# Three Essays in Labour Market Mobility

Rayhaneh Esmaeilzadeh

A Thesis

in

The Department

of

Economics

Presented in Partial Fulfillment of the Requirements

for the Degree of Doctor of Philosophy at

Concordia University

Montréal, Québec, Canada

March 2009

*Your file Votre référence*
*ISBN:* 978-0-494-63354-0
*Our file Notre référence*
*ISBN:* 978-0-494-63354-0

# ABSTRACT

Three Essays in Labour Market Mobility

Rayhaneh Esmaeilzadeh, Ph.D.

Concordia Unviersity, 2009

This dissertation contains three essays in labour market mobility. These essays employ a dynamic multinomial logit model with discrete factor approximation for the specification of unobserved individual heterogeneity and Wooldridge's approach for controlling the endogeneity problem of initial conditions. The dynamic structural of the model is assumed to follow a first order Markov process. The data is taken from longitudinal levels of Statistics Canada's Survey of Labour and Income Dynamics (*SLID*) and is restricted to males aged 25 to 55 between 1993 and 2004. I examine and discuss the importance of structural and spurious state dependence in three different aspects of labour market mobility. Relevant policy implications are discussed. The first essay compares immigrants and natives in self-employment transitions among four mutually exclusive and exhaustive states of paid-employment, self-employment, unemployment, and being out of the labour force. The second essay explores the factors explaining immigrant-native differences in stability, downward, and upward wage mobility rates. The final essay provides a comprehensive research on earnings dynamics of immigrants and natives within and between Canada and Denmark. This essay also employs Danish administrative registered dataset for the period 1994-2003. Empirical results show that state dependence exists in all states of labour market mobility with different degrees for immigrants and natives. Not all observed persistence is structural, some portion is due to the unobservable factors.

I dedicate this thesis to my parents, Tooran and Davood. Without their patience, understanding, support, and most of the love, the completion of this work would not have been possible.

# ACKNOWLEDGEMENTS

I would like to thank my adviser, Dr. Jorgen Hansen, for his enthusiasm, rich comments, kindness, constant encouragement, and availability. I would also like to thank my doctoral committee, Dr. Aretm Prokhorov and Dr. James McIntosh, for their support and guidance and their excellent feedback throughout the process. Many thanks to Graduate Program Director, Dr. Nikolay Gospodinov for his valuable comments on this research. I would like to thank my *HRSDC* colleagues, especially my director, Dr. Mokhtar Soussi, and my supervisor, Dr. Craig Eschuk for their warm supports and great cooperation at work, which helped me finish my thesis faster.

I would like to acknowledge the support of the Quebec Inter-University Centre for Social Statistics (*QICSS*) and Carleton Ottawa OUTAOUAIS Local *COOL* research data centers for their confidential data of *SLID*. I would also like to thank Dr. Michael Svarer and Dr. Henning Bunzel for the administrative registered data of Denmark.

I would like to express my gratitude to my wonderfully supportive friends, Aida, Angelina, Angelo, Behzad, Elise, Hagire, Nima, Parisa, Raha, Shideh, Sarah, Sohaila, Taravat, and Vahid.

My family has been a major source of support and love, and I would not be here if it were not for them. My special thanks to my mom, Tooran, my dad, Davood, my siblings, Tahmineh and Mohammad-Reza, and my brother-in-low, Arash. A big thank to my little nephew, Kian, for his sweet and beautiful smile.

| | |
|---|---|
| Praise Lord of Life, God the Wise | به نام خداوند جان و خرد |
| A worthier notion shall not arise | کزین برتر اندیشه برنگذرد |
| The God of fame in whom powers reside | خداوند نام و خداوند جای |
| Provider, Sustainer, the Ultimate Guide. | خداوند روزی ده رهنمای |
| Creator of the world & the orderly universal run | خداوند کیوان و گردان سپهر |
| The light giver to the Moon, Mercury and Sun. | فروزنده ماه و ناهید و مهر |
| Transcends all name, label and notion | ز نام و نشان و گمان برتر ست |
| Is the author of form and motion | نگارنده ی بر شده پیکر ست |
| Capable is he who is wise | توانا بود هر که دانا بود |
| Happiness from wisdom will arise. | ز دانش دل پیر برنا بود |

The Epic of the Kings, by Ferdowsi, Persian poet (935-1020), translated by Sh. Shahriari

شاهنامه فردوسی

# TABLE OF CONTENTS

# List of Tables

# List of Figures

# List of Symbols and Abbreviations

| | |
|---|---|
| AIC | Akaike Information Criteria |
| BIC | Bayesian Information Criteria |
| ARMA | Auto Regressive Moving Averages |
| ARUM | Additive Random-Utility Model |
| CPI | Consumer Price Index |
| CPS | Current Population Surveys |
| EEA | Employment Equity Act |
| EEA | European Economic Area |
| EI | Employment Insurance |
| GSOEP | German Socio-Economic Panel |
| IMDB | Longitudinal Immigration Database |
| LAD | Longitudinal Administrative Data |
| LMDG | Labour Market Dynamic Growth |
| MLE | Maximum Likelihood Estimation |
| NLSY | National Longitudinal Survey of Youth |
| OLS | Ordinary Least Square |
| PACO | Panel Comparability |
| PSID | Panel Study of Income Dynamics |
| QMR | Quintile Mobility Rates |
| SA | Social Assistance |
| SCF | Canadian Survey of Consumer Finances |
| SLID | Survey of Labour and Income Dynamics |
| WDI | World Development Indicators |

# Chapter 1

# Introduction

## 1.1 Contribution

This dissertation examines the importance of structural and spurious state dependence in observed persistence of three labour market processes: self-employment entry and exit decision, wage mobility, and earnings dynamics. These processes are in the front line of Canada's labour market mandates. For example, based on the study by Frenette (2002), self-employment has been growing in Canada since the 1990s. Compared to natives, immigrants are more likely to be self-employed and this likeliness has been increasing over time. There has been a discussion if the self-employment rate changes amongst immigrants and natives over time can be explained by the net entry-exit rate; and to what extent the entry-exit rate is due to the structural factors. Furthermore, it is of a great interest to examine significant factors affecting the probability of being self-employed in relation to the other labour market states. Studying wage mobility has also its own merit. It is believed that higher earnings mobility can reduce long-run income inequality (Friedman, 1962). As income inequality has increased in Canada over the period 1984-2004 (CANSIM, Table 202-0705), as well the economic fortunes of immigrants in Canada in

the recent years have declined (Ostrousky, 2008), analyzing factors affecting income inequality in Canada through a wage mobility process and separately for immigrants and natives would be motivating. Cross-country studies are always appealing for economists and policy makers. In the last essay, I compare immigrant-native earnings dynamics within and between Canada and Denmark. Danish and Canadian labour markets are very different in many aspects, such as immigration in Denmark is dominated through non-labour immigrants, whereas Canada has a very long history of labour immigrants. Further, compared to Canada, Denmark has the higher female labour force participation rate, higher replacement ratio of unemployment benefits for low wage earners, and relatively widespread eligibility for the unemployment benefit (Eriksson and Westergaard-Nielsen, 2007). Therefore, this study has also its own value.

The empirical model employed in this thesis has a dynamic non-linear nature that controls for both unobserved heterogeneity factors and endogenous initial conditions problem (spurious effects). According to Heckman (1981a), ignoring the effect of unobserved heterogeneity factors in observed persistence inflates the degree of state dependence and hence leads to erroneously policy making decisions. Heckman's approach (1981b) also pointed out the importance of controlling for the initial conditions problem in estimation of state dependence parameters in dynamic non-linear models. The phenomena discussed in this thesis exhibit serial persistence over time and therefore need a careful dynamic analysis considering both unobserved heterogeneity and endogenous initial conditions.

This is a panel-data study which analyzes individuals' flow rates into and out of labour market states over time. In order to distinguish between structural and spurious state dependence, longitudinal data with large cross-sectional sample size is required.

Given the content above, the outcome of this dissertation would be a valuable and reliable resource that benefits policy-makers in Canada and many other countries with similar labour market patterns.

## 1.2 Unobserved Heterogeneity and Initial Conditions Problem

Persistence in any labour market states can be a product of some unobserved individual heterogeneity, structural state dependence, and significant observable characteristics. Exploring the main reasons of persistence in any states of the labour market is essential in order to properly estimate the parameters of interest in dynamic analysis frameworks.

Following Heckman (1981a), the past experience may be a proxy for the temporally persistent of unobserved variables that gives rise to a conditional relationship between future and past experiences. Individuals may differ in certain unmeasured variables that influence their probability of experiencing the event but are not influenced by the experience of it. If these variables are correlated over time and are not properly controlled, the previous experience may appear to be determinant of the future experience only because it is a proxy for such temporally persistent unobserved variables. Improper treatments of unmeasured variables give rise to a conditional relationship between future and past experience that is termed spurious state dependence. State dependence is true or structural, if the past experience has a real effect on probability of observing the individual in a given current state.

If the observed persistence is true (structural state dependence), then changing labour market policies may be more effective in attracting individuals towards any labour market states. If the persistence is due to the permanent unobserved characteristics (spurious state dependence), then changing the nature of market policies

will have little real effect on labour market states. Based on the recent study by Brodaty (2007) on American earnings dynamics, public policies should act on both dimensions of state dependence (structural and spurious) to reduce income inequality. For example, human capital policies can be implemented to improve unobserved heterogeneity of the individuals who are unemployed or attracted towards the lower parts of the earnings distribution. On the other hand, it could be desirable to act on structural state dependence in order to make it more mobile, but it requires to give an economic meaning to state dependence in earnings mobility.

Initial conditions are typically assumed to be truly exogenous variables. According to Heckman (1981b), this assumption is valid only if the disturbances that generate the processes are serially independent; this is not the case in dynamic models. Therefore, treating initial conditions as exogenous variables yields biased and inconsistent parameter estimates. Assuming initial stationary process (steady state) as an alternative to the initial conditions problem may lead to a suitable solution of the problem, but this assumption is also unattractive in many applications, for example, when the time varying exogenous variables drive the stochastic process.

According to Chay and Hyslop (2000), there is a systematic commonality in the observed dynamics of some discrete processes such as social assistance, labour force participation, consumer purchases, and firm entry and exit decisions. Controlling for both unobserved characteristics and initial conditions problem is essential in order to properly estimate structural state dependence in these processes. For example, Hansen, Lofstorm, and Zhang (2006) analyze the transitions into and out of social assistance in Canada using a dynamic probit model, controlling for endogenous initial conditions problem and unobserved heterogeneity factors. Arulampalam, Booth, and Taylor (1998) estimate dynamic panel data models of the unemployment incidence of British men, in order to distinguish between the effects of unobserved individual heterogeneity and true state dependence.

## 1.3 Survey of Labour and Income Dynamics (*SLID*)

In order to distinguish between true and spurious state dependence and so control for unobserved individual heterogeneity and initial conditions problem, longitudinal levels of Statistics Canada's Survey of Labour and Income Dynamics (*SLID*) with a large cross-sectional sample size are required. Although public use files of *SLID* exist, the longitudinal dimension (two years) is not sufficient for the research.

In *SLID*, the focus extends from static measures to the whole range of transitions, durations, and repeat occurrences of people's financial and work situations. A relatively large sample size of micro-data is required as it is more representative of the total population in the survey.

*SLID* has three complete and one incomplete longitudinal data. Each complete panel covers six years for almost 15,000 households which is a suitable source of data for this research. A new panel of longitudinal respondents is selected every three years, so there is always an overlap between two panels of respondents.

The estimation results of the dynamic model in all three essays are based on annual longitudinal data of males who are between 25 and 55 years old between 1993 and 2004. The reason for such restriction is that men in this age group are less likely to be affected by the secular increases in participation rates, experience, or school attendance. The dynamic models examine annual data from the first three panels of *SLID*. The first panel is from December 1992 to the end of 1998, the second is from December 1995 to the end of 2001, and the third is from December 1998 to the end of 2004. The unit of analysis is the household to which the respondent belonged as of December 31 of the reference year.

# Chapter 2

# Essay I: A Dynamic Analysis of Canadian Male Self-Employment

## 2.1 Introduction

Self-employment has been growing substantially in both Canada and the United States since 1979. The growth of total self-employment[1] was much greater in Canada (around 75 percent) than in the United States (around 37 percent) over the period 1979-1997. The self-employment rate[2] has remained relatively constant (around 10 percent) in the United States since the 1990s, but it has largely increased in Canada (between 14 and 18 percent)(Manser and Picot, 1999a).

Based on an empirical study by Kuhn and Schuetze in 2001, the growth rate of unincorporated self-employment for Canadians aged 25 to 54, rose dramatically from 6.8 percent in 1982 to 9.5 percent in 1998. The male self-employment rate increased from 8.1 percent in 1982 to 11 percent in 1998. For females these figures were 5 and 7.8 percent in 1982 and 1998, respectively.[3]

[1]Incorporated plus unincorporated businesses with and without paid help.

[2]Ratio of self-employment to total employment. Total employment is the total of self-employment and paid-employment.

[3]These figures exclude individuals working in primary industries such as agriculture, forestry,

A monthly Labour Review of Statistics Canada (Manser and Picot, 1999b) examines the self-employment rate separately for men and women and as a whole for different categories of age, education, occupation, and industry for the years of 1979, 1989, and 1996. Based on this study, the men's self-employment rate was higher than the women's for each category and each specific year. However, the growth rate of women's self-employment was much greater than that of men's.[4]

A joint study by Nadja Kamhi and Danny Leung in 2005 shows that the self-employment rate[5] for Canadians aged 15 and over, fell to 15.2 percent in 2002 after reaching a peak of 17.3 percent in 1998. The rise and fall in self-employment was highly concentrated among unincorporated businesses and own-account self-employed. Changes in own-account self-employment (the self-employed without employees) accounted for the entire increase in the self-employment rate, and for the 60 percent decline. Based on this research, younger workers (aged 15 to 25) of both genders and older females (aged 55 and over) contributed to the decline, whereas the self-employment rate for older males hardly changed.

As seen, the pattern of the self-employment rate varied across all age and gender groups in the 1990s. The level and pattern of the self-employment rate also varied among immigrants and natives and changed from the 1980s to the 1990s. Male immigrants aged 20 to 59, who arrived in Canada in the 1990s, were more likely to be self-employed in unincorporated businesses than those who arrived in the 1980s, according to an empirical study by Frenette in 2002. In 1981, around 8 percent of male immigrant workers were self-employed. By 1996, this proportion had almost doubled to 14. The self-employment rate rose much faster among recent immigrant workers than among Canadian-born workers even after accounting for differences in

fisheries, and mining. self-employment refers to an individual's main job, and to unincorporated business only.

[4]The self-employment rates for men aged 16 and over were 13.2, 13.3, and 13 percent in 1979, 1989, and 1996, respectively. The equivalent figures for the women were 5.5, 6.9, and 7.6 percent.

[5]The self-employment rate here, includes unpaid family workers, unincorporated and incorporated businesses.

education, age, family composition, visible minority status, and geography.

What factors explain such behaviours? Are there any significant explanatory variables affecting people's propensity to be self-employed (rather than to be paid-employed, unemployed, or out of the labor force), or is it largely the product of some unobserved heterogeneity factors, individual's background, history of self-employment, or inertia?

To my knowledge, most previous studies of self-employment do not examine the dynamic transition into and out of self-employment, controlling for the unobserved individual heterogeneity and endogenous initial conditions problem. For example, Schuetze (2000) uses stock data of the Canadian Survey of Consumer Finances (*SCF*) and the U.S. Current Population Surveys (*CPS*) to examine the role of macroeconomic conditions and the income tax environment in explaining male self-employment trends in non-primary industries[6] in Canada and the United States for the period 1983-1994. He estimates a linear probability model by the Ordinary Least Square (*OLS*) method using the pooled cross-section time-series data for Canada and the United States combined with the province/state tax levels and unemployment rates data. He does not use the flow data of individuals in his analysis. Another empirical study by Kuhn and Schuetze (2001) analyzes the dynamics of male and female self-employment choices using the longitudinal data from the *SCF* for the period 1982-1998. It examines the flow rates into and out of unincorporated self-employment and estimates the steady-state rates of self-employment for Canadians aged 25 to 54, but disregards the effect of observed persistence due to unobserved individual heterogeneity.

This essay specifically examines the effect of both unobserved individual heterogeneity and observed structural persistence on the flow rate into and out of any

[6]Primary industries consist of agriculture, forestry, fisheries, and minings. The rest of industries are considered as non-primary industries.

of the four labour market states of self-employment, paid-employment, unemployment, and being out of the labour force, among Canadian males as a whole and separately for immigrants and natives. As well, this research examines the effect of labour market conditions on probabilities of being self-employed, paid-employed, unemployed, and out of the labour force. Given the content above, my goal in this essay is to answer the following questions:

1. What are the determinants of the transitions into and out of different labour market states?

2. Do the probabilities of transitions differ between immigrants and natives? If so, are these differences due to entry-exit rate gaps between immigrants and natives?

