State Dependence in Unemployment

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ABSTRACT: This study examines the extent state dependence among unemployed immigrants in a dynamic discrete choice framework. Three alternative methodologies are employed to control for the problem of the initial condition. The empirical findings show that there is a considerable correlation between the unobserved individual heterogeneity and the initial condition and that the degree of state dependence is overstated if we do not address this problem. The results show that an individual who was unemployed at period "*t-1*" has 6.5 percentage points higher probability of being unemployed again at period *t* compared to an individual who was employed at period "*t-1*".

Keywords: Immigrants; unemployment; state dependence; unobserved heterogeneity; dynamic random effects models.
JEL Classifications: C23; C25; J22

1. Introduction

High unemployment among immigrants has increasingly become a focus for policymakers in many countries. The effectiveness of public policy directed towards the unemployment problem might depend on the extent of state dependence in unemployment. For example, consider a policy change which has the effect of temporally moving unemployed workers into employment. If there is a positive true state dependence in employment, the policy intervention will cause a persistent increase in employment. Consequently, the intervention is likely to reduce the number of individuals who are dependent on benefits or live on a low income (Prowse, 2005). In this case, changes in benefit rules are also more likely to meet their objectives (Jörgen Hansen, Lofstrom, & Zhang, 2006). On the other hand, if the observed serial persistence in unemployment is due to the permanent unobserved heterogeneity, then the policy stated above is less likely to have an effect. But it is important to know whether the state dependence is driving employment prospects (known as true state dependence), or conversely, whether unobserved heterogeneity plays that role (known as spurious state dependence). Put differently, is the mere experience of being unemployed a relative disadvantage to a person, or can it be attributed to unobserved individual heterogeneity (Knights, Harris, & Loundes, 2002)?

Kari (2003) has described various reasons for true state dependence. For example, firms try to figure out the quality of workers from their labour market history (Katz & Gibbons, 1991). Similarly, firms can rank job applications based on the duration of unemployment of the job seekers (Blanchard & Diamond, 1994). Therefore, a firm might find it optimal to use different employment criteria for different groups of job seekers (Sattinger, 1998). In addition, Eriksson (2002) argues that discrimination based on employment status is an equilibrium hiring strategy. Even firms are allowed to set wages according to the workers' expected productivity. As a result, an unemployed person may be permanently affected when applying for vacancies. (Heckman & Borjas, 1980) describe how experience of unemployment may change the behaviour of the unemployed person by changing his preferences and constraints. Other reasons for true state dependence are reduced productivity due to deteriorating existing human capital and the prevention of the accumulation of human capital (Mincer

& Polachek, 1974). As explained in (Kari, 2003), the above discussion implies a causal relationship of previous unemployment with future unemployment.

Some persons may be observed continuously unemployed since their probabilities of getting a job are limited due to unobserved characteristics (e.g. lack of punctuality). If the unobserved characteristics among individuals remain uncontrolled and if they are correlated over time, previous unemployment may appear to determine further unemployment solely because it acts as a substitute for temporally persistent factors. This results in overestimation in the magnitude of state dependence and, accordingly, in false policy recommendations (Kari, 2003).

Several studies have investigated the issue of state dependence and unobserved heterogeneity in unemployment. Most recently, Stewart (2006) has examined the extent of the state dependence in unemployment for the UK, and the role played in this by low-wage employment. The study shows that an individual unemployed at *t-1* is more than twice as likely to be unemployed again at *t* as someone who was employed at t-1, but otherwise has the same observed and unobserved characteristics. However, Corcoran and Hill (1985) find that past unemployment does not increase the current unemployment probability for prime age men, once unobserved heterogeneity and data collection procedures are controlled for. But most of the studies show the existence of strong state dependence in unemployment, see for example, Narendranathan and Elias (1993) for Britain, Hyslop (1999) for the US, Frijters, Lindeboom, and Van den Berg (2009) for Holland, Haan (2006) for Germany, Islam (2006) for Sweden, among other studies.

Jorgen Hansen and Lofstrom (2009) have shown that immigrants have a greater degree of state dependence in welfare participation than native. They have also argued that the state dependence among the Swedes appears to be due to the unobserved heterogeneity, possibly welfare preferences, to a greater extent than it is among the immigrants from refugee countries. Le Maire and Scheuer (2006) have found evidence of a positive and significant state dependence for selected groups with weak labour market participation in the Danish labour market.

In this study, special attention is paid to control the unobserved heterogeneity and initial condition problem. These issues are addressed by using alternative estimators, i.e. the Wooldridge estimator and the Heckman estimator, and the results are compared to assess their robustness. The empirical findings reveal a significant state dependence in unemployment. The estimates also show considerable correlation between the unobserved individual heterogeneity and the initial condition, which implies that the degree of state dependence is overstated if we do not control for it. The results show that an individual who was unemployed at period *t-1* has 6.5 percentage points higher probability of becoming unemployed again at period *t* compared to an individual who was employed at period *t*-1. This average partial effect is the same for western compared to non-western immigrants and women compared to men.

The rest of this study is organized as follows: Descriptions of the behavioral model and econometric specification are presented in section 2 along with explanations of the alternative estimators used in this study. Section 3 gives a data description and some descriptive analysis. Empirical results are discussed in section 4. Section 5 concludes the study.

