000	– 0.719 (0.073)	– 0.067 (0.049)	– 0.305 (0.033)	– 0.704 (0.017)
Asia				
1970-74	– 0.205 (0.085)	– 0.046 (0.072)	– 0.184 (0.033)	– 0.304 (0.020)
1975-79	– 0.285 (0.086)	– 0.103 (0.075)	– 0.155 (0.034)	– 0.432 (0.020)
1980-84	– 0.296 (0.090)	– 0.191 (0.079)	– 0.248 (0.037)	– 0.508 (0.021)
1985-89	– 0.396 (0.092)	– 0.227 (0.085)	– 0.337 (0.039)	– 0.667 (0.023)
1990-94	– 0.618 (0.092)	– 0.238 (0.086)	– 0.211 (0.040)	– 0.750 (0.024)
1995-2000	– 0.690 (0.096)	– 0.252 (0.092)	– 0.347 (0.043)	– 0.803 (0.027)
Africa				
1970-74	– 0.503 (0.072)	– 0.109 (0.081)	– 0.435 (0.026)	– 0.054 (0.022)
1975-79	– 0.627 (0.071)	– 0.089 (0.086)	– 0.515 (0.028)	– 0.007 (0.025)
1980-84	– 0.697 (0.075)	– 0.052 (0.091)	– 0.440 (0.028)	– 0.082 (0.027)
1985-89	– 0.759 (0.075)	– 0.014 (0.096)	– 0.401 (0.030)	– 0.190 (0.029)
1990-94	– 1.034 (0.075)	– 0.015 (0.095)	– 0.616 (0.030)	– 0.281 (0.029)
1995-2000	– 0.962 (0.078)	– 0.088 (0.101)	– 0.428 (0.031)	– 0.409 (0.031)
Latin America				
1970-74	0.008 (0.072)	– 0.029 (0.072)	– 0.064 (0.023)	– 0.018 (0.019)
1975-79	– 0.116 (0.069)	– 0.041 (0.073)	– 0.062 (0.023)	0.035 (0.020)
1980-84	– 0.276 (0.072)	– 0.064 (0.076)	– 0.107 (0.024)	0.116 (0.020)
1985-89	– 0.277 (0.073)	– 0.108 (0.079)	0.050 (0.025)	0.271 (0.021)
1990-94	– 0.573 (0.074)	– 0.142 (0.079)	0.067 (0.025)	0.367 (0.022)
1995-2000	– 0.487 (0.076)	– 0.214 (0.085)	0.121 (0.025)	0.411 (0.024)

Notes: The reported cohort-effects are the marginal effects of estimated parameters for cohorts in participation and earnings-equations, See also the note in Tables 2 and 3a,b (standard errors in parentheses)