3. What are the proportions of spurious and structural state dependence in labour market states and how are they different between immigrants and natives?

4. How economic conditions improvement (or deterioration) affect probability of being self-employed among immigrants and natives?

5. What are the policy implications of the form of structural and spurious state dependence to encourage (or discourage) self-employment?

In this essay, I study men's (aged 25 to 55) self-employment rate rather than women's, who are less likely to be self-employed in Canada (Manser and Picot, 1999b). I calculate the percent distribution of labour market outcomes in Canada as a whole and separately for immigrants and natives over the period 1993-2004. I compare and analyze observed and estimated transition matrices and confine my analysis to entry-exit rates into and out of any of the four states of self-employment, paid-employment, unemployment, and being out of the labour force.

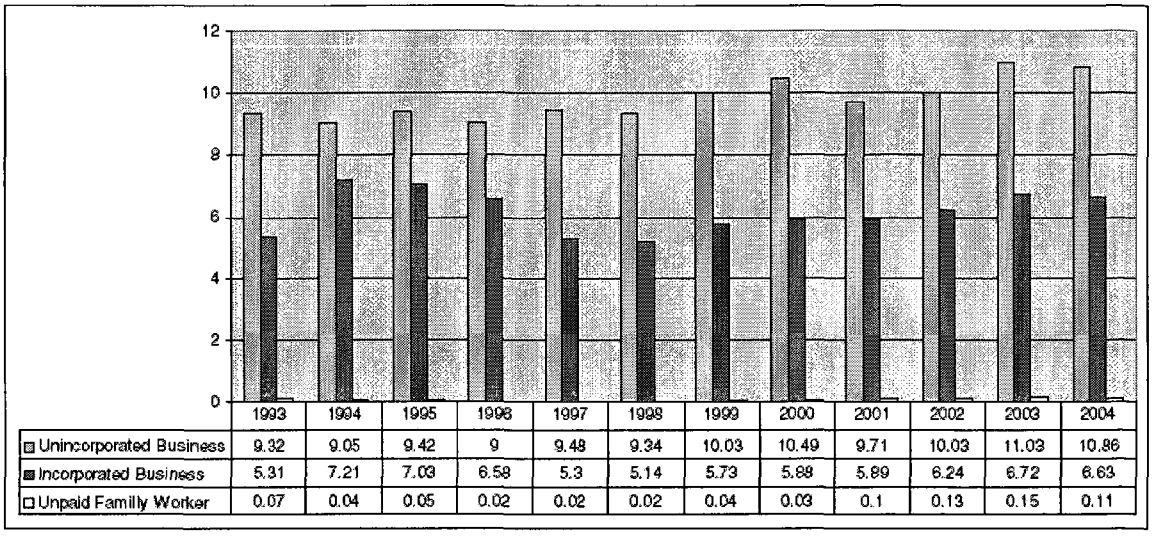
The observed data shows that persistence in self-employment is slightly higher among immigrants than among natives. Estimation results, on the other hand, indicate that this persistence is not highly structural. About 58 and 68 percent of the observed persistence is due to the unobserved effects for immigrants and natives, respectively. Compared to natives, immigrants were always more likely to be self-employed over the period 1994-2004. The gap between immigrants' and natives' self-employment rates is narrowing over the same period. The estimated entry-exit rates suggest that the immigrant-native gap in self-employment participation is due to a combination of both higher entry and lower exit rates among immigrants than similar natives. Further, the pattern of self-employment rates among immigrants and natives reveals that compared to natives, immigrants are more responsive to the variation in the unemployment rate. Estimation results show that immigrants are more likely to be self-employed in times of high unemployment rates. All state dependence parameters are positive and statistically significant.

The rest of the essay is organized as follows. Section 2.2 describes the data and descriptive statistics. Section 2.3 presents an empirical specification of the dynamic model, and section 2.4 reports the empirical results.

## 2.2 Data and Descriptive Statistics

As mentioned earlier in this thesis, the structural estimate of the dynamic model is based on annual data of the first three panels of *SLID*. I restricted the sample to males aged 25 to 55. A man is self-employed if his classification for the primary job in the reference year, as specified in the job characteristics section of *SLID*, is of the business type- incorporated or unincorporated- with or without paid help. I ignore the effect of unpaid-family workers in my analysis. Only a small fraction of self-employed workers in Canada are unpaid-family workers (Figure 2.1). I use

Figure 2.1: Trends in Self-employment (*Unincorporated, Incorporated, and Unpaid Family Workers*), Canada 1993-2004




| | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Unincorporated Business | 9.32 | 9.05 | 9.42 | 9 | 9.48 | 9.34 | 10.03 | 10.49 | 9.71 | 10.03 | 11.03 | 10.86 |
| Incorporated Business | 5.31 | 7.21 | 7.03 | 6.58 | 5.3 | 5.14 | 5.73 | 5.88 | 5.89 | 6.24 | 6.72 | 6.63 |
| Unpaid Family Worker | 0.07 | 0.04 | 0.05 | 0.02 | 0.02 | 0.02 | 0.04 | 0.03 | 0.1 | 0.13 | 0.15 | 0.11 |

**Note:** Source: Survey of Labour and Income Dynamics (*SLID*), 1993-2004, based on a sample of males aged 25 to 55. The figures are weighted with longitudinal weight variables provided by Statistics Canada in *SLID*.

the class of worker variable[7] of *SLID* in the reference year to determine if a man is self-employed in his main job. The main job for the year is defined as the one with the most paid hours in the year. If hours are identical between two jobs, the main job is the one with the greatest earnings or the longest tenure (if earnings are identical). The labour force status variable of *SLID* does not distinguish between self-employment and paid-employment status and considers both as employment. To distinguish between these two states, I used the class of worker variable along with the labour force status variable.

To control for the local labour market conditions where the individual resides, the dynamic model includes information on provincial unemployment rates extracted form CANSIM, Table 282-0055.[8] In addition to provincial unemployment rates, the model also controls for marital status, educational attainment, immigration

[7]The data provided for this variable is in concordance with the income information.

[8]CANSIM is Statistics Canada's key socioeconomic database.

status, parental background, and wealth. To see if expected wages of being self-employed versus being a paid-employee has a significant effect on probability of being in any labour market states, the model includes information on differences between predicted log-wages of being self-employed and paid-employed.[9]

To find if a man is married (or common-law), I use the marital status variable of *SLID*. I consider the number of years of schooling completed by a man at the time of entry to the panel as a proxy for his educational attainment.[10] To remove outliers, I consider only observations with the years of education greater than (or equal to) six years. For immigration status, I use a dummy variable indicating if a man is an immigrant at the time of entry to the panel.[11] I use the highest level of education completed by the man's father and mother as proxies for the parental background at the time of entry to the panel. A man's parents are educated if they have obtained at least a college diploma or a university degree. I use the investment income variable of *SLID* as a proxy for wealth in my estimation to see if a man has a positive investment income. Investment income includes actual amount of dividends (not taxable amount), interest, and other investment income, such as net partnership income and net rental income.

Table 2.1 presents the sample characteristics of 8651 males aged 25 to 55 for the period 1993-2004. As shown, almost 15.9 percent of males are self-employed in the sample and the rest are paid-employed, unemployed, or out of the labour force. Almost 74.7 percent of males are married and 11.9 percent are immigrants. The average rate of the provincial unemployment rate is close to 8.7 percent. Moreover, the average years of schooling is around 13.9 years. Almost 16.6 percent (and 14.6

[9]More details on how to derive this variable are provided in the model and empirical specification section.

[10]In this essay, educational attainment is measured by years of schooling. Alternatively, this could have been measured with indicator variables representing highest degree completed.

[11]There may be heterogeneity among different classifications of immigrants (independent, family, and refugee) in Canada. However, *SLID* does not have any information about different groups of immigrants in Canada.

Table 2.1: Descriptive Statistics of Males, Canada 1994-2003

| Variables | | Mean |
|---|---|---|
| Labour Market States | Self-Employment [1] | 0.159 |
| | Paid-Employment | 0.774 |
| | Unemployment | 0.025 |
| | Being Out of the Labour Force | 0.042 |
| Observed Characteristics | Married [2] | 0.747 |
| | Years of Education | 13.894 |
| | Immigrant | 0.119 |
| | Father Educated [3] | 0.166 |
| | Mother Educated [3] | 0.146 |
| | Positive Investment Income [4] | 0.297 |
| | Unemployment Rate | 8.652 |
| | Number of Observations | 51906 |
| | Number of Individuals | 8651 |

**Note:** Source: Survey of Labour and Income Dynamics (*SLID*), 1993-2004 for males aged 25-55. The figures are weighted with longitudinal weight variables provided by Statistics Canada in *SLID*.

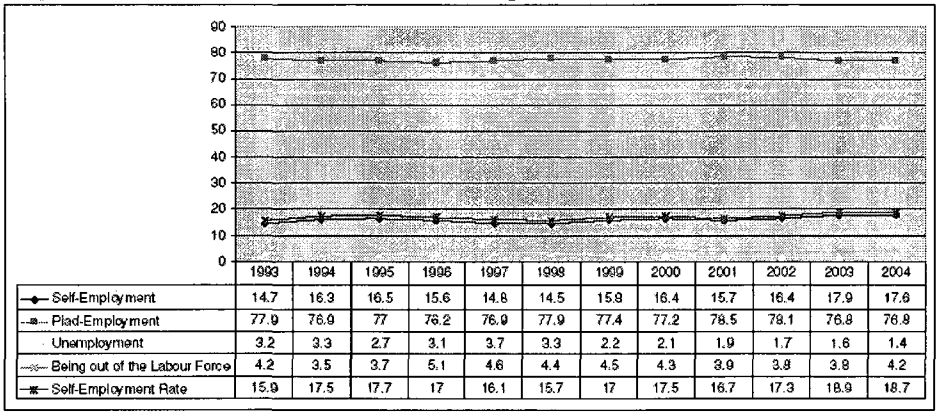
1. Incorporated plus unincorporated businesses with and without paid help.
2. Married or common-law.
3. If father (mother) has at least college diplomas or university degrees.
4. If a man has positive investment income (i.e. actual amount of dividends (not taxable amount), interest, and other investment income, such as net partnership income and net rental income).

percent) of males have educated fathers (and mothers) with at least college diplomas or university degrees. Almost 29.7 percent of males have positive investment incomes.

Figure 2.2 depicts trends in the labour market outcomes along with the average self-employment rate for the period 1993-2004. The self-employment rate varied between 15 and 19 percent over the period 1993-2004 with a rate increasing to 18.7 percent in 2004. The self-employment rate dropped to 15.7 percent in 1998 after reaching the peak of 17.7 percent in 1995.

Figure 2.3 shows the average self-employment rate separately for immigrants

Figure 2.2: Trends in Labour Market Participation, Canada 1993-2004

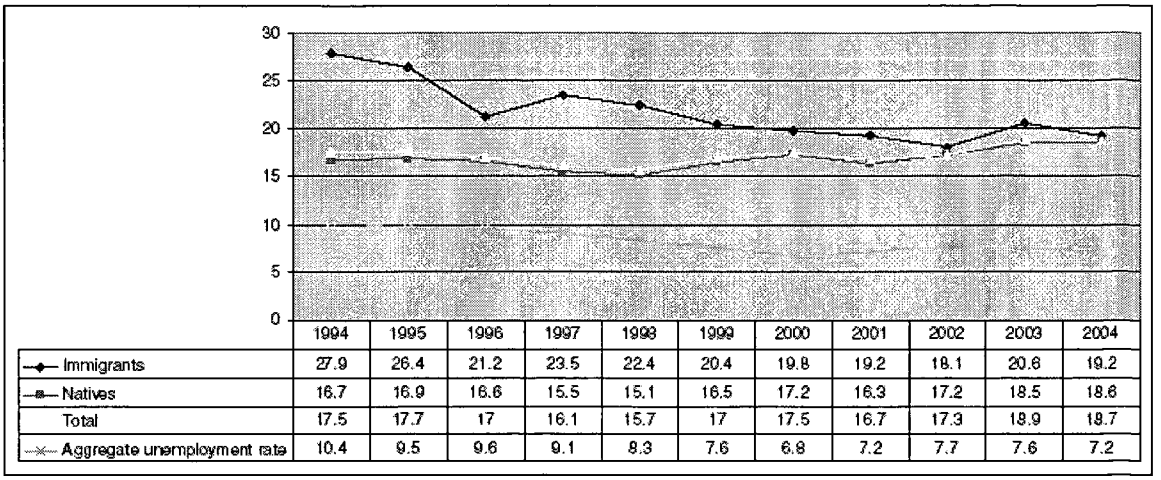



| | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Self-Employment | 14.7 | 16.3 | 16.5 | 15.6 | 14.8 | 14.5 | 15.9 | 16.4 | 15.7 | 16.4 | 17.9 | 17.6 |
| Paid-Employment | 77.9 | 76.9 | 77 | 76.2 | 76.9 | 77.9 | 77.4 | 77.2 | 78.5 | 78.1 | 76.8 | 76.9 |
| Unemployment | 3.2 | 3.3 | 2.7 | 3.1 | 3.7 | 3.3 | 2.2 | 2.1 | 1.9 | 1.7 | 1.6 | 1.4 |
| Being out of the Labour Force | 4.2 | 3.5 | 3.7 | 5.1 | 4.6 | 4.4 | 4.5 | 4.3 | 3.9 | 3.8 | 3.8 | 4.2 |
| Self-Employment Rate | 15.9 | 17.5 | 17.7 | 17 | 16.1 | 15.7 | 17 | 17.5 | 16.7 | 17.3 | 18.9 | 18.7 |

**Note:** Source: Survey of Labour and Income Dynamics (*SLID*), 1993-2004 for males aged 25-55. The figures are weighted with longitudinal weight variables provided by Statistics Canada in *SLID*.

and natives along with the aggregate unemployment rate. I use the class of worker in the reference year to clarify if a person is self-employed in his main job in either incorporated or unincorporated businesses with and without paid help. The information provided for this variable in *SLID* is in concordance with the income information that may change during the processing and can be different than the one provided by the respondent. Considering these criteria, I expect that the levels and trends of self-employment rates depicted in these figures are slightly different from the ones released by other researchers so far for Canada (See for example: Manser and Picot (1999b), Kuhn and Schuetze (2001), Kamhi and Danny Leung (2005)). The pattern of the self-employment rate among immigrants and natives indicates that immigrants are more responsive to the variation in the unemployment rate than natives. As seen, immigrants and natives behave differently with respect to unemployment rate changes. The unemployment rate decreased substantially during the period 1994-2000 and then slightly increased in the subsequent period 2000-2004. The gap between immigrants' and natives' self-employment rate has been narrowing gradually during the period 1994-2004. Immigrants' self-employment rate was always higher than natives' over the period 1994-2004. Natives' self-employment

Figure 2.3: Trends in Average Self-Employment Rate by Immigrants and Natives, Canada 1993-2004




| | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Immigrants | 27.9 | 26.4 | 21.2 | 23.5 | 22.4 | 20.4 | 19.8 | 19.2 | 18.1 | 20.6 | 19.2 |
| Natives | 16.7 | 16.9 | 16.6 | 15.5 | 15.1 | 16.5 | 17.2 | 16.3 | 17.2 | 18.5 | 18.6 |
| Total | 17.5 | 17.7 | 17 | 16.1 | 15.7 | 17 | 17.5 | 16.7 | 17.3 | 18.9 | 18.7 |
| Aggregate unemployment rate | 10.4 | 9.5 | 9.6 | 9.1 | 8.3 | 7.6 | 6.8 | 7.2 | 7.7 | 7.6 | 7.2 |

**Note:** Source: Survey of Labour and Income Dynamics (*SLID*), 1993-2004 for males aged 25-55. The figures are weighted with longitudinal weight variables provided by Statistics Canada in *SLID*.

rate and the unemployment rate moved almost in opposite directions over the period 1994-2004. They were only the periods 1996-1998 and 2001-2002, in which the native's self-employment and unemployment rates moved almost in the same directions. Immigrants' self-employment rate decreased gradually over the period 1994-2004, with a considerable jump-down in 1996 and a rate declining to 18.1 percent in 2002. No noticeable pattern of self-employment and unemployment rate changes has been observed among immigrants over the period 1994-2004. It was only the period 1997-2000, in which self-employment and unemployment rates moved in largely the same direction. Different behaviours of immigrants and natives with respect to unemployment rate changes during the period 1994-2004 suggest that cyclical factors alone can not explain the rise and decline of the self-employment rate among either immigrants or natives.