2. Behavioural Model and Econometric Specification

Discrete choice models of labour supply are based on the concept of random utility (Train, 2009). The theory of decision making is very simple. The aim of the decision maker *n* (individual) is to maximize his life time utility (U) by optimally choosing from a finite number of alternatives (J) of leisure and income at a specific time (T). U_{njt} is the utility that the decision maker n gets from the alternative j at time t. He will choose alternative i if and only if $U_{nit} > U_{njt} \quad \forall j \neq i, \forall t$. The researcher does not observe the actual utility obtained by the decision maker, but he observes some characteristics (S_{nt}) of the decision maker and some characteristics of the alternatives (X_{njt}) that may lead to the decisions made by the decision maker. For the researcher, this utility can be decomposed into two very general parts, i.e., representative utility (V_{njt}) and the unobserved part of utility (ε_{njt}), i.e., $U_{njt} = V_{njt} + \varepsilon_{njt}$. Here V_{njt} is a function which relates the observed factors to the decision

maker's utility, for example, in case of a linear representative utility $V_{njt} = \beta'X_{njt} + \delta'S_{nt}$. The inclusion of the lagged values of the choice variable makes this decision process dynamic.

Due to the unobserved factors, the researcher cannot predict the actual decisions, but he can make some probabilistic statements about the choices of the decision maker. These choice probabilities depend upon the characteristics of the decision maker, the attributes of alternatives and the assumptions about the unobserved part ε_{njt}. The choice probability for the alternative i can be written as follows:

$$P_{nit} = \text{Prob}\big(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt} \quad \forall j \neq i \text{ and } \forall t\big) \tag{1}$$

By using an indicator function and the distribution of unobserved components, the choice probability can be written as follows:

$$P_{nit} = \int I\big(\varepsilon_{njt} - \varepsilon_{nit} < V_{nit} - V_{njt} \forall j \neq i \text{ and } \forall t\big) f(\varepsilon_n) d\varepsilon_n \tag{2}$$

Here *I(.)* equals *1* if the statement in the brackets is true. Otherwise it is 0. The assumptions about ε_n will lead to various econometric specifications of the discrete choice models.

2.1 Modelling State Dependence and Unobserved Heterogeneity (True or Spurious State Dependence)

State dependence is a behaviour in which an individual's preference in a particular state at time t will increase the probability of being in the same state at period at period t+1, conditional on the observable characteristics. In the context of the labour market, the working behaviour of the last period affects the current labour supply decision. Heckman and Willis (1977) have discussed two possible types of state dependence. First, *true state dependence* will be observed if an individual's presence in a state at time *t* changes prices, preferences or constraints which are relevant for their future behaviour. For example, this could take the form of a past unemployment experience decreasing the individual's stock of human capital, which in turn decreases his future wage (Mincer & Polachek, 1974). Alternatively, fixed costs related to job search can make unemployment more attractive if the individual is already unemployed instead of employed (Heckman & Borjas, 1980). Secondly, *spurious state dependence* will be observed if there is inter-temporally correlated unobserved individual specific heterogeneity. This heterogeneity can be time varying or time invariant, or a combination of both. For policy makers it is important to know whether the state dependence drives the unemployment prospects or, conversely, if it is heterogeneity.

State dependence can be modelled by introducing a lagged unemployment state indicator y_{nt-1} into the representative utility. If the representative utility is linear in the observed factors, then the utility function will take the following form: $U_{njt} = \beta'X_{njt} + \delta'S_{nt} + \gamma'y_{nt-1} + \varepsilon_{njt}$. There will be a positive true state dependence if $\gamma > 0$, with the assumption that the unobserved components ε_{njt} are independently distributed over *n, j and t*. In the above specification it is also assumed that only the previous year's employment status matters to the current behaviour. Hence, true state dependence is Markovian. This specification is based on the presence of search and transition costs (see, for example, Hyslop (1999)). Heckman and Borjas (1980) have also discussed several other representations of the true state dependence. Any dynamics related to observed factors can be handled by using a conditional discrete choice specification, which consistently estimates the model. If the unobserved components ε_{njt} are not independently distributed due to the possible existence of unobserved heterogeneity, then these can be decomposed into two parts, i.e., $\alpha'S_{nt}^*$ and $\in_{njt}$, where S_{nt}^* represents the unobserved individual specific attributes. Now the utility function will take the form:

$$U_{njt} = \beta'X_{njt} + \delta'S_{nt} + \gamma'y_{nt-1} + \alpha'S_{nt}^* + \in_{njt}. \tag{3}$$

Many studies have used this equation to analyse state dependence in unemployment, using a dynamic random effects probit model, for example Stewart (2007).

2.2 Econometric Specification

This paper uses several dynamic estimators to model the probability of unemployment. These estimators include a lag dependent variable to allow for state dependence. Special attention is given to

the treatment of unobserved heterogeneity and initial conditions, since ignoring these can produce overstatement of the true state dependence in unemployment.

2.2.1 Standard Random Effects Probit Model

The dynamic empirical model of unemployment probability involves consistent estimation of the following reduced form equations of the behavioural process described in equation (3):

$$\Pr(y_{it} = 1 \mid y_{it-1}, X_{it}, \varepsilon_i) = I(\gamma y_{it-1} + X'_{it}\beta + \varepsilon_i + u_{it} \geq 0) \quad (i = 1,...,N; t = 2,...,T) \tag{4}$$

where y_{it} is an indicator function for unemployment, X_{it} is a vector of explanatory variables (includes personal and other characteristics). β and γ are the unknown parameters to be estimated. ε_i is an individual specific component which captures the time invariant unobserved human capital and taste, and u_{it} is a possibly serially correlated error term that can vary over i and t[2]. Asymptotics of the model depend on N, whereas T is small and taken as fixed. Depending on the assumptions made about unobserved heterogeneity and explanatory variables, different estimators are used in order to consistently estimate the model.

The unemployment probability is modeled using a dynamic random effects probit model given in the following equation:

$$y^*_{it} = \gamma y_{it-1} + X'_{it}\beta + \varepsilon_i + u_{it} \tag{5}$$
$$\Pr(y_{it} = 1 \mid y_{it-1}, X_{it}, \varepsilon_i) = I(y^*_{it} > 0)$$
$$u_{it} \sim N(0, \sigma^2_u)$$

Where y^*_{it} is a latent variable and we observe $y_{it} = 1$ if $y^*_{it} > 0$. The standard probit model assumes that ε_i is uncorrelated with the explanatory variables X_{it}. For identification purposes, normalization is required since y is a binary variable. A convenient one is to assume $\sigma^2_u = 1$. The composite error term $(v_{it} = \varepsilon_i + u_{it})$ will be correlated over time due to individual specific time invariant ε_i terms, even if u_{it} is assumed to be *iid*. In this case, the correlation of the composite error term $(v_{it} = \varepsilon_i + u_{it})$ over time is given as follows:

$$Corr(v_{it}, v_{is}, \; t \neq s) = \rho = \frac{\sigma^2_\varepsilon}{\sigma^2_\varepsilon + 1} \tag{6}$$

The estimated parameters of the standard random effects probit model are biased if unobserved variables are correlated with observed variables. Mundlak (1978) and Chamberlain (1982) provide another estimator that allows correlation either between ε_i and the time means of the explanatory variables or the combination of their lags and leads. In other words, the estimator assumes that the relationship between X_{it} and ε_i is completely captured by including the means of time varying explanatory variables or combinations of their lags and leads. The relationship can be written as follows:

$$\varepsilon_i = \overline{X}'_i a + \alpha_i \qquad \text{or} \qquad \varepsilon_i = \sum_{t=1}^{T} X'_{it} a + \alpha_i \qquad \text{where} \quad \alpha_i \sim iidN(0, \sigma^2_\alpha) \tag{7}$$

Substituting this expression with the first expression in equation (5), we get the following extended specifications of the standard random effects models, known as correlated random effects model.

$$y^*_{it} = \gamma y_{it-1} + X'_{it}\beta + \overline{X}_i a + \alpha_i + u_{it} \quad \text{where } u_{it} \sim N(0, \sigma^2_u) \tag{8}$$

$$\text{or } y^*_{it} = \gamma y_{it-1} + X'_{it}\beta + \sum_{t=0}^{T} X_{it} a_t + \alpha_i + u_{it} \quad \text{where } u_{it} \sim N(0, \sigma^2_u) \tag{9}$$

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[2] To make these standard models comparable with Heckman estimator we estimated all models from t =2,…T.

In this study the specification in equation (8) is used for estimating random effects models. Again, normalization is necessary and it is assumed that $\sigma_u^2 = 1$. The correlation between the composite error term $v_{it} = \alpha_i + u_{it}$ for the different periods can be written as follows:

$$Corr(v_{it}, v_{is}, \; t \neq s) = \rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + 1} \tag{10}$$

An advantage of this specification is that one can perform a standard Wald type test to verify the correlation between X_{it} and α_i.

2.2.2 Heckman's Estimator[3]

The inclusion of the lag dependent variables creates the problem of initial condition, which implicitly assumes that the initial observations are independent of the unobserved variables (as assumed in section 2.2.1 and 2.2.2). In simple terms, this assumption means that the start of the behavioral process coincides with the start of the observation period for each individual. This assumption is too strong for this study, since this study uses data from 1994 to 2003, and clearly 1994 is not the start of the behavioral process for some individuals. Therefore, estimation requires some assumptions about the initial observation y_{i1} and the unobserved heterogeneity α_i. Heckman (1981) has specified the following reduced form equation for the initial observation.

$$y_{i1}^* = z_{i1}'\pi + \eta_i \tag{11}$$

where z_{i1} includes X_{i1} or other exogenous variables and η_i is allowed to be correlated with α_i, but uncorrelated with u_{it} for $t \geq 2$. It can be written as: $\eta_i = \theta\alpha_i + u_{i1}; \theta > 0$ using orthogonal projection, with α_i and u_{i1} independent of one another. It is also assumed that u_{i1} satisfies the same distributional assumptions as u_{it} for $t \geq 2$. The linearized reduced form for the initial period can therefore be written as follows:

$$y_{i1}^* = z_{i1}'\pi + \theta\alpha_i + u_{i1} \tag{12}$$

The outcome probability and the joint likelihood function of $(y_{i1},...y_{it})$ for an individual i given α_i can be written as follows:

$$\Phi\left[(z_{i1}'\pi + \theta\alpha_i)(2y_{i1} - 1)\right]\prod_{t=2}^{T}\Phi\left[(X_{it}'\beta + \gamma y_{it-1} + \overline{X}_i'a + \alpha_i)(2y_{i1} - 1)\right]$$

$$L = \prod_{i=1}^{N}\int_{\alpha^*}\left\{\Phi\left[(z_{i1}'\pi + \theta\sigma_\alpha\alpha^*)(2y_{i1} - 1)\right]\prod_{t=2}^{T}\Phi\left[(X_{it}'\beta + \gamma y_{it-1} + \overline{X}'a + \sigma_\alpha\alpha^*)(2y_{i1} - 1)\right]\right\}dF(\alpha^*) \tag{13}$$

This expression is maximized for a random sample of individuals. Φ is a standard normal cumulative distribution function. F is the distribution function of $\alpha^* = \alpha/\sigma_\alpha$ and $\sigma_\alpha = \sqrt{\rho/(1-\rho)}$. Stewart (2006) has provided a new STATA command, "-redprob-" for estimating Heckman's estimator. In this procedure, the integral over α^* is evaluated using the Gaussian-Hermite Quadrature, (Stewart, 2006).