Tables 2.2 and 2.3 report transition probability matrices for the whole sample and separately for immigrants and natives. In these tables, I examine the issue of state dependence in the raw data. The observed data shows a high persistence of self-employment and paid-employment among males aged 25 to 55. However,

Table 2.2: Transition Matrix, Conditional Probabilities of Leaving Previous Year's State, Canada 1993-2004

| Origin State | Destination State | | | |
|---|---|---|---|---|
| | Self-Employment | Paid-Employment | Unemployment | Being out of the Labour Force |
| Self-Employment | **0.891** | 0.100 | 0.005 | 0.004 |
| Paid-Employment | 0.020 | **0.962** | 0.009 | 0.009 |
| Unemployment | 0.051 | 0.322 | **0.535** | 0.091 |
| Being out of the Labour Force | 0.030 | 0.144 | 0.068 | **0.758** |

this persistence is not very different between immigrants and natives (Table 2.3). Compared to natives, persistence in self-employment is slightly higher among immigrants. Persistence in unemployment is not very high for the whole sample (and for immigrants and natives separately). Persistence in unemployment is higher among immigrants than among natives, while natives have slightly higher persistence in being out of the labour force state than immigrants. Further, about 32.2 percent of males move from unemployment to paid-employment in consecutive years. Looking at immigrants and natives separately, almost 24.1 percent of immigrants move from unemployment to paid-employment in consecutive years. The equivalent transition probability for natives is close to 34.6 percent; which is higher than that for immigrants. The probability of being self-employed next year, if being in any state of paid-employment, unemployment, or out of the labour force this year, is higher among immigrants than among natives. Natives are more likely than immigrants to find a job (and less likely to be unemployed) next year if they are out of the labour force this year. Persistence of being out of the labour force is slightly higher among natives than among immigrants. Natives are less likely than immigrants to lose their jobs and be unemployed next year if they are paid-employed this year.

Table 2.3: Transition Matrix, Conditional Probabilities of Leaving Previous Year's State by Immigrants and Natives, Canada 1993-2004

| Origin State | Destination State | | | |
|---|---|---|---|---|
| | Self-Employment | Paid-Employment | Unemployment | Being out of the Labour Force |
| **Immigrants** | | | | |
| Self-Employment | **0.905** | 0.088 | 0.003 | 0.004 |
| Paid-Employment | 0.021 | **0.959** | 0.012 | 0.007 |
| Unemployment | 0.061 | 0.241 | **0.669** | 0.029 |
| Being out of the Labour Force | 0.049 | 0.097 | 0.106 | **0.748** |
| **Natives** | | | | |
| Self-Employment | **0.888** | 0.102 | 0.005 | 0.004 |
| Paid-Employment | 0.020 | **0.962** | 0.008 | 0.009 |
| Unemployment | 0.048 | 0.346 | **0.495** | 0.110 |
| Being out of the Labour Force | 0.027 | 0.151 | 0.063 | **0.759** |

One of objectives of this paper is to study the factors affecting transitional rates into and out of any of the four labour market states. To do this, I calculate the mean characteristics of Canadian males aged 25 to 55 for different transitional states. Table 2.4 provides this information. This table does not cover all possible transitions into and out of any of the four labour market states. For the sake of simplicity, I have only reported the four cases that are most relevant to my study. It appears that any persistence in self-employment is associated with being immigrant, being married, being educated, having a considerably high positive investment income, and living in provinces with relatively low unemployment rates. A man who enters the self-employment from the paid-employment is likely to be immigrant, be married, be educated, and have educated parents. Regarding the transition from self-employment into paid-employment, it appears to be associated with being married, having a significantly high level of education, having

educated parents, and living in provinces with relatively low unemployment rates. Compared to other transitions, men who move into the unemployment from the self-employment appear to be less immigrant, less married, less educated, and live in provinces with higher unemployment rates. Noticeably low investment incomes have been observed in transition from self-employment into unemployment. Accessibility to investment income (liquidity constraint) appears to be a determinant of transition into and out of self-employment, as observed data shows. There has been a discussion if and how liquidity constraints affect self-emolument decisions. The study by Hurst and constraint (2004) on liquidity constraints and self-employment decision shows that liquidity constraints are important causal effects of entry into self-employment. Their results demonstrate that the oft-cited positive relationship between entry rates and assets is actually unchanging as assets increase from the 1st to the 95th percentile of the asset distribution, but rise considerably after this point. Fairlie and Krashinsky (2006) revised Hurst and Lusardi's (2004) paper and demonstrates that self-employment decision of workers who enter the self-employment after job loss and those who do not, should be analyzed separately. This is due to the fact that these two groups face different incentives, and thus have different solutions to the entrepreneurial decision (Evans and Jovanovic, 1989). Entry rates into self-employment increase steadily as assets rise for each sub sample, indicating that liquidity constraints is an important issue for individuals who are considering starting businesses.

## 2.3 Model and Empirical Specification

To analyze transitions into and out of different labour market states, I choose a dynamic unordered multinomial logit model.[12] I analyze the dynamic structure of

[12]It has been discussed by Cameron and Trivedi (2005) that when there is a natural ordering of alternatives, a much more parsimonious model and sensible model is the one that takes account of the ordering. However, in this essay, it is not obvious that outcomes are ordered, so a multinomial

Table 2.4: Mean Characteristics by Different Labour Market Transitions, Canada 1993-2004

| **Observed Characteristics** | **Persistence in** Self-Employment | **Transition from** | | |
|---|---|---|---|---|
| | | Self-Employment to Paid-Employment | Self-Employment to Unemployment | Paid-Employment to Self-Employment |
| Married | 0.824 | 0.772 | 0.606 | 0.744 |
| Years of Education | 13.758 | **14.292** | 12.444 | 13.956 |
| Immigrant | **0.141** | 0.122 | 0.075 | **0.114** |
| Father Educated | 0.165 | 0.212 | 0.247 | 0.194 |
| Mother Educated | 0.142 | 0.197 | 0.121 | 0.175 |
| Positive Investment Income | **0.406** | 0.286 | **0.063** | 0.290 |
| Unemployment Rate | 8.279 | 8.523 | **9.855** | 8.489 |
| Number of Observation | 6278 | 714 | 36 | 722 |

the model as a first-order Markov process.[13] Let assume that individual $i$ belongs to state (alternative) $k$ at time $t$. I suppose that utility $V^*_{ikt}$ is the sum of a deterministic component, $U_{ikt}$, that depends on regressors and unknown parameters, and an unobserved random component $\epsilon_{ikt}$:

$$V^*_{ikt} = U_{ikt} + \epsilon_{ikt} \tag{2.1}$$

This is called an Additive Random-Utility Model ($ARUM$). I observe the outcome $Y_{it}$= $k$ if alternative $k$ has the highest utility of the alternatives. It follows that:

$$Pr(Y_{it} = k) = Pr(V^*_{ikt} \geq V^*_{ijt}) = Pr(V^*_{ijt} - V^*_{ikt} \leq 0), forall j \tag{2.2}$$

and given (2.1),

$$Pr(Y_{it} = k) = Pr(\epsilon_{ijt} - \epsilon_{ikt} \leq U_{ikt} - U_{ijt}), \tag{2.3}$$

Now assume that individuals indexed by $i$ ($i$= $1, 2, \ldots, N$) belong to any of the following four mutually exclusive and exhaustive states (alternatives) of $k$ at time $t$ ($t$= $1, 2, \ldots, T$): self-employment ($k_t$ = $1$), paid-employment ($k_t$ = $2$), unemployment ($k_t$ = $3$), and being out of the labour force ($k_t$ = $4$). Let the value for individual $i$, of belonging to state $k$ at time $t$ ($U_{ikt}$) be specified as:

$$U_{ikt} = X_{it}.\beta_{1k} + E_{it}.\beta_{2k} + L_{it}.\beta_{3k} + D_i.\beta_{4k} + I_{it}.\beta_{5k} + Z_{it}.\gamma_k \tag{2.4}$$

and given (2.1), $V^*_{ikt}$ can be written as:

$$V^*_{ikt} = X_{it}.\beta_{1k} + E_{it}.\beta_{2k} + L_{it}.\beta_{3k} + D_i.\beta_{4k} + I_{it}.\beta_{5k} + Z_{it}.\gamma_k + \epsilon_{ikt} \tag{2.5}$$

logit model seems appropriate.

[13]To find a more general model one can consider the dynamic structure as a higher order Markov process. It leads to the more flexible dynamic model which explicitly captures the duration of state dependence.

Where error term, $\epsilon_{ikt}$, is composed of an individual-specific unobserved effect (time-invariant but varying across individuals) and a random error (varying both across time and individuals) as below:

$$\epsilon_{ikt} = \mu_{ik} + \upsilon_{ikt} \tag{2.6}$$

$X_{it}$ is a vector of time varying observed variables, including marital status and investment income (wealth). $E_{it}$ includes information on expected wages of being self-employed (versus being a paid-employee). To derive this variable, I used a pooled ($OLS$) estimation method and regressed the log hourly wages of being self-employed (and paid-employed) on significant covariates including age, educational attainment, marital status, immigration status, regional status, and time dummies. The predicted values, after that, have been used to generate the exogenous explanatory variable, $E_{it}$, as:

$$E_{it} = \hat{Y_{it}^S} - \hat{Y_{it}^P} \tag{2.7}$$

Where $\hat{Y_{it}^S}$ and $\hat{Y_{it}^P}$ are the predicted hourly wage of being self-employed and paid-employed, respectively (for individual $i$ at time $t$).[14] $L_{it}$ describes the local labour market conditions where the individual $i$ resides at time $t$. It includes information on the unemployment rate at the provincial level. $D_i$ is a vector of time-invariant variables including the individual's immigration status, parental background, and educational attainment at the time of entry to the panel (initial

[14] I assume that the correlation between $E_{it}$ ($\hat{Y_{it}^S}$ and $\hat{Y_{it}^P}$) and the error component, $\epsilon_{ikt}$, is zero (exogeniety assumption). Relaxing this assumption leads to biased and inconsistent parameter estimates. To correct for the possible bias this might generate, Greene (2000) suggested a method introduced by Murphy and Topel (1985). Murphy and Topel (1985) proposed a theorem in which two-step **non-linear** least squares estimators are consistent and asymptotically normally distributed with the corrected asymptotic covariance matrix. In general, two-step **linear** least squares estimators to generate regressors are asymptotically consistent and their standard errors and test statistitics are all asymptotically valid. This is not the case for **non-linear** models and therefore the asymptotic variances also need to be adjusted in this case.

conditions). To allow the effect of local labour market conditions (provincial unemployment rates) and wealth differs between immigrants and natives, the model controls for the possible interaction terms between these variables, termed $I_{it}$. $Z_{it}$ is a vector of dummy variables indicating the previous labour market state occupied by the individual $i$ (time state dependence). For the usual identification purpose, I take the state of being out of the labour force as the reference state.

The assumption regarding the error term, $\epsilon_{ikt}$, can be summarized as follows: $\epsilon_{ikt}$ is composed of the two terms: $\upsilon_{ikt}$ and $\mu_{ik}$. Where $\upsilon_{ikt}$ is assumed to follow a Type I extreme value distribution and $\mu_{ik}$ is an unobserved, individual specific factor, and independent of $X_{it}$, $E_{it}$, $L_{it}$, $D_i$, and $L_i$, but not $Z_{it}$ (endogeneity problem). If $\mu_{ik}$ is treated as a parameter to be estimated (fixed effects approach), then there is a severe incidental parameter problem. According to Heckman (1981b), an unobserved time-invariant effect allows for a particular form of serial correlation in $\epsilon_{ikt}$. Following Chamberlain (1984), the consistency of the maximum likelihood estimator requires that $T \longmapsto \infty$. *SLID*, as well as most household panel data sets, contains many individuals but only a small and fixed number of $T$. Random effects analysis in this context may therefore seem more applicable than fixed effects analysis.

Given the distribution assumptions of $\upsilon_{ikt}$, the probability of observing individual $i$ in state $k$ at time $t$, conditional on $X_{it}$, $E_{it}$, $L_{it}$, $D_i$, $Z_{it}$, and $\mu_{ik}$ can be written as a four-state multinomial logit as:

$$P_{it}(k/X, \mu_{ik}) = \frac{exp(X_{it}.\beta_{1k} + E_{it}.\beta_{2k} + ... + Z_{it}.\gamma_k + \mu_{ik})}{\sum_{j=1}^{4} exp(X_{it}.\beta_{1j} + E_{it}.\beta_{2j} + ... + Z_{it}.\gamma_j + \mu_{ij})} \tag{2.8}$$

Where $X$ is a vector of all explanatory variables in the model. The model also controls for endogenous initial conditions. The initial conditions problem arises when the start of the observation period does not coincide with the start of the stochastic process that generates individuals' participation experience. Individuals' participation in the first period can be due to the previous history of the participation

experience or because of some observable (such as personal wealth, level of education, or parental background) and unobservable (such as personal preferences or abilities) information dated to prior to the first period. If pre-sample history of the process is unobserved, then mis specifying the initial conditions will lead to inconsistent estimates. The extent of such initial conditions bias is inversely related to the length of the panel and can be quite serious in short panels such as *SLID*.

According to Chay and Hyslop (2000), dynamic discrete choice models that assume initial conditions are exogenous are effectively ignoring the serial dependence attributable to unobserved heterogeneity and therefore lead to upwardly biased estimates of the structural state dependence. To account for this problem, I adopt the method suggested by Wooldridge (2005). Following him, I consider the distribution of the unobserved effects, $\mu_{ik}$, conditional on $Z_{i1}$ and the mean values of non-redundant time-varying explanatory variables over time ($\bar{X}_i$). Wooldridge'approach relaxes the need to explicitly specify a distribution for the initial condition which is quite appropriate in this context. $Z_{i1}$ is a vector of initial participation states of self-employment, paid-employment, and unemployment. $\mu_{ik}$ can be written as:

$$\mu_{ik} = \bar{X}_i.\lambda_k + Z_{i1}.\rho_k + \nu_{ik} \tag{2.9}$$

Therefore conditional probability of (2.4) can be modified as:

$$P_{it}(k/X, \bar{X}_i, Z_{i1}, \nu_{ik}) = \frac{exp(X_{it}.\beta_{1k} + ... + Z_{it}.\gamma_k + \bar{X}_i.\lambda_k + Z_{i1}.\rho_k + \nu_{ik})}{\sum_{j=1}^{4} exp(X_{it}.\beta_{1j} + ... + Z_{it}.\gamma_j + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{2.10}$$

Following Mroz (1999), I assume that the probability distribution of $\nu_{ik}$ can be approximated by a discrete factor distribution with a finite number of support points. Assuming a discrete distribution for the unobserved factors implies that the cumulative distribution function is approximated by a step function. In particular, the distribution of $\nu_{ik}$ is given by:

$$Pr(\nu_{ik} = \nu_k^m) = \pi_m, m= 1, 2,\ldots, M \tag{2.11}$$

where,

$$\pi_m > 0 \tag{2.12}$$

$\pi_m$ is the probability that unobserved factors take on the values of $\nu_k^m$. To be specific, I assume that are $m$ types of individuals and each individual at any states of $k$ is endowed with a set of unobserved characteristics, $\nu_k^m$. To estimate simultaneously the parameters $\beta_{1k}$, $\beta_{2k}$, $\beta_{3k}$, $\beta_{4k}$, $\beta_{5k}$, $\gamma_k$, $\lambda_k$, $\rho_k$, $(\nu_k^1, \ldots, \nu_k^M)$, and $(p_1, \ldots, p_M)$, I use a logistic transformation as:

$$\pi_m = \frac{exp(p_m)}{\sum_{j=1}^{M} exp(p_m)} \tag{2.13}$$

where,

$$0 < \pi_m < 1 \tag{2.14}$$

and

$$\sum_{m=1}^{M} \pi_m = 1 \tag{2.15}$$

To select the number of support points, I calculate the value of $AIC$ (Akaike Information Criteria) and $BIC$ (Bayesian Information Criteria),[15] when an additional point of support is added. I stop adding more support points to the model when either value starts increasing.

The likelihood contribution for individual $i$ with observed states $k_1, \ldots, k_T$ given all observed and unobserved effects can be written as:

[15] $AIC$ and $BIC$ are measures of goodness of fit. In fact, they show how well the model fits the data. $AIC$ penalizes free parameters less strongly than does $BIC$. $AIC$ and $BIC$ are obtained by *AIC= -2.f+ 2.npar* and *BIC= -2.f+ log(n).npar*, where $f$ is the value of the objective function, $n$ is the number of individuals, and *npar* is the number of parameters.

$$L_i(\nu_i) = \prod_{t=2}^{T} P_{it}(k/X, \bar{X}_i, Z_{i1}, \nu_{ik}) \tag{2.16}$$

and therefore,

$$L_i(\nu_i) = \prod_{t=2}^{T} \frac{exp(X_{it}.\beta_{1k} + ... + Z_{it}.\gamma_k + \bar{X}_i.\lambda_k + Z_{i1}.\rho_k + \nu_{ik})}{\sum_{j=1}^{4} exp(X_{it}.\beta_{1j} + ... + Z_{it}.\gamma_j + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{2.17}$$

Where $\nu_i$ is a vector of $\nu_{ik}$ for $k_t$= *1, 2, 3, 4*. As earlier mentioned there are $m$ types of individuals with the set of unobserved characteristics, $\nu_k^m$, which is a vector of $(\nu_k^1, \ldots, \nu_k^M)$. Therefore, I can write unconditional log-likelihood function for individual $i$ as:

$$LogL_i(\nu_i) = \log \sum_{m=1}^{M} \pi_m.L_i(\nu_k^m) \tag{2.18}$$

and finally,

$$L_{NT} = \sum_{i=1}^{N} \log \sum_{m=1}^{M} \prod_{t=2}^{T} \pi_m.\frac{exp(X_{it}.\beta_{1k} + ... + Z_{it}.\gamma_k + \bar{X}_i.\lambda_k + Z_{i1}.\rho_k + \nu_{ik})}{\sum_{j=1}^{4} exp(X_{it}.\beta_{1j} + ... + Z_{it}.\gamma_j + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{2.19}$$

### 2.3.1 Estimated Entry and Exit Rates

Following Wooldridge (2005), to obtain estimated entry and exit rates from self-employment as well as any other labour market states, I average out the distribution of the unobserved heterogeneity, $\nu_{ik}$, and compute participation probabilities as:

$$\hat{Pr}(k_{it} = k/X_{it}, ..., Z_{i1}) = N^{-1} \sum_{m=1}^{M} \sum_{i=1}^{N} \pi_m.\frac{exp(X_{it}.\beta_{1k} + E_{it}.\beta_{2k} + ... + \bar{X}_i.\lambda_k + Z_{i1}.\rho_k + \nu_{ik})}{\sum_{j=1}^{4} exp(X_{it}.\beta_{1j} + E_{it}.\beta_{2j} + ... + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{2.20}$$

To obtain the estimates of the entry rate into state $k_{it}$=$k$ ($k$ is any states of self-employment (1), paid-employment (2), unemployment (3), or being out of the labour force (4).), I evaluate the equation above when the individual $i$ at time *t-1*

is not in the state of $k$. The estimates of the exit rates simply are one minus the probability of persistence in state $k$.

## 2.4 Empirical Results

In this section, I report estimation results from maximizing the likelihood function of the multinomial logit model controlling for both endogenous initial conditions problem and unobserved heterogeneity factors (Table 2.6). As an illustration of the importance of these factors, I also report estimation results of a model when there is no control for endogenous initial conditions problem and unobserved heterogeneity (Table 2.5). As *SLID* is not a representative random sample, the likelihood function is weighted with sample weights provided by Statistics Canada.

I experimented with different support points and found that a model with four support points fitted the data well. Table 2.7 reports *AIC*, *BIC*, number of parameters, and the value of objective function for different model specifications. I used *BIC* to choose the number of support points in the estimation.

As expected, assuming that the initial conditions are exogenous and also ignoring unobserved factors generates inflated estimates of the degree of state dependence. Because the model presented in this paper has a non-linear nature, the magnitudes of the coefficient estimates provide little information about the size of the effects of the observable covariates. Therefore, my attention in this research focuses on the transition probabilities, the proportion of the estimated state dependence that is spurious, and estimated entry-exit rates (Tables 2.8 to 2.14). The estimated transition matrices are evaluated at the corresponding sample means and are based on the estimates reported in Tables 2.5 and 2.6.

Table 2.5: Dynamic Multinomial Logit Model of Labor Market States, *(No Control for Endogenous Initial Conditions and Unobserved Heterogeneity)*

| Explanatory Variables | | Estimated Equations | | |
|---|---|---|---|---|
| | | Self-Employment | Paid-Employment | Unemployment |
| State Dependence | Self-Employment | 8.559** (0.258) | 4.739** (0.229) | 2.653** (0.305) |
| | Paid-Employment | 3.822** (0.162) | 6.067** (0.092) | 2.368** (0.1302) |
| | Unemployment | 2.557** (0.234) | 2.957** (0.138) | 4.134** (0.1458) |
| Explanatory Variables | Married | 0.858** (0.109) | 0.818** (0.089) | -0.034 (0.1136) |
| | Years of Education | 0.090** (0.015) | 0.118** (0.013) | 0.016 (0.0173) |
| | Immigrant | -0.047 (0.449) | 0.289 (0.393) | 0.282 (0.450) |
| | Father Educated | 0.707** (0.168) | 0.660** (0.150) | 0.568** (0.185) |
| | Mother Educated | -0.183 (0.162) | -0.100 (0.143) | -0.259 (0.196) |
| | Positive Investment Income | 0.694** (0.124) | 0.360** (0.112) | -0.461** (0.172) |
| | Unemployment Rate | -0.026** (0.013) | -0.009 (0.011) | 0.038** (0.013) |
| Interaction Terms | Positive Investment & Immigrant | -0.152 (0.348) | 0.047 (0.318) | 0.120 (0.394) |
| | Unemployment Rate & Immigrant | 0.020 (0.052) | -0.057 (0.045) | 0.048 (0.050) |
| Derived Exogenous Variable | Expected Wage [1] | -0.044 (0.158) | -0.023 (0.136) | -0.280 (0.174) |
| | Intercept | -4.825** | -3.558** | -3.105** |
| | Number of Observation | 51906 | Log-Likelihood | -11592.8 |
| | Number of Individuals | 8651 | AIC | 23269.6 |
| | Number of Parameters | 42 | BIC | 23566.3 |

Note: Figures inside the parentheses are the standard errors.
** Parameter estimate is significant at 5 % or 1% level of significance.
* Parameter estimate is significant at 10% level of significance.
1- Expected wages of being self-employed versus being a paid-employee.

Table 2.6: Dynamic Multinomial Logit Model of Labor Market States, *(Control for Endogenous Initial Conditions and Unobserved Heterogeneity)*

| Explanatory Variables | | | Estimated Equations | | |
|---|---|---|---|---|---|
| | | | Self-Employment | Paid-Employment | Unemployment |
| State Dependence | | Self-Employment | 6.330** (0.308) | 3.576** (0.324) | 2.355** (0.407) |
| | | Paid-Employment | 2.639** (0.204) | 3.375** (0.157) | 1.191** (0.205) |
| | | Unemployment | 2.115** (0.293) | 1.367** (0.212) | 2.513** (0.214) |
| Explanatory Variables | | Married | 0.940** (0.128) | 0.962** (0.125) | 0.141 (0.145) |
| | | Years of Education | 0.095** (0.019) | 0.135** (0.019) | 0.034 (0.021) |
| | | Immigrant | -0.948* (0.576) | 0.040 (0.552) | -0.368 (0.605) |
| | | Father Educated | 0.721** (0.196) | 0.746** (0.193) | 0.677** (0.223) |
| | | Mother Educated | -0.438** (0.182) | -0.297* (0.178) | -0.550** (0.230) |
| | | Positive Investment Income | 0.366* (0.214) | 0.072 (0.195) | 0.043 (0.156) |
| | | Unemployment Rate | -0.026* (0.014) | 0.001 (0.015) | 0.039** (0.017) |
| Interaction Terms | | Positive Investment & Immigrant | -0.216 (0.419) | -0.196 (0.398) | -0.072 (0.157) |
| | | Unemployment Rate & Immigrant | 0.166** (0.071) | -0.013 (0.068) | 0.131* (1.866) |
| Derived Exogenous Variable | | Expected Wage[1] | -0.254 (0.190) | -0.239 (0.187) | -0.498** (0.217) |
| Pr 1 | 43% | Type 1 | -7.945** | -7.049** | -4.212** |
| Pr 2 | 8.9% | Type 2 | -7.189** | -9.590** | -7.140** |
| Pr 3 | 33% | Type 3 | -6.327** | -2.394** | -1.572** |
| Pr 4 | 15.1% | Type 4 | -2.650** | -2.144** | -6.327 |
| | | Number of Observation | 51906 | Log-Likelihood | -10981.2 |
| | | Number of Individuals | 8651 | AIC | 22094.3 |
| | | Number of Parameters | 66 | BIC | 22560.7 |

Note: Figures inside the parentheses are the standard errors.
** Parameter estimate is significant at 5 % or 1% level of significance.
* Parameter estimate is significant at 10% level of significance.
1- Expected wages of being self-employed versus being a paid-employee.

Table 2.7: Model Specification, Information Criteria (*AIC and BIC*), Number of parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 23269.6 | 23566.3 | 42 | -11592.8 |
| No | Yes | 1 | 22577.1 | 22958.6 | 54 | -11234.5 |
| Yes | Yes | 2 | 22275.9 | 22685.7 | 58 | -11080 |
| Yes | Yes | 3 | 22142.2 | 22580.3 | 62 | -11009.1 |
| Yes | Yes | 4 | 22094.3 | 22560.7 | 66 | -10981.2 |
| Yes | Yes | 5 | 22077.3 | **22571.9*** | 70 | -10968.7 |

**Note:** The figures are based on the estimation results presented in Tables 2.5 and 2.6.

However, before any discussions on transition probability matrices and estimated entry-exit rates, my overall conclusions from Table 2.6 are as follows[16]:

- The unemployment rate is statistically significant in self-employment and unemployment equations, but not in the paid-employment equation. The marginal effect of unemployment rate is negative in the self-employment equation, indicating that males tend to be self-employed when economic conditions (measured by the unemployment rate) are good (the unemployment rate is low), all other factors being fixed. Kamhi and Leung (2005) also found a negative significant correlation between self-employment and unemployment rates in Canada over the period 1976-2002, which is consistent with my findings. This is also similar to what Simpson and Sproule (1998) have shown. Using 1994 cross-sectional data from *SLID*, they found that lower unemployment

[16] I discuss the sign of marginal effects with respect to their parameter significance in the multinomial logit model. Causality might require a significance test based on standard errors of these probabilities. No such standard errors have been computed for the marginal effects in this paper. However, it seems likely that highly significant parameter estimates will also have statistically significant marginal effects.

rates are associated with increased self-employment activities for men, reflecting what they termed in their paper the "prosperity pull" hypothesis. Further, the marginal effects of estimates in Table 2.6 suggest that this is not the case for immigrants. Male immigrants who are residing in provinces with relatively high unemployment rates tend to be self-employed, everything else held constant. As seen, immigrants behave quite differently from the whole sample of men (and natives) aged 25 to 55 with respect to unemployment rate changes. This, at least partially, can explain the variations in self-employment rates with respect to the unemployment rate changes among immigrants over the period 1997-2000, in which self-employment and unemployment rates moved in largely the same direction (Figure A.2.2). During the poor economic conditions, immigrants may feel some uncertainty about labour market conditions and prefer to have their own businesses. One explanation for this is that immigrants may face discrimination in the labour market (preference based or because of lack of information on behalf of the employers (statistical discrimination)) that makes them more likely enter the self-employment state than comparable natives. Further, the unemployment experience may be very different between immigrants and natives. This possible difference in unemployment experience is not observed in the data and therefore enters the "unobserved heterogeneity" component in the dynamic model. This makes immigrants and natives behave differently in times of high unemployment rates. The high unemployment rate pushes immigrants into self-employment more than natives. Based on the Frenette's findings (2002), the push hypothesis may very well be at work for immigrants, given the possible barriers to entry into the paid workforce. These barriers may result from a number of factors, such as gaps in training, a lack of knowledge of one of Canadas official languages, or labour market discrimination. In terms of immigrant self-employment, the push hypothesis is

referred to as the "blocked mobility" hypothesis. My estimation results show that the barriers to enter the paid-employed sectors will be highlighted during high unemployment rates for immigrants.

- Positive investment income is statistically significant in the self-employment equation, but not in paid-employment and unemployment equations. The marginal effect of investment income indicates that males with positive investment incomes tend to be self-employed, all other factors fixed. This effect will be highly significant when the model does not control for unobserved heterogeneity factors and endogenous initial conditions problem (spurious effects) (Table 2.5). A possible explanation is the likely correlation between investment income and unobserved heterogeneity factors. Individuals with positive investment income may have different motivations to start up a business. The individual heterogeneity can be due to some unobserved characteristics such as labour market preferences, skills, abilities, or entrepreneurial spirit. These unobserved effects are spurious and captured in the error term when control for spurious effects are taken into account in the estimation. Failure to control for these factors will falsely attribute significant effects of investment income to self-employment decisions. Many researchers so far have examined different features of wealth and self-employment relationships. Cressy (1996) showed that there is a spurious relationship between wealth and self-employment choices which is quite interesting. He found that the correlation between financial wealth and self-employment status is difficult to predict, because financial wealth is likely to be determined by human capital. Cressy, using a large sample of the UK bank database and an econometric model of self-employment found that statistical significance of financial variables disappears once variables capturing the human capital (education and experience) are included in the model. In fact he found that correlation between wealth

and self-employment survival or status is spurious. Hurst and Lusardi (2004), using the distribution of wealth studied the relationship between wealth and self-employment choices. They found that the propensity to become a business owner is a nonlinear function of wealth. The relationship between wealth and entry into entrepreneurship is essentially flat over the majority of the wealth distribution. It is only at the top of the wealth distribution (after the ninety-fifth percentile) that a positive relationship can be found. They also, using inheritance as an instrument for wealth, found that both past and future inheritances predict current business entry, indicating that inheritances capture more than simply liquidity.

- Expected wage of being self-employed (versus being a paid-employee) is statistically significant in the unemployment equation, but not in paid-employment and self-employment equations. Expectation of having a higher salary in self-employment sectors (compared to the paid-employment sectors) decreases the logit (log-odd) probability of the being unemployed, all other factors fixed. However, this expectation has no significant effect on probability of being either self-employed or paid-employed. A possible explanation is the non pecuniary benefits that individuals may obtain when they are self-employed or paid-employed. Hamilton's research (2000) on earnings differentials in paid-employment and self-employment, to some extent, confirms my findings. Based on his study, non pecuniary benefits of self-employment are substantial. Most entrepreneurs enter and persist in business despite the fact that they have both lower initial earnings and lower earnings growth than in paid employment.

- Father's and Mother's level of education are statistically significant in all equations of self-employment, paid-employment, and unemployment. The mother's level of education has a negative effect and the father's has a positive effect

Table 2.8: Transition Matrix, Estimated Conditional Probabilities of Leaving Previous Year's State, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Origin State | Destination State | | | |
|---|---|---|---|---|
| | Self-Employment | Paid-Employment | Unemployment | Being out of the Labour Force |
| Self-Employment | **0.889** | 0.103 | 0.005 | 0.004 |
| Paid-Employment | 0.010 | **0.963** | 0.008 | 0.009 |
| Unemployment | 0.059 | 0.452 | **0.407** | 0.082 |
| Being out of the Labour Force | 0.042 | 0.217 | 0.058 | **0.683** |

Note: Calculations are based on the estimation results presented in Table 2.5.

on logit probability of being self-employed, paid-employed, and unemployed, all other factors fixed. However for males whose parents are both educated, the total effect is positive in self-employment and paid-employment equations and negative in the unemployment equation.

- The marginal effects of education and marriage have the expected signs (positive) for self-employment and paid-employment equations. All state dependence variables are positive and statistically significant in all equations of self-employment, paid-employment, and unemployment.

Tables 2.8 to 2.11 report estimated conditional probabilities of leaving previous year's state with and without controlling for endogenous initial conditions problem and unobserved heterogeneity.