2.2.3 Wooldridge's Conditional Maximum Likelihood Estimator[4]

The Heckman estimator approximates the joint distribution of all the outcomes of the endogenous variables. However, it is very rarely used since standard software does not include estimation routines to estimate the Heckman estimator. Alternatively, Wooldridge (2005) has provided a simple solution to approximate the initial condition problem by specifying the distribution of the unobserved individual heterogeneity, conditional on the initial condition. The main advantage as claimed by Wooldridge is that it can be implemented using standard econometrics software. In Wooldridge estimators the distribution of the unobserved effect can be specified as follows:

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[3] This discussion is derived from Stewart (2007), the detailed discussion about this estimator can be found in Heckman (1981b)

[4] This discussion is based (Chrysanthou, 2008)

$$\varepsilon_i / y_{i1}, X_i \sim N\left(X_i'\beta + \gamma y_{it-1} + \overline{X}'a + \alpha_1 y_{i1}, \sigma_\alpha^2\right), \ X_i = \{X_{i1}, ..., X_{iT}\} \tag{14}$$

The explanatory variables for all periods under consideration are included in a row vector X_i. Generally, if the above density is allowed to depend on all elements of X_i then the way in which any time-constant exogenous variables can appear in the structural density is restricted. To increase the explanatory power, we can include time-constant explanatory variables, but we will not be able to identify separately the partial effect of the time constant variables from its partial correlation with α_i (Wooldridge, (2005): p.44). The density of the observed decision $(y_{i1}, ... y_{it})$, conditional on $y_{i1} = y_1, X_i = X$, and $\alpha_i = \alpha$, can be written as follows:

$$\prod_{t=1}^{T} \left\{ \phi\left(X_t'\beta + \gamma y_{it-1} + \alpha_1 y_{i1} + \overline{X}'a + \alpha\right)^{y_t} \left[1 - \phi\left(X_t'\beta + \gamma y_{it-1} + \alpha_1 y_{i1} + \overline{X}'a + \alpha\right)\right]^{1-y_t} \right\} \tag{15}$$

In order to find the joint distribution, we need to integrate out α_i against the Normal $\left(0, \sigma_\alpha^2\right)$. This will give the likelihood function as follows:

$$\int_R \prod_{t=1}^{T} \left\{ \phi\left(X_t'\beta + \gamma y_{it-1} + \alpha_1 y_{i1} + \overline{X}'a + \alpha\right)^{y_t} \left[1 - \phi\left(X_t'\beta + \gamma y_{it-1} + \alpha_1 y_{i1} + \overline{X}'a + \alpha\right)\right]^{1-y_t} \right\} (1/\sigma_\alpha)\phi(\alpha/\sigma_\alpha)d\alpha$$

This expression of the likelihood function is identical to the structure of the standard random effects probit model; the only difference is that the explanatory variables at time *t* now also include the initial value of the dependent variables i.e., y_{i1}. It is assumed that the data are observed for each cross-sectional unit in all time periods. Although, given a specific sample selection, mechanisms can be employed for the subset of the observations forming a balanced panel. The estimation can be carried out by adding y_{i1} and X_i as the additional explanatory variables *n* at each time period and using a computationally easy standard random affects probit software (e.g. -xtprobit- in STATA).

In this study we have estimated both Heckman and its approximation by the Wooldridge estimator to see the robustness of our results. Stewart (2007) has analyzed alternative estimators, including Heckman and Wooldridge type estimators, for dynamic discrete choice models. Their paper gives an examination of the relative merits of the Heckman, Orme and Wooldridge estimators. It also analyzes the differences between the three estimators. In the context of an empirical illustration, it uses a model of unemployment probability, after which, it presents a Monte Carlo experiment for finite sample performance.

3. Data and Descriptive Analysis

The data used in this study is drawn from Danish administrative registers supplied by Statistics Denmark to the Danish Institute of Local Government Studies (AKF)[5]. It is yearly panel data which includes the full population of immigrants in Denmark, aged 15 and above[6]. It covers approximately 20% of the immigrant population in the period from 1994 to 2003. The sample contains information on a very large number of labour market and demographic characteristics of the individuals and their families.

In order to avoid selection problems due to education and retirement, the sample is restricted to individuals between age 25 and 59 (both included). The analysis is also restricted to married or cohabiting individuals because explanatory variables include spouse information. Self-employed and wage earners have different behaviour regarding labour supply, hence the former are excluded from the sample. In order to avoid biasness due to frequent entry and exit of immigrants, we restricted the analysis on a balance panel. The final sample consists of 6767 individuals.

The disposable income of the spouse is used to capture the effect of the exogenous income on the unemployment. It is approximated by using the following expression:

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[5] I would like to thanks AKF for providing the data.
[6] The data is recorded every year in the third week of November.

Disposable Income[7] *= Personal Income + Capital Income + Family Benefits +*
Housing Benefits + Flow Value of Property – Total Taxes

Personal income is the actual taxable income of a person during the calendar year. It does not include pension or labour market contributions, tax free loans, housing transfers, child benefits, other tax free income, etc. Family Benefits mainly include child benefits or other family transfers from the government. To correct the homeowners' disposable income, so that it is comparable to that of those