As expected, when controls for these factors are incorporated in the model, there is a reduction in the estimated state dependence for all states of self-employment, paid-employment, unemployment, and being out of the labour force (Tables 2.9 and 2.11). My overall conclusions from Tables 2.8 and 2.10 are as follows:

- For the whole sample, persistence in self-employment and paid-employment is

Table 2.9: Transition Matrix, Estimated Conditional Probabilities of Leaving Previous Year's State, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| **Origin State** | **Destination State** | | | |
|---|---|---|---|---|
| | Self-Employment | Paid-Employment | Unemployment | Being out of the Labour Force |
| Self-Employment | **0.288** | 0.697 | 0.009 | 0.006 |
| Paid-Employment | 0.078 | **0.899** | 0.006 | 0.017 |
| Unemployment | 0.131 | 0.755 | **0.080** | 0.034 |
| Being out of the Labour Force | 0.081 | 0.787 | 0.026 | **0.106** |

**Note:** Calculations are based on the estimation results presented in Table 2.6.

Table 2.10: Transition Matrices, Estimated Conditional Probabilities of Leaving Previous Year's State by Immigrants and Natives, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| **Immigrants** | | | | |
|---|---|---|---|---|
| **Origin State** | **Destination State** | | | |
| | Self-Employment | Paid-Employment | Unemployment | Being out of the Labour Force |
| Self-Employment | **0.909** | 0.079 | 0.009 | 0.003 |
| Paid-Employment | 0.027 | **0.935** | 0.026 | 0.012 |
| Unemployment | 0.049 | 0.300 | **0.592** | 0.060 |
| Being out of the Labour Force | 0.044 | 0.179 | 0.118 | **0.659** |
| **Natives** | | | | |
| Self-Employment | **0.888** | 0.104 | 0.004 | 0.004 |
| Paid-Employment | 0.020 | **0.964** | 0.008 | 0.009 |
| Unemployment | 0.060 | 0.462 | **0.394** | 0.083 |
| Being out of the Labour Force | 0.042 | 0.220 | 0.054 | **0.684** |

**Note:** Calculations are based on the estimation results presented in Table 2.5.

Table 2.11: Transition Matrices, Estimated Conditional Probabilities of Leaving Previous Year's State by Immigrants and Natives, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| **Immigrants** | | | | |
|---|---|---|---|---|
| **Origin State** | **Destination State** | | | |
| | Self-Employment | Paid-Employment | Unemployment | Being out of the Labour Force |
| Self-Employment | **0.378** | 0.600 | 0.018 | 0.004 |
| Paid-Employment | 0.104 | **0.862** | 0.019 | 0.015 |
| Unemployment | 0.151 | 0.658 | **0.165** | 0.026 |
| Being out of the Labour Force | 0.104 | 0.731 | 0.071 | **0.095** |
| **Natives** | | | | |
| Self-Employment | **0.285** | 0.700 | 0.009 | 0.006 |
| Paid-Employment | 0.077 | **0.900** | 0.006 | 0.017 |
| Unemployment | 0.130 | 0.759 | **0.076** | 0.035 |
| Being out of the Labour Force | 0.080 | 0.800 | 0.025 | **0.106** |

**Note:** Calculations are based on the estimation results presented in Table 2.6.

quite high, about 88.9 and 96.3 percent, respectively. The probability of being paid-employed next year, if a man is self-employed this year, is 10.3 percent; which is higher than that of being unemployed or out of the labour force next year. Men who are either unemployed or out of the labour force this year, 45.2 and 21.7 percent are likely to find a job in the paid-employment sectors next year, respectively.

- Persistence in self-employment and paid-employment is quite high among immigrants and natives. Immigrants have slightly higher persistence in self-employment than natives, while natives have higher persistence in paid-employment.

- Persistence in unemployment is higher among immigrants than among natives, while natives have a somewhat higher persistence of being out of the labour force.

- Natives have better chances finding a job in the paid-employment sector than immigrants. Looking at all transitions from any states of self-employment, unemployment, or being out of the labour force into paid-employment, transition probabilities are higher among natives than among immigrants.

The transition probabilities that are reported in Tables 2.8 to 2.11 can be used to decompose the estimated state dependence into structural and spurious state dependence. The distinction between true and spurious state dependence is very crucial for economic policy-making. Ignoring the effect of spurious state dependence in observed persistence leads to erroneous policy decision-making. As shown, persistence in all states of self-employment, paid-employment, unemployment, and being out of the labour force for both immigrants and natives are overestimated if controls for endogenous initial condition and unobserved heterogeneity factors are not incorporated in the model. The probabilities of persistence in self-employment

for immigrants and natives are quite close together, about 90.9 and 88.8 percent, respectively, when the model does not control for unobserved factors and endogenous initial conditions problem (spurious effects). However, when controls for these factors are taken into account, a considerable reduction in probability of persistence in self-employment, as well as the probabilities of other state dependence variables will occur. The probabilities of persistence in self-employment for immigrants and natives, when control for unobserved factors and endogenous initial conditions problem are taken into account, are 37.8 and 28.5 percent, respectively. Further, immigrant-native differences in persistence in any labour market states can be realized when the spurious effects are removed from the estimation. One explanation is due to the possible differences between immigrants and natives in unobserved characteristics such as labour market preferences (some barriers to the labour market for immigrants due to the labour market discrimination), abilities, or unemployment experiences.

Table 2.12 shows the percentage of structural and spurious state dependence in the labour market states for the whole sample and separately for immigrants and natives. This table clearly illustrates the effect of spurious effects in immigrant-native differences in all states of labour market. As seen, structural state dependence in self-employment is higher among immigrants than among natives. Instead, natives are estimated to have higher spurious effects in self-employment state than similar immigrants. For immigrants much less in paid-employment state, about 41.6 percent of self-employment state dependence is structural. The equivalent value for natives is 32.1 percent. In particular, persistence in self-employment, to a greater extent, stems from unobserved heterogeneity, possibly in self-employment preferences, skills, abilities, or entrepreneurial spirit. For the paid-employment state, previous experience has a strong causal effect on the current experience. Persistence

Table 2.12: Percentage of Structural and Spurious State Dependence in Labour Market States by Immigrants and Natives, Canada 1993-2004

| | Self-Employment | | Paid-Employment | | Unemployment | | Being Out of the Labor Force | |
|---|---|---|---|---|---|---|---|---|
| | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious |
| **Immigrants** | **41.6** | 58.4 | **92.1** | 7.9 | **27.8** | 72.2 | **14.4** | 85.6 |
| **Natives** | **32.1** | 67.9 | **93.4** | 6.6 | **19.4** | 80.6 | **15.5** | 84.5 |
| **Total** | **32.4** | 67.6 | **93.3** | 6.7 | **19.6** | 80.4 | **15.5** | 84.5 |

**Note:** Calculations are based on the estimation results presented in Tables 2.5 and 2.6.

in paid-employment is highly structural for both immigrants and natives. However, natives have slightly higher structural persistence in paid-employment than immigrants. Only 7.9 percent of paid-employment persistence among immigrants is attributed to unobserved factors and initial conditions problem. The equivalent value for natives is 6.6 percent. Observed persistence in unemployment and being out of the labour force, to some extent, is due to unobserved factors. Structural state dependence in unemployment is higher among immigrants than among natives, while natives have slightly more persistence in being out of the labour force. For natives, the structural state dependence in unemployment and being out of the labor force states is almost 19.4 and 15.5 percent, respectively. For immigrants, the equivalent proportions of structural state dependence are 27.8 and 14.4 percent.

Tables 2.13 and 2.14 report estimated entry-exit probability rates for all labour market states, for a whole sample, and separately for natives and immigrants. For the model which ignores the roles of unobserved heterogeneity and endogenous initial conditions, the estimated entry rates into self-employment for immigrants and

Table 2.13: Estimated Exit-Entry Probability Rates by Immigrants and Natives, (*No control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| | Self-Employment | | Paid-Employment | | Unemployment | | Being Out of the Labor Force | |
|---|---|---|---|---|---|---|---|---|
| | Exit | Entry | Exit | Entry | Exit | Entry | Exit | Entry |
| **Immigrants** | **0.091** | 0.033 | **0.065** | 0.178 | **0.408** | 0.033 | **0.341** | 0.032 |
| **Natives** | **0.112** | 0.027 | **0.036** | 0.222 | **0.606** | 0.011 | **0.316** | 0.032 |
| **Total** | **0.111** | 0.027 | **0.037** | 0.220 | **0.593** | 0.012 | **0.317** | 0.032 |

**Note:** Calculations are based on the estimation results presented in Table 2.5.

natives are 3.3 and 2.7 percent, respectively. The estimated entry rates suggest that the higher self-employment rates among immigrants relative to natives, are partially due to higher incidences of entering self-employment state in any given time period. When controls for these factors are incorporated into the model, I found significant increases in the estimated entry rates for immigrants and natives. The equivalent figures for immigrants and natives change to 10.2 and 7.9 percent, when controls for unobserved heterogeneity and endogenous initial conditions are taken into account. The reason is due to the correlation of time-invariant unobserved effects and time state dependence variables. The model which ignores the effects of these factors, falsely assumes that this correlation is zero.

The estimated exit rates, presented in Tables 2.13 and 2.14, show that immigrants have lower exit rates from self-employment state than comparable natives. The model which ignores the effect of endogenous initial conditions and time invariant unobserved heterogeneity underestimates exit rates from self-employment state

Table 2.14: Estimated Exit-Entry Probability Rates by Immigrants and Natives, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| | Self-Employment | | Paid-Employment | | Unemployment | | Being Out of the Labor Force | |
|---|---|---|---|---|---|---|---|---|
| | Exit | Entry | Exit | Entry | Exit | Entry | Exit | Entry |
| **Immigrants** | **0.627** | 0.102 | **0.156** | 0.706 | **0.718** | 0.022 | **0.854** | 0.024 |
| **Natives** | **0.714** | 0.079 | **0.113** | 0.759 | **0.846** | 0.007 | **0.835** | 0.029 |
| **Total** | **0.712** | 0.080 | **0.114** | 0.757 | **0.840** | 0.008 | **0.835** | 0.028 |

**Note:** Calculations are based on the estimation results presented in Table 2.6.

and consequently overestimates persistence in self-employment. The significant differences between these two models in estimating the self-employment exit rates, highlight the substantial proportion of persistence in self-employment, which is due to unobserved heterogeneity such as labour market preferences, skills, abilities, entrepreneurial spirit, and/or any other time-invariant variables omitted from the set of observables (initial conditions problem). The estimated transition rates presented in these two tables suggest that the immigrant-native gap in self-employment participation is due to a combination of both higher entry and lower exit rates among immigrants than similar natives.

For the paid-employment state, immigrants have lower entry and higher exit rates than comparable natives. The net entry rate into the paid-employment state is positive for both immigrants and natives, implying that on average immigrants and natives are likely to move into the paid-employment state from any other labour market states. Immigrants' entry (exit) rates into (out of) unemployment are higher

Table 2.15: Predicted and Observed Distribution of Labour Market States, 1993-2004

| | Observed | | | Predicted | | |
|---|---|---|---|---|---|---|
| Year | Self-Employment | Paid-Employment | Unemployment | Self-Employment | Paid-Employment | Unemployment |
| 1994 | 0.163 | 0.769 | 0.033 | 0.155 | 0.798 | 0.017 |
| 1995 | 0.165 | 0.770 | 0.027 | 0.151 | 0.810 | 0.014 |
| 1996 | 0.156 | 0.762 | 0.031 | 0.150 | 0.812 | 0.013 |
| 1997 | 0.148 | 0.769 | 0.037 | 0.154 | 0.801 | 0.016 |
| 1998 | 0.145 | 0.779 | 0.033 | 0.145 | 0.813 | 0.014 |
| 1999 | 0.158 | 0.774 | 0.022 | 0.143 | 0.813 | 0.014 |
| 2000 | 0.164 | 0.772 | 0.021 | 0.157 | 0.798 | 0.012 |
| 2001 | 0.157 | 0.785 | 0.019 | 0.156 | 0.803 | 0.011 |
| 2002 | 0.164 | 0.781 | 0.017 | 0.161 | 0.801 | 0.010 |
| 2003 | 0.179 | 0.768 | 0.016 | 0.157 | 0.805 | 0.009 |
| 2004 | 0.176 | 0.768 | 0.015 | 0.159 | 0.803 | 0.009 |

Note: Predicted values are calculated based on the estimation results presented in Table 2.6.

Table 2.16: Fit of the Model (*Likelihood Ratio Index*)

| LL[1] (No Model) | LL (Full Model) | Likelihood Ratio Index |
|---|---|---|
| -29113.1 | -10981.2 | 0.62 |

Note: 1. Model with all explanatory variables restricted to zero.

(lower) than natives', while natives have lower exit and higher entry rates into the being out of the labour force state than immigrants.

Finally, Table 2.15 shows the predicted and observed distributions of labour market states for a balanced panel for the period 1994-2004. The predicted distributions are calculated for each year between 1994 and 2004 ($t=2,...,12$). Overall, the predicted distributions are, to some extent, similar to the observed frequencies, indicating that the empirical model fit the data well. One measure of goodness of fit in discrete choice modeling is likelihood ratio test. This measure is defined as $1 - [LL(\hat{\beta})/LL(0)]$, where $LL(\hat{\beta})$ is the value of the log-likelihood function at the estimated parameters and LL(0) is the value with all parameters equal to zero. The index ranges from zero (no model) to one (perfect model). Table 2.16 reports the likelihood ratio index for the final models.

# Chapter 3

# Essay II: Immigrant-Native Differences in Wage Mobility Process

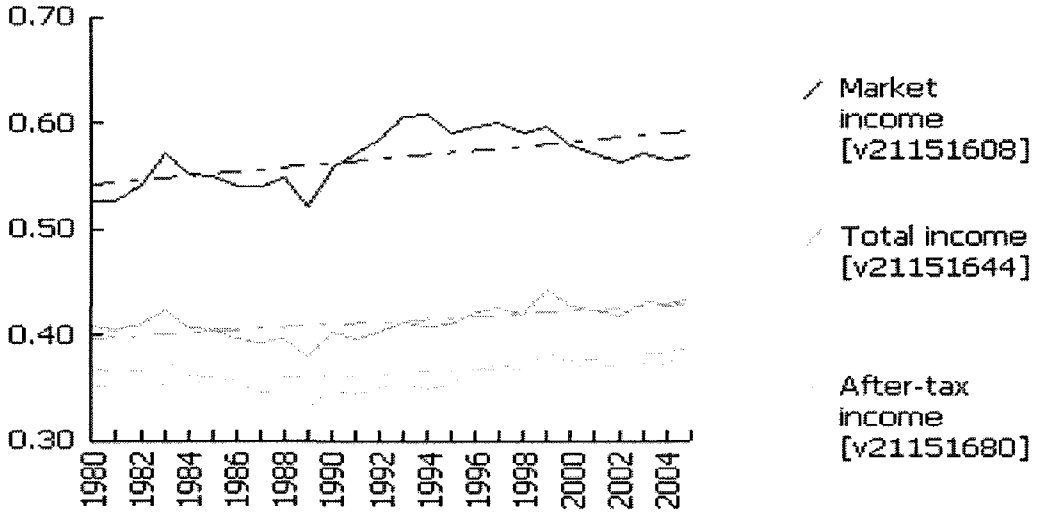
## 3.1 Introduction

Based on the National Statistics Agencies of Canada and the data extracted from CANSIM, Table 202-0705, the individual's after-tax income and total income inequalities increased over the period 1989-2004. The individual's market-income[1] inequality increased between 1989 and 1993, falling down slowly over the period 1993-2004. However, all levels of inequality including total, market, and after-tax income inequalities were still higher than the ones observed in 1989 (Figure 3.1).

In the United States, after-tax income inequality rose by 0.033 from 1986 to 2000, which was slightly larger than the one observed in Canada over the same period. However in both countries, the increase in after-tax income inequality has

[1]The average market income is the sum of earnings (from employment and self-employment), investment income, (private) retirement income, and any other sources of income. It is equivalent to the total income minus government transfers (Statistics Canada, CANSIM, Table 202-0202).

Figure 3.1: Trends in Gini Coefficients (1), Market, Total, and After-Tax Income, Canada 1993-2004




**Note:** Source: Statistics Canada, CANSIM Table 202-0705

1-The most widely used index on income inequality. It ranges from zero to one, with zero representing complete equality and one complete inequality.

been accompanied by an inequality in individual's market-income and not a reduction in income redistribution attributed to changes in Employment Insurance ($EI$) or Social Assistance ($SA$) programs (Heisz, 2007). Based on a study by Mahler and Jesuit (2005), after-tax income inequality also rose in other industrialized countries such as Finland, Germany, Norway, Sweden, and the United Kingdom over the same period. The same explanation might apply for understanding the rise in inequality in these countries which does not rule out the country-specific causes.

The increase of income inequality in Canada since the 1990s has given rise to an important literature on income mobility. Only a few researchers so far have determined whether any changes in income inequality have been associated by an increase or decrease in income mobility rates or not (See for example for the United States, Lillard and Willis (1978), Burkhauser, et al. (1997), Gottschalk and Moffitt (1998), and Buchinsky and Hunt (1999)).

The most recent study by Brodaty (2007) on the dynamics of American earnings reveals that state dependence in the earnings mobility process is statistically significant and its magnitude is upwardly biased if individual unobserved heterogeneity is not considered. State dependence exists in earnings mobility in the United States. For every quintile but the first, it creates more stability than mobility and it favors upward movements rather than downwards. This study also shows that each individual is attracted towards a specific quintile, which makes the quintile distribution very segmented. Moreover, males, white, and the more educated are attracted towards the upper part of the distribution, while females, non-white, and the less educated tend towards the lower.

Two other studies that analyze earning mobility rates are the one by Weber (2002) which examines the behavior of individual movements in the wage distribution over the period 1986-1998 in Austria using the Austrian social security records data set, and the other one by Grodner (2000) which analyzes the factors affecting earning mobility rates in the United States and Germany for the years 1985-1987, using a harmonized dataset prepared by Panel Comparability ($PACO$) project. Weber (2002), using a fixed effects multinomial logit model and conditional likelihood maximization found that ignoring unobserved individual heterogeneity greatly overestimates the degree of state dependence in the wage mobility process. Based on Weber's finding, women are less mobile than men and have a tendency to be stuck in the lower part of the wage distribution. This tendency can be due to the possible existence of some barriers for women to move out of the lower part of the wage distribution to the upper part. Grodner (2000) found that any changes in self-employment status (relatively to being employed in both periods) increase the probability of moving both up and down in the United States and Germany, with much higher effects for the moving down in Germany. Higher education has a positive effect on the wage mobility process in both countries with the higher magnitude

for Germany. Moreover, individuals aged 35 to 44 in Germany and 25 to 34 in both countries have the highest probability of moving up.

For Canada, some studies so far have analyzed earnings (income) inequality and redistribution of income since the 1990s (see for example, Morissette (1996), Picot (1998), Schwanen (2001), and Heisz (2007)). Another study by Beach and Finnie (2001) using longitudinal income-tax-based data for Canada examines the cyclical pattern of changes in the earnings distribution and earnings mobility by sex, age groups, and analyzing their cyclical sensitivity over the period 1982-1996.

To my knowledge, most of these studies do not consider the flow rates of individuals moving into and out of any hourly wage quintiles, controlling for all observed and unobserved effects. Moreover, many of them look at the annual earnings (salary) as a whole and disregard the effect of hours of working in their calculation. The study by Morissette (1996) using hourly wage rates explains increases in earnings inequality rates in Canada since the 1990s. However, his explanation is based on a macroeconomic study and growing dispersion of hourly wages not using a micro data and considering unobserved individual heterogeneity effects for a wage mobility model.

Brodmann (2006), using Danish registered data that stems from national administrative records (1986-2002) and German Socio-Economic Panel data (*GSOEP*)(1984-2004), analyzed the factors that determine earnings mobility of the first generation male immigrants and natives, as well as earnings assimilation of immigrants in the host country. According to her research, the main explanatory variables for immigrants are educational attainments, age, marital status, unemployment rate at arrival, years since immigration, and dummy variables for the country of origin.[2] A recent study by Ostrousky (2008) on dynamics of immigrant earnings inequality

[2]I had no access to the whole paper at the time of writing this essay to get complete information about empirical results and model specification.

in Canada reveals that the economic fortunes of immigrants in Canada in the recent years have declined. Those who entered the labour market in the mid-1980s generally experienced lower levels of earnings instability in the first several years of their working careers in Canada than those who entered the labour market in the mid-1990s. Ostrousky in this essay using the Longitudinal Administrative Data bank (*LAD*) linked with the Longitudinal Immigration Database (*IMDB*) shows that the foreign education, birthplace, and the ability to speak English or French play important roles in immigrant earnings inequality.

Immigrants today account for a large and increasing proportion of labour force growth in Canada. According to a recent survey by Statistics Canada (2008), immigrants who arrived during the 1990s accounted for about 70 percent of the net labour force growth between 1991 and 2001. Data from the 2001 Census show that between 1991 and 2000 alone, 2.2 million immigrants were admitted to Canada, the highest number for any decade in the past century. Therefore, studying the dynamic wage mobility process, specifically for natives and immigrants, can be of an important issue in this context. Given the content above, my main objectives in this essay is answering the following questions:

1. What are the determinants of the transitions into and out of any hourly wage quintiles of immigrants and natives?

2. What are the proportions of spurious and structural state dependence in wage mobility process and how are they different between immigrants and natives?

3. How do economic conditions at the time of entry to the labour market (for natives) or arrival in Canada (for immigrants) affect the probability of being in any of the five hourly wage quintiles and quintile zero?

4. What are unobserved type-specific transition matrices and how are they different between immigrants and natives?

5. What are the policy implications of the form of spurious and structural state dependence to improve wage mobility process and therefore reduce income inequality?

In this essay, I carefully analyze the factors affecting income inequality in Canada for the period 1993-2004 under a wage dynamic process. I estimate Quintile Mobility Rates ($QMR$) and proportions of structural and spurious state dependence for both immigrants and natives. I examine if immigrants and natives with hourly wages in the upper (or lower) parts of the wage distribution this year tend to stay in or leave the hourly wage quintile the year after and how this intention is different between immigrants and natives. Further, to analyze how immigrants and natives are stuck in the lower or upper parts of the wage distribution based on their unobserved types, I calculate type-specific transition matrices based on the estimation results. Wage mobility process can be a product of some measured and unmeasured heterogeneity factors. These factors are different between immigrants and natives and therefore should be carefully distinguished.

The raw data shows that compared to the lowest part of the wage distribution, both immigrants and natives in the uppermost part are more educated and experienced, and more likely to be married. Immigrants in the uppermost part are less likely to be from a visible minority group, younger at arrival, been in Canada longer, and more likely to have arrived when the aggregate unemployment rate was lower. Compared to natives, immigrants have less Canadian experiences but are more educated. Estimation results show that immigrants and natives with higher levels of education have greater chances to work in the uppermost part of the wage distribution. The marginal effect of education is higher among immigrants. Further, immigrants who are younger at arrival are more likely to work in the middle part of the wage distribution. State dependence exists in all hourly wage quintiles. All state dependence variables and their initial values are highly statistically significant

in all hourly wage quintiles. Not all observed persistence is structural. Some portion is due to the unobservable factors.

The rest of the essay is organized as follows. Section 3.2 describes the data and Descriptive Statistics. Section 3.3 presents an empirical specification of the dynamic model and section 3.4 reports the empirical results.

## 3.2 Data and Descriptive Statistics

The structural estimate of the dynamic model is based on two separate samples of immigrants[3] and natives. In this essay, I only look at men aged 25-55 who are paid-employed in their main jobs. I ignore self-employed workers in my analysis. The dynamic models for immigrants and natives control for the aggregate unemployment rate, extracted form CANSIM, Table 282-0055. The unemployment rate for immigrants is the rate when they arrived in Canada.[4] For natives this is the rate at the time of entry to the labour market.[5] In addition to the aggregate unemployment rate, the models also control for the level of education, marital status, levels of Canadian work experience, and specifically for immigrants, visible minority status, years since immigration, and age at immigration.

For level of education, I use a dummy variable indicating if a person has at least 12 years of schooling (high-school degree) at the time entry to the labour market. Marital status is defined if a person is married or common-law. Levels of Canadian work experience are set of dummy variables indicating if a person has at most 10, between 10 and 20, or more than 20 years of Canadian work experience.[6]

[3]Based on *SLID*, a man is immigrant if he comes to Canada through the immigration process as an independent immigrant, through the family class, or a refugee. *SLID* does not distinguish between different groups of immigrants and considers all as immigrants.

[4]For immigrants under 25 at arrival, this rate is the rate when they are 25 years old; otherwise the rate at arrival has been applied.

[5]For natives, age 25 is the age of entry to the labour market.

[6]People with lower experience, are expected to have lower earnings profiles; therefore levels of Canadian work experience are measured by indicator variables representing different levels of work experience.

Visible minority status includes five categories of immigrants (Black, South East Asian or Oceanic, West Asian or North African (Arab), Latin American, and other groups than minorities). I ignore the effect of this variable for natives in my analysis. My calculation shows that only a small fraction of natives (about 2 percent of men aged 25-55) belongs to the visible minority groups. Years since immigration is a continuous variable indicating the individual's years of residing in Canada and finally age at immigration is a continuous variable indicating the age of immigrant at the time of arrival in Canada.

Table 3.1 presents the mean characteristics of 756 male immigrants and 7919 male natives aged 25-55 for the period 1993-2004. As weighted data shows, almost 44.6 percent of immigrants are visible minorities coming from South East Asia and Pacific Islands (29.8 percent), North Africa and West Asia (6.2 percent), and Latin America (3.1 percent). Further, about 5.5 percent of minorities are black. About 77 percent of immigrants and 73.4 percent of natives are married (or common-law) in the sample. The average unemployment rate at the time of entry to the labour market for immigrants and natives is almost 8.8 percent. About 75.7 percent of natives have at least 12 years of schooling, considerably lower than that of immigrants, which is 82.8 percent. On average, immigrants appear to have less Canadian experiences than natives, as expected. Only 21.2 percent of natives have less than 10 years of Canadian experiences. The equivalent figure for immigrants is 40.7 percent, which is noticeably higher than that of natives. A larger portion of natives has more than 10 years of Canadian experiences. Almost 35 percent of immigrants and 39.1 percent of natives have 20 to 30 years of work experience. Further, about 24.3 percent of immigrants and 39.7 percent of natives appear to have more than 30 years of work experience. Immigrants, on average, are more likely to be educated but have less Canadian experiences than comparable natives. This is consistent with Frenette and Morissette's (2003).

Table 3.1: Mean Characteristics of Males by Immigrants and Natives, Canada 1993-2004

| Variables | | Immigrants | Natives |
|---|---|---|---|
| Quintile Dummies | $Q_0$: People who do not work (quintile zero)[1] | 0.087 | 0.075 |
| | $Q_1$: People with hourly wages in the first quintile | 0.202 | 0.164 |
| | $Q_2$: People with hourly wages in the second quintile | 0.166 | 0.180 |
| | $Q_3$: People with hourly wages in the third quintile | 0.167 | 0.193 |
| | $Q_4$: People with hourly wages in the fourth quintile | 0.181 | 0.196 |
| | $Q_5$: People with hourly wages in the fifth quintile | 0.195 | 0.192 |
| Observed Characteristics | Educated [2] | 0.828 | 0.757 |
| | Black | 0.055 | - |
| | South East Asian and Oceanic | 0.298 | - |
| | North African and West Asian (Arab) | 0.062 | - |
| | Latin American | 0.031 | - |
| | Age at arrival | 21.096 | - |
| | Married [3] | 0.770 | 0.734 |
| | Unemployment Rate [4] | 8.741 | 8.748 |
| | Years Since Immigration | 20.783 | - |
| | Less Experienced [5] | 0.407 | 0.212 |
| | More Experienced [6] | 0.350 | 0.391 |
| | Number of Observations | 4536 | 47514 |
| | Number of Individuals | 756 | 7919 |

**Note:** Source: Survey of Labour and Income Dynamics (*SLID*), 1993-2004 for males aged 25-55. The figures are weighted with longitudinal weight variables provided by Statistics Canada in *SLID*.

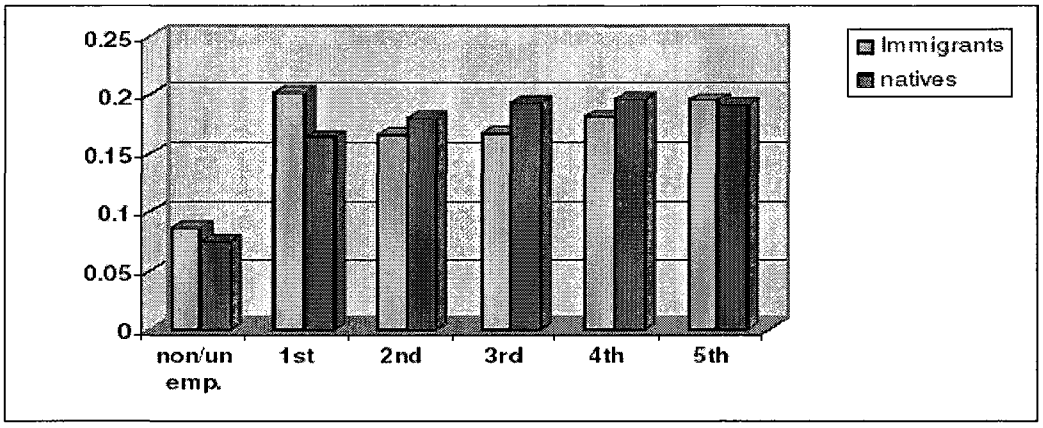
1. Unemployed or non-employed.
2. At least 12 years of schooling at the time of entry to the panel.
3. Married or common-law.
4. Unemployment rate at the time of entry to the labour market.
5. At most 10 years of Canadian full-time work experiences.
6. Between 10 and 20 years of Canadian full-time work experiences.

Table 3.1 also provides information regarding hourly wage quintiles of immigrants and natives. As data shows, there is a slight difference in the probability of being unemployed or non-employed between immigrants and natives. Almost 8.7 percent of immigrants do not work in the sample. The equivalent figure for natives is 7.5 percent. The differences between immigrants and natives are prominent along the wage distribution. Immigrants are more accumulated in the first and last quintiles and less in the middle, while natives are almost evenly distributed (Figure 3.2). The differences between immigrants and natives will be more observed if the heterogeneity between immigrant groups is considered. Figure 3.3 shows some disparities among different groups of immigrants in probability of being in the upper and lower parts of the wage distribution. As seen, Arabs, South East Asians and Oceanics, and Latin Americans are more concentrated in the first and second quintiles, while blacks are more observed in the second and third quintiles. Moreover, immigrants from other groups than minorities are more accumulated in the last quintiles (and less observed in the first) than natives are. In general, immigrants from visible minority group are more likely to be unemployed (or non-employed) in the sample than natives.[7]

Figure 3.4 compares immigrants' and natives' observed rates of participation in each hourly wage quintile over the period 1993-2004. As seen, the gap between immigrants and natives in the state of unemployment or non-employment had a cyclical movement over the period 1993-2004. Except for the period 1998-2001, natives had always been less unemployed (or non-employed) than similar immigrants in the sample. Further, observed rates of participation in quintile one were always higher for immigrants than for natives. The gap between immigrants and natives in quintile one has been narrowing gradually during the period 1993-2004. Rates of participation in the middle quintiles (quintiles two to four) changed cyclically

[7]Only blacks are less likely to be unemployed (or non-employed) than natives. About 6.5 percent of blacks in the sample do not work, lower than the percentage of natives, which is 7.5 percent.

Figure 3.2: Wage Distribution by Immigrants and Natives, Canada 1993-2004

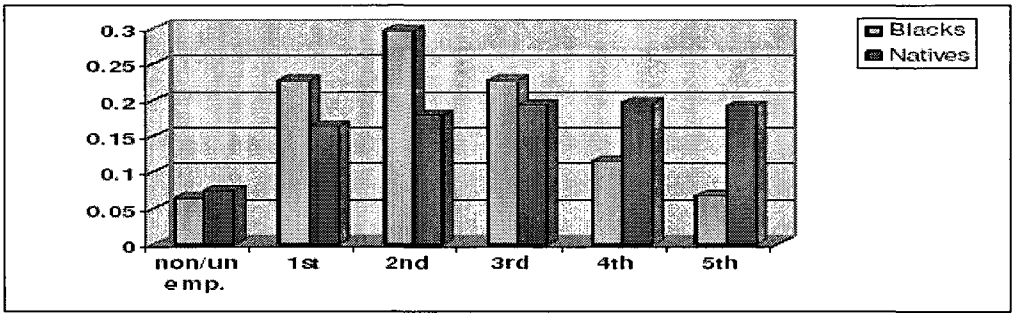


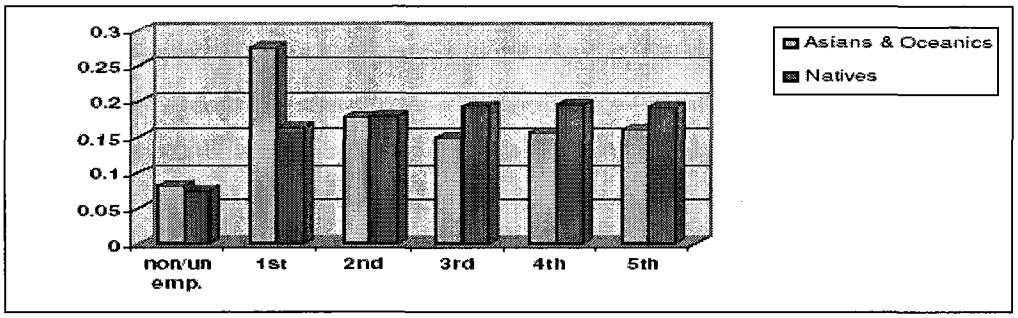

Note: Source: Survey of Labour and Income Dynamics (SLID), 1993-2004, based on a sample of males aged 25 to 65.