Table 1 Mean Characteristics of Immigrants in Denmark 1994-2003

	Overall			Unemployed		
	All Immigrants	**Non-Western**	**Western**	**All Immigrants**	**Non-Western**	**Western**
Unemployment	0.092	0.147	0.042	1.000	1.000	1.000
Lag unemployment	0.095	0.153	0.042	0.530	0.567	0.414
Employed Spouse	0.774	0.663	0.876	0.567	0.496	0.796
Age	42.728	40.812	44.482	39.456	38.243	43.359
Children (0-2)	0.156	0.196	0.120	0.275	0.310	0.163
Children (3-6)	0.288	0.356	0.226	0.423	0.473	0.263
Children (7-9)	0.246	0.306	0.190	0.311	0.365	0.137
Country of Origin (Western)	0.522	0.000	1.000	0.237	0.000	1.000
Country of Origin Spouse (Western)	0.071	0.015	0.123	0.060	0.011	0.215
Years of experience	10.598	9.296	11.790	6.007	5.462	7.759
Unemployment insurance	0.898	0.941	0.859	0.976	0.981	0.960
Descendant	0.051	0.010	0.088	0.010	0.001	0.038
High School	0.070	0.076	0.064	0.082	0.082	0.084
Vocational Training	0.325	0.257	0.388	0.258	0.197	0.455
Post Secondary Education	0.307	0.200	0.406	0.164	0.125	0.289
Female	0.469	0.423	0.511	0.493	0.468	0.574
Permanent Disposable income Spouse*	14.165	12.978	15.251	11.036	10.866	11.584
Temporary Disposable income Spouse*	0.000	0.000	0.000	-1.105	-1.065	-1.234
Observations	51160	24450	26710	4724	3604	1120

Data Source: Registered Administrative Datasets, 1994-2003, supplied by Statistics Denmark to Anvendt Kommunal Forskning (AKF). Based on a balance panel used in this study for a sample of 20% married Immigrants aged 25 to 59 and excluding self-employed and out of labour force individuals.
* Annual income of spouse measured in Danish Kroner and divided by 10000.

renting their home, the flow value of property is calculated by multiplying the value of property with the interest rate[8]. Permanent and transitory definitions of the spouse's disposable income are used as explanatory variables to illustrate the effect of the exogenous changes in income (similar to Hyslop (1999) and Croda and Kyriazidou (2005)). The permanent income is just the average income of the individual over the years, whereas the transitory income is the annual deviation from this average.

Immigrants are sub-divided into two main categories, namely western and non-western immigrants. Statistics Denmark classifies the following as western countries: 27 EU-Countries, Iceland, Norway, Andorra, Liechtenstein, Monaco, San Marino, Switzerland, the State of Vatican City, Canada, USA, Australia and New Zealand. All other countries are classified as non-western countries. Approximately 52% of the immigrants in the sample are from non-western countries.

The dependent variable used in this study is the status of unemployment. A person is considered unemployed if he or she does not have a job, but has searched for it, and is available for work. The unemployment status and other explanatory variables are recorded in the 3rd week of November every year. The data does not include information about the duration of unemployment, so we cannot distinguish between longer and shorter unemployment spells. The lists of the explanatory variables along with the summary statistics are reported in Table 1. The table shows that 9.2% of all immigrants

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[7] Disposable income is adjusted for inflation using consumer price index with 1994 as base period.
[8] Annual bond yields (All central-government bonds and mortgage-credit bonds) are used as interest rate (It really does not matter which interest rate we use). It is taken from the website of Denmark's National Bank.

in the sample (1994-2004) are unemployed. Non-western immigrants have much higher unemployment (14.2%) compared to western immigrants (4.2%). Moreover, the comparison of individual characteristics shows that non-western immigrants are relatively young, have a high proportion of young children, a low proportion of post-secondary education, a low proportion of employed spouse and they are considerably less experienced compared to western immigrants. For example, the average age, proportion of young children, years of experience, and proportion of post-secondary education for non-western immigrants are 40.81, 0.19, 9.29, and 0.20 respectively. Whereas the equivalent figures for non-western immigrants are 44.48, 0.12, 11.79, and 0.406, respectively.

The probabilities of unemployment, conditional and unconditional on the previous unemployment status at (t-1) for various groups, are reported in Table 2 for the sample period 1994-2003. The raw unconditional probability of being unemployed for all immigrants is 9.23% in the sample. The probability of being unemployed conditional on being employed in the previous period is 4.40%, while the conditional on being unemployed in the previous period is 46.9%. In simple words, about 46.9% of the individuals who were unemployed at period *t-1* are still unemployed at period *t*. Thus, the probability of being unemployed at period t is much higher for those who were also unemployed at t-1. Hence there is a strong evidence of state dependence in unemployment.

Table 2. Conditional and Unconditional Probabilities of Unemployment

	Unconditional Probabilities (1)	Conditional Probabilities		Partial effect (4) = (3) - (2)	Probability Ratio (5) = (3) / (2)
		Employed at t-1 (2)	Unemployed at t-1 (3)		
All Immigrants	0.092	0.044	0.469	0.425	10.66
Western (42.8%)	0.042	0.024	0.382	0.358	15.92
Non-western (57.2%)	0.147	0.068	0.495	0.427	7.28
Male	0.088	0.042	0.449	0.407	10.69
Female	0..097	0.045	0.489	0.444	10.87

Columns 4 and 5 in table 2 formalise state dependence by presenting two descriptive measures. Column 4 shows the partial effect of previous year unemployment status on the probability of unemployment in the current period. Raw data shows that an individual who was unemployed at period *t-1* has about 42.5 percentage points higher probability of being unemployed again at period *t* compared to an individual who was employed at period *t*-1. Column 5 shows how many times more likely it is for those who stay unemployed in comparison to those who move into unemployment in the next period. Someone unemployed at *t-1* is more than 10 times as likely to be unemployed at *t* as someone employed at *t-1*. These partial effects and probability ratios are higher for western compared to non-western immigrants and women compared to men. These figures clearly show strong evidence of state dependence in the raw probabilities, but the question is how much of this observed state dependence is due to observed and unobserved characteristics and how much stems from true state dependence.

4. Results

The results of different models, described in the previous section, are reported and discussed in this section. First, the results for all immigrants are analysed. Second, the issue of state dependence is analysed across gender and country of origin.