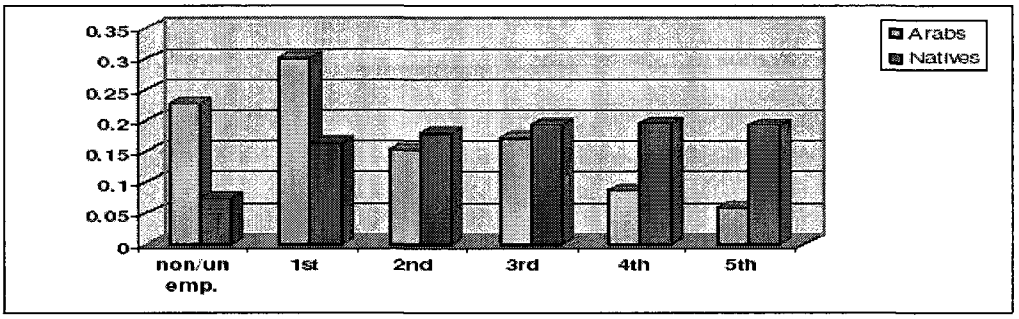
for immigrants over the period 1993-2004. Natives' rates of participation changed smoothly in quintile four, but declined substantially in quintiles two and three. Immigrants' and natives' rates of participation in the last quintile (fifth quintile) inclined dramatically over the period 1993-2004.

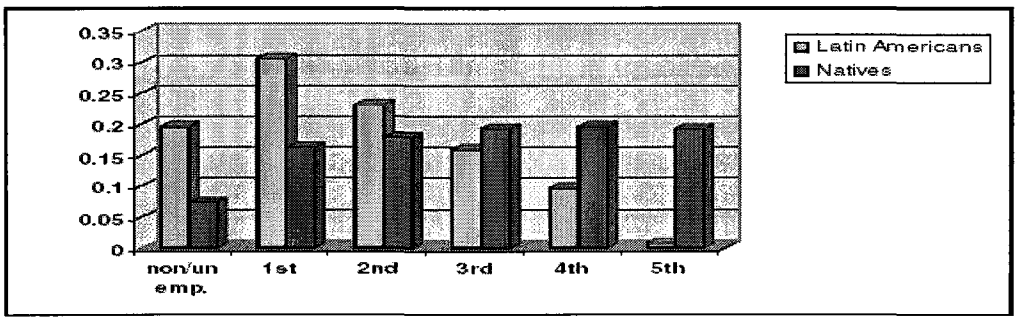
One of the objectives of this essay is to study the factors affecting transitional rates into and out of any of the five hourly wage quintiles and quintile zero. To do this, I calculate the mean characteristics of different transition and persistence states for immigrants and natives. Tables 3.2-3.5 provide this information. As seen, for immigrants any persistence in (or transitions into and out of) the lowest part of the wage distribution is associated with having less Canadian experiences, being less likely to be married (or common-law), being less likely to be educated, being more from visible minority groups (mostly from South East Asia and Pacific Islands), being older at arrival, having lower years since immigration, and facing the higher unemployment rate at the time of entry to the labour market. Moving from the lowest part of the wage distribution to the uppermost part, immigrants are more likely to be educated, more experienced, more likely to be married, less from visible minority group, and younger at arrival. They also have higher years

Figure 3.3: Wage Distribution by Different Minority Groups, Canada 1993-2004



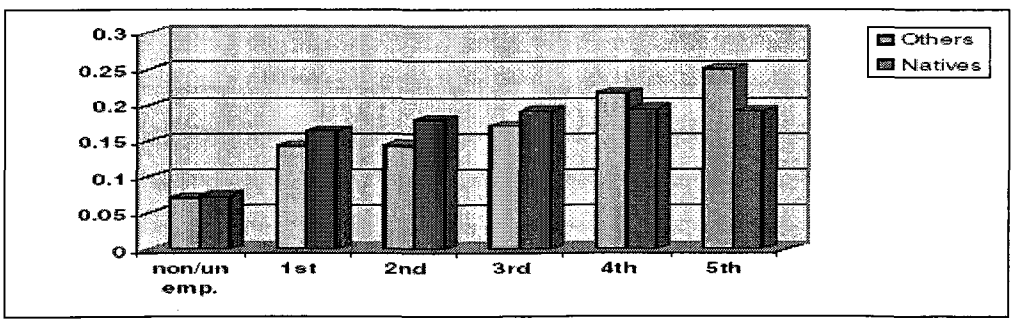



Figure 3.4: Observed Probability of the Hourly Wage Quintiles by Immigrants and Natives, Canada 1993-2004

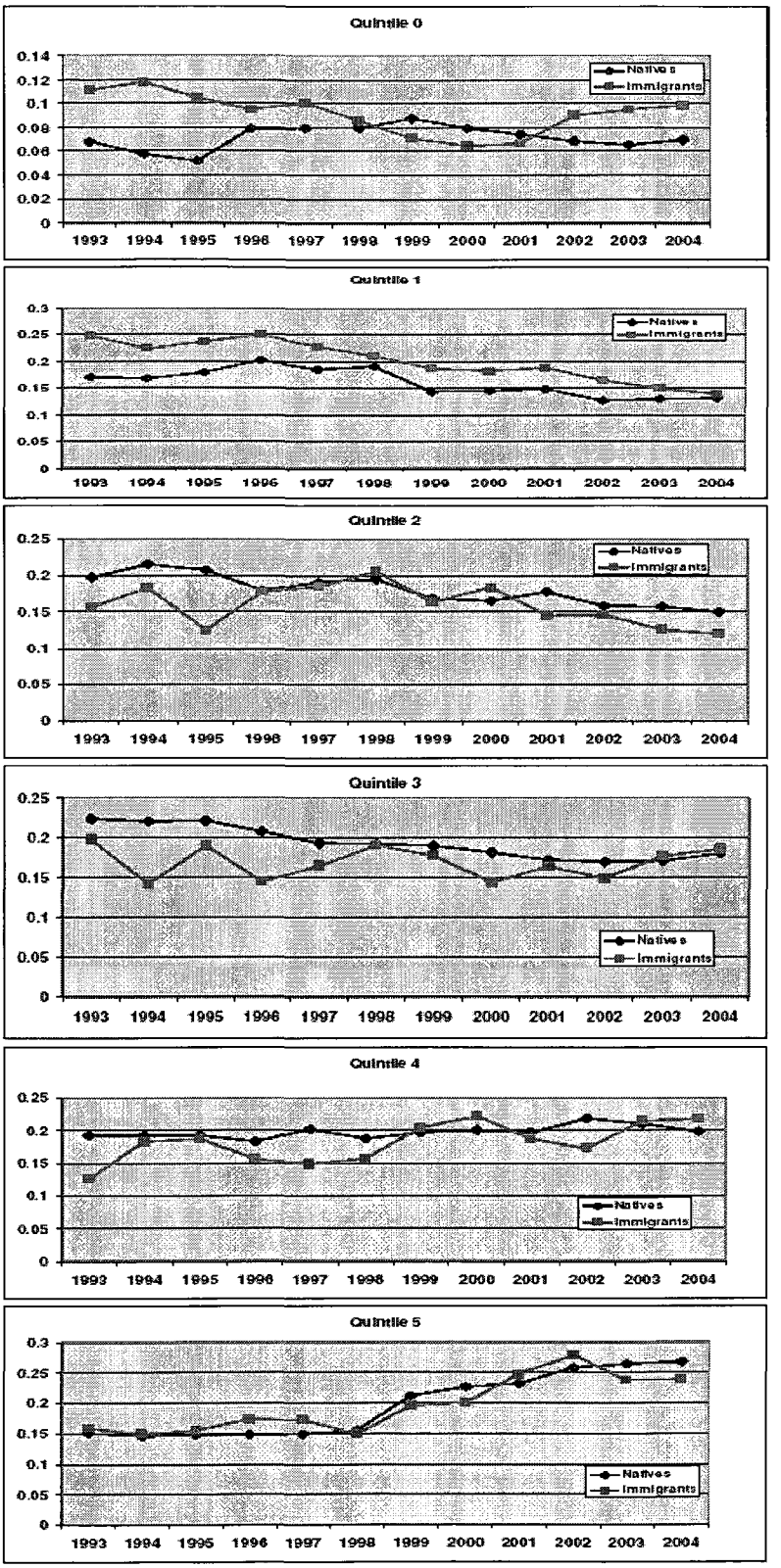


Table 3.2: Mean Characteristics by Persistence in Hourly Wage Quintiles, Immigrants, Canada 1993-2004

| Observed Characteristics | Immigrants | | | | | |
|---|---|---|---|---|---|---|
| | Persistence in | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
| **Educated** | 0.768 | 0.726 | 0.783 | 0.862 | 0.852 | 0.959 |
| **Black** | 0.036 | 0.061 | 0.124 | 0.091 | 0.025 | 0.011 |
| **South East Asian and Oceanic** | 0.267 | 0.455 | 0.336 | 0.258 | 0.252 | 0.248 |
| **North African and West Asian** | 0.147 | 0.087 | 0.051 | 0.045 | 0.021 | 0.015 |
| **Latin American** | 0.075 | 0.048 | 0.036 | 0.025 | 0.025 | 0.002 |
| **Age at Arrival** | 22.740 | 24.621 | 22.635 | 18.525 | 18.757 | 18.550 |
| **Married** | 0.616 | 0.688 | 0.820 | 0.817 | 0.805 | 0.834 |
| **Unemployment Rate** | 8.527 | 9.336 | 9.240 | 8.630 | 8.343 | 8.246 |
| **Years Since Immigration** | 21.383 | 14.840 | 17.103 | 23.817 | 24.589 | 25.521 |
| **Less Experienced** | 0.554 | 0.614 | 0.500 | 0.246 | 0.263 | 0.256 |
| **More Experienced** | 0.312 | 0.295 | 0.388 | 0.473 | 0.317 | 0.350 |
| **Number of Observations** | 154 | 493 | 376 | 440 | 508 | 603 |

since immigration, and arrived in Canada when the aggregate unemployment rate was lower. The same pattern has been observed among natives. Moving from the first quintile to the fifth, natives are more likely to be married and educated, more experienced, and face a relatively lower unemployment rate at the time of entry to the labour market. Comparing immigrants and natives, immigrants are more likely to have at least 12 years of schooling everywhere in the wage distribution. Immigrants, on average, have less Canadian experiences but are more likely to be educated.

Table 3.6 shows conditional probability of leaving previous year's quintile for

Table 3.3: Mean Characteristics by Persistence in Hourly Wage Quintiles, Natives, Canada 1993-2004

| Observed Characteristics | Natives | | | | | |
|---|---|---|---|---|---|---|
| | Persistence in | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
| Educated | 0.357 | 0.598 | 0.690 | 0.768 | 0.839 | 0.953 |
| Married | 0.416 | 0.596 | 0.716 | 0.759 | 0.832 | 0.843 |
| Unemployment Rate | 8.123 | 9.099 | 8.912 | 8.759 | 8.640 | 8.557 |
| Less Experienced | 0.531 | 0.330 | 0.174 | 0.182 | 0.121 | 0.113 |
| More Experienced | 0.265 | 0.386 | 0.453 | 0.379 | 0.373 | 0.414 |
| Number of Observations | 2202 | 5340 | 4991 | 4498 | 4942 | 4968 |

the period 1993-2004 by immigrants and natives. This table reveals several interesting relationships and patterns among immigrants and natives. I examine the issue of state dependence in the raw data. There are some similarities and differences in the dynamic hourly wage quintiles between immigrants and natives. As seen, both immigrants and natives have more persistence in the bottom and top quintiles and less in the middle. Immigrants compared to natives have less persistence in quintile zero and more movement to the quintile one. One possible reason for this pattern is the presence of new immigrants in the sample who are unemployed and so have more chances to find a job in the lower part of the wage distribution. This is consistent with Finnie's (1997) findings on earnings mobility for Canada. Moreover, reasons to be unemployed (or out of the labour force) are different between immigrants and natives and can be due to the factors which are not observed in the data. Natives are more likely to move up to the next quintiles, if they are initially in quintiles one and two. Immigrants and natives in the middle and upper parts of the wage distribution have almost the same chances to move up to their next quintiles. Downward mobility rates from any hourly wage quintiles are higher for natives

Table 3.4: Mean Characteristics by Transitions into and out of Hourly Wage Quintiles, Immigrants, Canada 1993-2004

| Observed Characteristics | Immigrants | | | | | |
|---|---|---|---|---|---|---|
| | Transition from | | | | | |
| | Lowest Part of the Wage Distribution | | Middle Part of the Wage Distribution | | Uppermost Part of the Wage Distribution | |
| | $Q_1$ to $Q_2$ | $Q_2$ to $Q_1$ | $Q_2$ to $Q_3$ | $Q_3$ to $Q_2$ | $Q_4$ to $Q_5$ | $Q_5$ to $Q_4$ |
| Educated | 0.802 | **0.804** | 0.845 | **0.805** | 0.900 | **0.867** |
| Black | 0.072 | **0.059** | 0.037 | **0.081** | 0.052 | **0.043** |
| South East Asian and Oceanic | 0.293 | **0.337** | 0.189 | **0.212** | 0.229 | **0.207** |
| North African and West Asian | 0.094 | **0.124** | 0.066 | **0.055** | 0.019 | **0.012** |
| Latin American | 0.054 | **0.050** | 0.060 | **0.068** | ~ 0 | **~ 0** |
| Age at Arrival | 22.125 | **24.009** | 22.351 | **19.058** | 20.713 | **18.898** |
| Married | 0.706 | **0.735** | 0.815 | **0.722** | 0.840 | **0.802** |
| Unemployment Rate | 9.220 | **8.825** | 8.996 | **8.923** | 8.380 | **8.238** |
| Years Since Immigration | 16.450 | **16.212** | 18.600 | **21.899** | 21.843 | **23.954** |
| Less Experienced | 0.594 | **0.608** | 0.514 | **0.335** | 0.352 | **0.256** |
| More Experienced | 0.294 | **0.256** | 0.303 | **0.365** | 0.330 | **0.424** |
| Number of Observations | 106 | **101** | 89 | **91** | 130 | **139** |

Table 3.5: Mean Characteristics by Transitions into and out of Hourly Wage Quintiles, Natives, Canada 1993-2004

| Observed Characteristics | Natives | | | | | |
|---|---|---|---|---|---|---|
| | Transition from | | | | | |
| | Lowest Part of the Wage Distribution | | Middle Part of the Wage Distribution | | Uppermost Part of the Wage Distribution | |
| | $Q_1$ to $Q_2$ | $Q_2$ to $Q_1$ | $Q_2$ to $Q_3$ | $Q_3$ to $Q_2$ | $Q_4$ to $Q_5$ | $Q_5$ to $Q_4$ |
| Educated | 0.697 | **0.642** | 0.772 | **0.750** | 0.904 | **0.898** |
| Black | 0.711 | **0.713** | 0.738 | **0.762** | 0.844 | **0.846** |
| South East Asian and Oceanic | 9.105 | **8.859** | 9.053 | **8.836** | 8.711 | **8.436** |
| North African and West Asian | 0.294 | **0.230** | 0.276 | **0.180** | 0.149 | **0.111** |
| Latin American | 0.423 | **0.449** | 0.387 | **0.416** | 0.427 | **0.378** |
| Number of Observations | 1028 | **1139** | 1012 | **1237** | 1147 | **1190** |

than for immigrants. The full transition matrices show that overall upward mobility rate is almost the same between immigrants and natives (16.8 and 16.7 percent for immigrants and natives, respectively). However, immigrants compared to natives have lower downward mobility rate (14.4 and 16 percent for immigrants and natives, respectively). One reason for such a pattern is due to the higher stability and lower downward mobility rates for immigrants compared to natives along the wage distribution. Moreover, wage distribution for immigrants is skewed towards quartile one. The vast majority of movements reach an adjacent quintile for immigrants and natives. For immigrants, the probability of moving from quintile one to two is 12 percent, higher than that of moving from quintile one to five, which is 1.6 percent. The equivalent probabilities for natives are 14.8 and 2.2 percent. There is a positive correlation between the initial quintile and downward mobility and a negative correlation with upward mobility for immigrants and natives. Thus the quintile and its lag are not independent, and being in one quintile one year increases the probability

Table 3.6: Quintile Mobility Rates, Conditional Probability of Leaving Previous Year's Quintile by Immigrants and Natives, Canada 1993-2004

| Immigrants | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Origin Quartile | Destination Quartile | | | | | | Direction | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | **0.711** | 0.180 | 0.041 | 0.047 | 0.009 | 0.011 | 0 | **0.711** | 0.289 |
| $Q_1$ | 0.055 | **0.718** | 0.120 | 0.056 | 0.034 | 0.016 | 0.055 | **0.718** | 0.227 |
| $Q_2$ | 0.019 | 0.146 | **0.645** | 0.126 | 0.035 | 0.029 | 0.165 | **0.645** | 0.19 |
| $Q_3$ | 0.014 | 0.055 | 0.155 | **0.578** | 0.143 | 0.054 | 0.225 | **0.578** | 0.197 |
| $Q_4$ | 0.011 | 0.025 | 0.035 | 0.152 | **0.621** | 0.155 | 0.224 | **0.621** | 0.155 |
| $Q_5$ | 0.002 | 0.016 | 0.018 | 0.030 | 0.157 | **0.777** | 0.223 | **0.777** | 0 |
| **Total** | **0.100** | **0.211** | **0.170** | **0.170** | **0.173** | **0.176** | **0.144** | **0.688** | **0.168** |
| **Natives** | | | | | | | | | |
| $Q_0$ | **0.758** | 0.130 | 0.053 | 0.030 | 0.019 | 0.010 | 0 | **0.758** | 0.242 |
| $Q_1$ | 0.043 | **0.687** | 0.148 | 0.061 | 0.037 | 0.022 | 0.043 | **0.687** | 0.270 |
| $Q_2$ | 0.016 | 0.153 | **0.626** | 0.146 | 0.042 | 0.017 | 0.169 | **0.626** | 0.205 |
| $Q_3$ | 0.012 | 0.048 | 0.164 | **0.589** | 0.145 | 0.043 | 0.223 | **0.589** | 0.188 |
| $Q_4$ | 0.010 | 0.025 | 0.035 | 0.164 | **0.616** | 0.150 | 0.234 | **0.616** | 0.150 |
| $Q_5$ | 0.008 | 0.014 | 0.013 | 0.033 | 0.157 | **0.774** | 0.226 | **0.774** | 0 |
| **Total** | **0.083** | **0.170** | **0.183** | **0.190** | **0.189** | **0.186** | **0.160** | **0.674** | **0.167** |

to be in the same quintile the year after (state dependence). These results are consistent with Broday's (2007). Overall, immigrants are less mobile (more persistent) than natives.[8] The steady-state rate for immigrants is 68.8 percent, slightly higher than that for natives, which is 67.4 percent.