The estimation results of random effects probit models for the probability of being unemployed, using different estimators are reported in Table 3. A lag dependent variable is included in all models to allow for state dependence. Yearly dummies are included to control for the time effect. Pooled probit estimates are shown in column 2 for the comparison. This model assumes the whole panel as a large cross section; therefore, it does not allow any correlation across different periods. This restrictive pooled probit model provides inefficient parameter estimates, but it is an initial consistent estimate of the parameters (Maddala, 1987).

Table 3. Estimation Results for Unemployment Probabilities of All Immigrant

Variable	Pooled Probit Coefficient (S.E)	Random effects Probit Coefficient (S.E)	Wooldridge Estimator Coefficient (S.E)	Heckman's Estimator Coefficient (S.E)
Lag Unemployment	1.004** (0.036)	0.785** (0.041)	0.750** (0.041)	0.722** (0.041)
Unemployment Status (Period 1)			0.216** (0.037)	
(Lag Unemployment) (Western)	0.243** (0.053)	0.177** (0.058)	0.172** (0.059)	0.148** (0.059)
(Lag Enemployment) (Female)	0.053 (0.046)	0.068 (0.051)	0.044 (0.051)	0.048 (0.051)
Employment status of spouse	-0.139** (0.025)	-0.151** (0.029)	-0.152** (0.030)	-0.151** (0.030)
Age	-0.086** (0.014)	-0.093** (0.017)	-0.123** (0.017)	-0.124** (0.017)
Age Squared	0.001** (0.000)	0.001** (0.000)	0.002** (0.000)	0.002** (0.000)
Children (0-2)	0.106** (0.026)	0.136** (0.029)	0.213** (0.035)	0.215** (0.036)
Children (3-6)	0.041** (0.020)	0.062** (0.023)	0.098** (0.026)	0.097** (0.026)
Children (7-9)	0.012 (0.021)	0.022 (0.024)	0.026 (0.025)	0.023 (0.025)
Contry of Origin (Western)	-0.207** (0.029)	-0.227** (0.036)	-0.177** (0.037)	-0.223** (0.038)
Country of Origin Spouse (Western)	0.046 (0.044)	0.050 (0.057)	0.026 (0.059)	0.017 (0.060)
Experience	-0.147** (0.011)	-0.198** (0.014)	-0.131** (0.015)	-0.133** (0.015)
Experience Squared	0.003** (0.001)	0.005** (0.001)	0.005** (0.001)	0.005** (0.001)
Insured	0.668** (0.053)	0.779** (0.065)	0.643** (0.093)	0.654** (0.093)
Descendant	-0.126* (0.074)	-0.150* (0.091)	-0.152* (0.093)	-0.138 (0.094)
Homeownership	-0.190** (0.024)	-0.206** (0.030)	-0.204** (0.031)	-0.195** (0.031)
High School	-0.065* (0.040)	-0.075 (0.053)	-0.042 (0.055)	-0.057* (0.056)
Post Secondary Education	-0.052** (0.026)	-0.069** (0.034)	-0.042 (0.035)	-0.060* (0.036)
Vocational Traning	-0.253** (0.030)	-0.314** (0.039)	-0.274** (0.040)	-0.311** (0.041)
Female	0.005 (0.026)	0.016 (0.032)	-0.023 (0.034)	-0.013 (0.034)
Permanent Spouse's Income /10000	-0.004** (0.002)	-0.006** (0.003)	-0.005 (0.003)	-0.004 (0.003)
Temporary Spouse's Income	0.004 (0.003)	0.005 (0.003)	0.004 (0.003)	0.005 (0.003)
Constant	0.800** (0.290)	1.058** (0.351)	1.875** (0.378)	1.988** (0.380)
σ_u		0.456** (0.023)	0.480** (0.023)	
ρ		0.172** (0.014)	0.187** (0.015)	0.204** (0.015)
θ				0.913** (0.111)

Note: - Estimation results include year dummies and arrival cohorts in all specifications.
** Parameter estimate is significant at 5% level of significance.   S.E (Standard Error)
* Parameter estimate is significant at 10 % level of significance.

The estimated degree of state dependence will be overestimated in the model, since serial dependence over time in unobserved factors is estimated as state dependence. The likelihood ratio test can be applied in random effects specification to test zero correlation over time, i.e., $\rho = 0$. The test was rejected, i.e., $\rho \neq 0$, implying that reported pooled probit estimates are rejected in favour of the random effects probit estimates.

In random-effects models the likelihood (for an independent unit *i*) is expressed as an integral, which is computed using the Gauss-Hermite quadrature. After fitting the model, the quadrature checks are undertaken, and the results show that the parameter estimates were nearly invariant to the quadrature point variation. Hence, the estimated results can be explained confidently. All models, except pooled probit models, are estimated with the assumption that the explanatory variables could be correlated with the unobserved heterogeneity (correlated random effects). This correlation is allowed by augmenting the standard random effects model with means of explanatory variables.

The argument that correlation between the initial condition and the unobserved heterogeneity results in an over-estimation of the extent of state dependence in employment is confirmed by Wooldridge's and Heckman's estimators. One of the major advantages of Wooldridge's estimator is its computational simplicity, which reduces the estimation process quite a lot, as compared to Heckman's estimator, developed by Stewart (2006)[9]. The proportion of the total error variation attributed to unobserved individual heterogeneity, ρ, was significantly higher in this estimator.

Tests of the exogeneity of the initial conditions can be performed in both Wooldridge's and Heckman's estimators. In Wooldridge estimator, the coefficient on the initial value of unemployment status is statistically significant. With regard to the Heckman estimator, the exogeneity of the initial condition requires that $\theta = 0$, which is also strongly rejected. This indicates considerable correlation between the initial condition and unobserved heterogeneity, and thus must be taken into account.

The coefficient of the lagged unemployment status is highly significant in all the estimated models. This indicates a positive state dependence in unemployment after controlling for the unobserved effects. Random effects probit and pooled probit estimates use different normalizations for identification; hence for comparison these estimates should be adjusted. Random effects use $\sigma_u^2 = 1$, and therefore the reported parameter estimates are the ratio of the true parameters with the σ_u, whereas, the reported estimated parameters of the pooled probit model are the ratio of the σ_v, as it uses the normalization $\sigma_v^2 = 1$. Hence, the random effects parameter estimates have to be multiplied by the factor $\sqrt{1 - \hat{\rho}} = \sigma_u / \sigma_v$ for the comparison (see Arulampalam (1999) for details).

The rescaled lagged unemployment coefficients in the random effects models are reduced to 0.714, 0.676 and 0.644 for the random effects, the Woodridge and Heckman estimators respectively. These results confirm that the correlation between the initial condition and the unobserved individual heterogeneity provides inconsistent pooled probit estimates and overstates the extent of the state dependence.

The magnitude of parameters in non-linear models is difficult to interpret directly; instead it can be used to calculate partial effects with respect to an explanatory variable. In discrete choice models, such as random effects probit models, these effects depend on all other parameters and levels of the explanatory variables. The inclusion of lagged dependent variable in our formulation allows us to find transition probabilities in the estimated model, i.e. we can find the probability of unemployment conditional on the unemployment status in the previous period. Table 4 shows such conditional probabilities. For comparison, column one reports the raw conditional probabilities from the observed data (already reported in table 2). The table shows that about 46.9% of the unemployed individuals at period t-1 are still unemployed at period t. This observed state dependence in unemployment is reduced by more than half in the pooled probit model where we have controlled for observed explanatory variables, but still no serial correlation in the unobserved part is allowed. State dependence further reduces to 9.7% in the random effects probit model which confirms that there is

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[9] In this study, the Heckman estimator took approximately 9 days to achieve convergence with our sample data, whereas, the Woolldridge estimator converged in 2 hours.

serial persistence in unemployment due to unobserved heterogeneity. Finally, state dependence reduces to 8.8% and 7.7% in the Wooldridge and Heckman estimators, which solves the initial condition problem. Similarly, the observed transitional probability (4.4%), i.e. the probability of unemployment in the current period conditional on being employed in the previous period, reduces to 1.2% after controlling for unobserved heterogeneity and initial condition.

Table 4: Estimated Conditional Probabilities of Unemployment

	Observed		Pooled Probit Model		Random Effect Probit		Wooldridge Estimator		Heckman's Estimator	
	Unemp t-1	Emp t-1	Unemp t-1	Emp t-1	Unemp t-1	Emp t-1	Unemp t-1	Emp t-1	Unemp t-1	Emp t-1
All Immigrants	0.469	0.044	**0.202** (0.009)	**0.023** (0.001)	**0.097** (0.008)	**0.014** (0.001)	**0.082** (0.008)	**0.012** (0.001)	**0.077** (0.007)	**0.012** (0.001)
Western	0.382	0.024	**0.207** (0.013)	**0.018** (0.001)	**0.093** (0.011)	**0.010** (0.001)	**0.081** (0.009)	**0.009** (0.001)	**0.072** (0.009)	**0.009** (0.001)
Non-western	0.495	0.068	**0.197** (0.009)	**0.030** (0.002)	**0.102** (0.009)	**0.018** (0.002)	**0.082** (0.008)	**0.015** (0.001)	**0.083** (0.008)	**0.017** (0.002)
Male	0.449	0.042	**0.195** (0.010)	**0.023** (0.001)	**0.091** (0.009)	**0.013** (0.001)	**0.080** (0.008)	**0.012** (0.001)	**0.075** (0.008)	**0.013** (0.001)
Female	0.489	0.045	**0.211** (0.011)	**0.023** (0.001)	**0.105** (0.010)	**0.014** (0.001)	**0.083** (0.008)	**0.011** (0.001)	**0.080** (0.009)	**0.012** (0.001)

* Unemp: Unemployed   Emp: Employed

The average partial effect (APE)[10] with respect to the unemployment status of the previous period is the change in the predicted probability of unemployment when lagged unemployment status changes from 0 to 1. The estimated average partial effects at average values of explanatory variables for different groups are reported in Table 5. The pooled probit model gives an average partial effect of 17.9%, less than half of the observed effect. The Wooldridge and Heckman estimators reduce the observed APE by about one-sixth, i.e. 6.9% and 6.5% respectively. An individual with a given set of observed and unobserved characteristics has about 6.5% percentage points higher probability of being unemployed again if he was unemployed at period t-1 compared to an individual who was employed at period t-1. Stewart (2007) found APE of 15 percentage points for low wage employment in UK. Similarly, Kari (2003) found an analogous effect to be 9-25% for Finland. The magnitude of predicted probability ratio (PR) shows that an individual with a given set of observed and unobserved characteristics has about 6 times higher probability of being unemployed again if he was unemployed at period t-1 compared to an individual who was employed at period t-1.

In Denmark, the unemployment rate is much higher for non-western immigrants as compared to western immigrants. There are various reasons for this which can be seen in the observed characteristics of the two groups. For example immigrants of non-western countries are less educated, have less labor market experience and have less vocational training than western immigrants. They are also different in unobserved personal characteristics, for example, religion and attitude towards work. So, the first hypothesis is to test the difference in the magnitude of state dependence for western and non-western immigrants with the assumption that both of these groups have the same observed and unobserved characteristics. This test is carried out by including an interaction term[11] of lag-unemployment status with western immigrants in the model and statistically testing the difference between average partial effects for western and non-western immigrants[12]. The standard errors are calculated using the delta method. The results show that there is no statistical difference in the APE of the previous year's unemployment status for western and non-western immigrants.

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[10] $APE = \Phi\left(\gamma Y_{t-1} = 1, X'_{it}\beta\right) - \Phi\left(\gamma Y_{t-1} = 0, X'_{it}\beta\right)$

[11] Following Ai and Norton (2003), the correct partial effect of an interaction term is obtained involving two dummy variables.

[12] $APE(Western) = \Phi\left[(Y_{t-1} = 1, western = 1, X'_{it}\beta\right] - \Phi\left[(Y_{t-1} = 0, western = 1, X'_{it}\beta\right]$

Table 5: Average Partial Effect (APE) and Probability Ratios (PR)

	Observed		Pooled Probit Model		Random Effect Probit		Wooldridge Estimator		Heckman's Estimator	
	APE	PR	APE	PR	APE	PR	APE	PR	APE	PR
All Immigrants	0.425	10.66	**0.179** (0.008)	8.78	**0.084** (0.008)	6.92	**0.069** (0.007)	6.83	**0.065** (0.007)	6.41
Western	0.358	15.92	**0.189** (0.013)	11.5	**0.083** (0.010)	9.3	**0.072** (0.009)	9.01	**0.063** (0.009)	8.00
Non-western	0.427	7.28	**0.167** (0.009)	6.56	**0.084** (0.007)	5.66	**0.067** (0.007)	5.47	**0.066** (0.007)	4.88
Male	0.407	10.69	**0.172** (0.010)	8.47	**0.077** (0.008)	7.00	**0.068** (0.007)	6.67	**0.062** (0.007)	5.77
Female	0.444	10.87	**0.188** (0.010)	9.17	**0.091** (0.009)	7.5	**0.072** (0.008)	7.55	**0.068** (0.008)	6.67

* Standard errors are reported in parenthesis.

Women's choice of labor supply is specifically influenced by various factors such as children and gender specific role in marriage. Sociological theories suggest that attitudes toward gender roles and the appropriate allocation of time between labour and non-labour market differ across religious groups, (Maneschiöld & Haraldsson, 2007). So, it would be interesting to test the difference in the magnitude of state dependence across gender. Theoretically, there is no prior expectation about this comparison; hence this is purely an empirical question. Again, the hypothesis of no difference in the partial effect of state dependence across gender is carried out under the assumption that both male and female have the same observed and unobserved characteristics. Again the results show that there is no statistically significant difference in the APE for men and women.

It is assumed that the income of the person is exogenous to the labour supply of his or her partner. In other words an individual observes his partners income before taking his participation decision. In the literature on the topic, this is not an unlikely assumption (see for example, Hyslop (1999) and Croda and Kyriazidou (2005)). The partner's income is divided into a permanent and a transitory component. The theoretical expectations about the effects of these components of income on the participation decision are explained in Hyslop (1999). He argues that transitory non-labour income has a direct effect on the labour supply (since the individual expects to have permanent income in all future periods, which is already taken into account in the first period). Hence, according to Hyslop, changes in temporary income are important determinants of the participation decision. Alternatively, in the classical labour supply model, people optimize their labour supply subject to budget constraint. Therefore, labour supply is directly affected by changes in the permanent income, whereas, changes in temporary income are only important if there are credit constraints.

In the empirical literature, the evidence of the effect of the permanent income of the spouse on labour force participation is mixed. Hyslop (1999) has found a negative effect of permanent income on the employment participation of married women in the US. Using similar methodology, Croda and Kyriazidou (2005) also found a negative effect of permanent spouse income on the participation probability of married women in Germany. Interestingly, using the same methodology, (Islam (2006)) found a statistically positive and significant effect of the permanent spouse income for married women in Sweden. The study argues that this finding may also reflect the predominant dual-income family-structure in Sweden, while Hyslop's (1999) findings reflect the U.S. single-income family-structure. All the above-mentioned studies, however, report a negative effect of temporary spouse income. In this study I found a negative effect of the permanent and a positive effect of the temporary income on the unemployment probability, but these effects are statistically insignificant.

Regarding other determinants of unemployment, a significantly negative effect is found for the linear term of age. However, on the other hand, the quadratic term of age is statistically positive. The combined effect of the linear and quadratic term of age suggests that relatively young people have a lower probability of unemployment than old people. The estimated parameters of the different levels of education show that post-secondary education and vocational training have negative effects on the unemployment probability. The results show that children of different age groups increase the probability of unemployment. Especially, pre-school age children were found to have a much stronger effect on the unemployment probability than relatively older kids. This is in accordance with the fact that young children decrease the preference for work, especially for women. The parameter estimates

for the descendent, homeownership, experience, and the employment of spouse show a negative and statistically significant effect on the unemployment probability.

5. Conclusion

The labour market behaviour of immigrants is examined in a dynamic discrete choice framework. The random effects probit specification is used for the estimation. Particular attention is paid to control for the unobserved heterogeneity and the initial condition. The specific objective is to analyze the issue of state dependence and the unobserved heterogeneity in unemployment.

The empirical findings show a considerable correlation between the unobserved heterogeneity and the initial condition. Ignoring it could result in an overstatement of the extent of the state dependence. The results show an evidence of state dependence in the unemployment behaviour of immigrants. The extent of state dependence is reduced by almost one-sixth of the observed persistence after observed and unobserved factors are controlled for. The results show that an individual (with the same observed and unobserved characteristics) who was unemployed at period *t-1* has 6.5 percentage points higher probability of being unemployed again at period *t* compared to an individual who was employed at period *t*-1. This average partial effect is the same for western compared to non-western immigrants and women compared to men.

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