To see if there is any heterogeneity in these dynamics among immigrants, I calculate transition matrices by immigrant groups, presented in Table 3.7. There are substantial differences among visible minority groups in persistence in (and transition into and out of) any hourly wage quintiles. As seen, Arabs and Latin Americans have more persistence in the last quintile (100th percentile), while South East Asians and Oceanics are more stable in the first and blacks are more stable in the second part of the wage distribution. Moreover, blacks and Arabs have less persistence in

[8]Yet, a comparison between the entries in Table 3.6 and those in Table 3.7 illustrates that Blacks and Arabs are more unstable (more mobile) than natives.

the fourth quintile, while South East Asians, Oceanics and Latin Americans are less stable in the third part of the wage distribution. The full transition matrices show that among different groups of immigrants, Latin Americans are the most stable and have the least downward mobility rate. Moreover, they have the lowest mobility rate from quintile five and the highest mobility rate from quintile one. Further, Arabs have the highest and South East Asians and Oceanics have the lowest upward mobility rates. In general, stability rates among immigrants except for blacks are less in the middle part of the wage distribution than natives. The vast majority of the movements reach an adjacent quintile for almost all groups of immigrants. There is a positive correlation between the initial quintile and downward mobility and a negative correlation with upward mobility for almost all groups of immigrants, as expected.

## 3.3 Model and Empirical Specification

To analyze any movements into and out of any hourly wage quintiles and quintile zero (unemployed and non-employed), I choose a dynamic unordered multinomial logit model.[9] I analyze the dynamic structure of the model as a first-order Markov process. Let assume that individual $i$ belongs to alternative $q$ at time $t$. I suppose that utility $V^*_{iqt}$ is the sum of a deterministic component, $U_{iqt}$, that depends on regressors and unknown parameters, and an unobserved random component, $\epsilon_{iqt}$:

$$V^*_{iqt} = U_{iqt} + \epsilon_{iqt} \tag{3.1}$$

[9] An ordered model could possibly have been used in this essay, but it is not clear to what extent this would have changed the results. There are some discussions by Cameron and Trivedi (2005) on ordered models that they fit the data better than multinomial unordered models when there is a natural ordering of alternatives. The effectiveness of these discussions has not been addressed in this essay but is of great interest for the future work.

Table 3.7: Quintile Mobility Rates, Conditional Probability of Leaving Previous Year's Quintile by Immigrant Minority Groups, Canada 1993-2004

| Origin Quintile | Destination Quintile | | | | | | Direction | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up | Total |
| **Immigrants (Black)** | | | | | | | | | | |
| $Q_0$ | **0.496** | 0.458 | 0.016 | ~ 0 | 0.031 | ~ 0 | 0 | **0.496** | 0.504 | **0.084** |
| $Q_1$ | 0.109 | **0.637** | 0.099 | 0.093 | 0.034 | 0.028 | 0.109 | **0.637** | 0.254 | **0.237** |
| $Q_2$ | ~ 0 | 0.103 | **0.802** | 0.046 | 0.024 | 0.026 | 0.103 | **0.802** | 0.095 | **0.255** |
| $Q_3$ | ~ 0 | 0.044 | 0.154 | **0.637** | 0.136 | 0.030 | 0.197 | **0.637** | 0.166 | **0.251** |
| $Q_4$ | 0.020 | 0.007 | 0.050 | 0.327 | **0.404** | 0.191 | 0.405 | **0.404** | 0.191 | **0.118** |
| $Q_5$ | ~ 0 | 0.055 | 0.022 | 0.017 | 0.325 | **0.583** | 0.417 | **0.583** | 0 | **0.055** |
| **Total** | | | | | | | 0.146 | **0.659** | 0.194 | **1** |
| **Immigrants (Asian and Oceanic)** | | | | | | | | | | |
| $Q_0$ | **0.716** | 0.195 | 0.039 | 0.036 | 0.003 | 0.010 | 0 | **0.716** | 0.284 | **0.10** |
| $Q_1$ | 0.040 | **0.800** | 0.089 | 0.040 | 0.022 | 0.008 | 0.040 | **0.800** | 0.16 | **0.277** |
| $Q_2$ | 0.016 | 0.153 | **0.674** | 0.089 | 0.035 | 0.033 | 0.169 | **0.674** | 0.157 | **0.163** |
| $Q_3$ | 0.014 | 0.058 | 0.133 | **0.589** | 0.169 | 0.038 | 0.204 | **0.589** | 0.207 | **0.164** |
| $Q_4$ | 0.004 | 0.025 | 0.031 | 0.152 | **0.664** | 0.124 | 0.212 | **0.664** | 0.124 | **0.157** |
| $Q_5$ | ~ 0 | 0.017 | 0.023 | 0.055 | 0.140 | **0.764** | 0.236 | **0.764** | 0 | **0.143** |
| **Total** | | | | | | | 0.128 | **0.723** | 0.149 | **1** |
| **Immigrants (Arab)** | | | | | | | | | | |
| $Q_0$ | **0.642** | 0.181 | 0.029 | 0.149 | ~ 0 | ~ 0 | 0 | **0.642** | 0.358 | **0.327** |
| $Q_1$ | 0.077 | **0.757** | 0.097 | 0.020 | 0.029 | 0.020 | 0.077 | **0.757** | 0.166 | **0.266** |
| $Q_2$ | 0.053 | 0.199 | **0.550** | 0.176 | 0.014 | 0.008 | 0.252 | **0.550** | 0.198 | **0.141** |
| $Q_3$ | 0.065 | 0.128 | 0.195 | **0.400** | 0.156 | 0.057 | 0.387 | **0.400** | 0.213 | **0.152** |
| $Q_4$ | 0.108 | 0.103 | 0.032 | 0.283 | **0.389** | 0.084 | 0.527 | **0.389** | 0.084 | **0.060** |
| $Q_5$ | ~ 0 | ~ 0 | 0.021 | ~ 0 | 0.120 | **0.859** | 0.141 | **0.859** | 0 | **0.054** |
| **Total** | | | | | | | 0.135 | **0.659** | 0.206 | **1** |
| **Immigrants (Latin American)** | | | | | | | | | | |
| $Q_0$ | **0.721** | 0.219 | 0.047 | 0.013 | ~ 0 | ~ 0 | 0 | **0.721** | 0.279 | **0.217** |
| $Q_1$ | 0.093 | **0.737** | 0.087 | 0.064 | 0.019 | ~ 0 | 0.093 | **0.737** | 0.17 | **0.380** |
| $Q_2$ | 0.029 | 0.200 | **0.621** | 0.150 | ~ 0 | ~ 0 | 0.229 | **0.621** | 0.15 | **0.205** |
| $Q_3$ | 0.024 | 0.062 | 0.309 | **0.487** | 0.105 | 0.013 | 0.395 | **0.487** | 0.118 | **0.106** |
| $Q_4$ | ~ 0 | 0.110 | ~ 0 | ~ 0 | **0.890** | ~ 0 | 0.110 | **0.890** | 0 | **0.085** |
| $Q_5$ | ~ 0 | ~ 0 | ~ 0 | ~ 0 | 0.026 | **0.974** | 0.026 | **0.974** | 0 | **0.007** |
| **Total** | | | | | | | 0.100 | **0.730** | 0.176 | **1** |
| **Immigrants (Others)** | | | | | | | | | | |
| $Q_0$ | **0.771** | 0.122 | 0.056 | 0.007 | 0.020 | 0.024 | 0 | **0.771** | 0.229 | **0.064** |
| $Q_1$ | 0.049 | **0.631** | 0.169 | 0.075 | 0.051 | 0.025 | 0.049 | **0.631** | 0.32 | **0.153** |
| $Q_2$ | 0.019 | 0.139 | **0.616** | 0.153 | 0.041 | 0.031 | 0.158 | **0.616** | 0.226 | **0.169** |
| $Q_3$ | 0.009 | 0.047 | 0.159 | **0.594** | 0.121 | 0.070 | 0.215 | **0.594** | 0.191 | **0.171** |
| $Q_4$ | 0.011 | 0.022 | 0.037 | 0.128 | **0.624** | 0.178 | 0.198 | **0.624** | 0.178 | **0.206** |
| $Q_5$ | 0.0025 | 0.016 | 0.016 | 0.022 | 0.161 | **0.783** | 0.217 | **0.783** | 0 | **0.236** |
| **Total** | | | | | | | 0.156 | **0.673** | 0.171 | **1** |

This is called an Additive Random-Utility Model ($ARUM$). I observe the outcome $Y_{it}$= $q$ if alternative $q$ has the highest utility of the alternatives. It follows that:

$$Pr(Y_{it} = q) = Pr(V^*_{iqt} \geq V^*_{ijt}) = Pr(V^*_{ijt} - V^*_{iqt} \leq 0), forallj \tag{3.2}$$

and given (3.1),

$$Pr(Y_{it} = q) = Pr(\epsilon_{ijt} - \epsilon_{iqt} \leq U_{iqt} - U_{ijt}), \tag{3.3}$$

Now assume that individuals indexed by $i$ ($i$= *1, 2, . . . , N*) belong to any of the following six mutually exclusive and exhaustive boundaries (alternatives) of wage quintiles of $q$ at time $t$ ($t$= *1, 2, . . . , T*) as below:

- $q_t$ = *0* [0] (People who do not work)
- $q_t$ = *1* (0,20] (People with wages in the range from minimum observed wage to the 20th percentile)
- $q_t$ = *2* (20,40] (People with wages between the 20th and the 40th percentile)
- $q_t$ = *3* (40,60] (People with wages between the 40th and the 60th percentile)
- $q_t$ = *4* (60,80] (People with wages between the 60th and the 80th percentile)
- $q_t$ = *5* (80,100] (People with wages above the 80th percentile)

Let the value, for individual $i$, of belonging to quintile $q$ at time $t$ ($U_{iqt}$) be specified as:

$$U_{iqt} = X_{it}.\beta_q + Z_{it}.\gamma_q + D_i.\delta_q \tag{3.4}$$

and given (3.1), $V^*_{iqt}$ can be written as:

$$V^*_{iqt} = X_{it}.\beta_q + Z_{it}.\gamma_q + D_i.\delta_q + \epsilon_{iqt} \tag{3.5}$$

Where error term, $\epsilon_{iqt}$, is composed of an individual-specific unobserved effect (time-invariant but varying across individuals) and a random error (varying both across time and individuals) as below:

$$\epsilon_{iqt} = \mu_{iq} + \upsilon_{iqt} \tag{3.6}$$

$X_{it}$ is a vector of observed time varying variables, including marital status, levels of Canadian work experience, and years since immigration. $Z_{it}$ is a vector of dummy variables indicating the previous wage quintile occupied by the individual $i$ (time state dependence). For the usual identification purpose, I take quintile zero as the reference quintile. $D_i$ is a vector of time-invariant variables, including level of education, age at immigration, the aggregate unemployment rate at the time of entry to the labour market, and visible minority status.

The assumption regarding the error term, $\epsilon_{iqt}$, can be summarized as follows: $\epsilon_{iqt}$ is composed of the two terms: $\upsilon_{iqt}$ and $\mu_{iq}$. Where $\upsilon_{iqt}$ is assumed to follow a Type I extreme value distribution and $\mu_{iq}$ is an unobserved, individual specific factor and independent of $X_{it}$ and $D_i$, but not $Z_{it}$ (endogeneity problem).

Given the distribution assumptions of $\upsilon_{iqt}$, the probability of observing individual $i$ in quintile $q$ at time $t$, conditional on $X_{it}$, $D_i$, $Z_{it}$, and $\mu_{iq}$ can be written as a six-state mutinomial logit as:

$$P_{it}(q/X, \mu_{iq}) = \frac{exp(X_{it}.\beta_q + Z_{it}.\gamma_q + D_i.\delta_q + \mu_{iq})}{\sum_{j=0}^{5} exp(X_{it}.\beta_j + Z_{it}.\gamma_j + D_i.\delta_j + \mu_{ij})} \tag{3.7}$$

Where $X$ is a vector of all explanatory variables in the model. To control for endogeneity problem, I adopt the method suggested by Wooldridge (2005). Following him, I consider the distribution of the unobserved effects, $\mu_{iq}$, conditional on $Z_{i1}$

and the mean values of exogenous time-varying variables over time ($\bar{X}_i$). $Z_{i1}$ is a vector of initial hourly wage quintiles. $\mu_{iq}$ can be written as:

$$\mu_{iq} = \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq} \tag{3.8}$$

Therefore conditional probability of (3.3) can be modified as:

$$P_{it}(q/X, \bar{X}_i, Z_{i1}, \nu_{iq}) = \frac{exp(X_{it}.\beta_q + ... + \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq})}{\sum_{j=0}^{5} exp(X_{it}.\beta_j + ... + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{3.9}$$

Following Mroz (1999), the distribution of $\nu_{iq}$ can be written as:

$$Pr(\nu_{iq} = \nu_q^m) = \pi_m, m = 1, 2, \ldots, M \tag{3.10}$$

Where,

$$\pi_m > 0 \tag{3.11}$$

$\pi_m$ is the probability that the unobserved factor takes on the values of $\nu_q^m$. To be specific, I assume that there are $m$ types of individuals and each individual at any quintiles of $q$ is endowed with a set of unobserved characteristics, $\nu_q^m$. To estimate simultaneously the parameters $\beta_q$, $\gamma_q$, $\delta_q$, $\lambda_q$, $\rho_q$, $(\nu_q^1, \ldots, \nu_q^M)$, and $(p_1, \ldots, p_M)$, I use a logistic transformation as:

$$\pi_m = \frac{exp(p_m)}{\sum_{j=1}^{M} exp(p_m)} \tag{3.12}$$

Where,

$$0 < \pi_m < 1 \tag{3.13}$$

and

$$\sum_{m=1}^{M} \pi_m = 1 \tag{3.14}$$

To select the number of support points, I calculate the value of $AIC$ and $BIC$ when an additional point of support is added. I stop adding more support points to the model when either value starts increasing.

The likelihood contribution for individual $i$ with observed quintile states $q_1, \ldots, q_T$ given all observed and unobserved effects can be written as:

$$L_i(\nu_i) = \prod_{t=2}^{T} P_{it}(q/X, \bar{X}_i, Z_{i1}, \nu_{iq}) \tag{3.15}$$

and therefore,

$$L_i(\nu_i) = \prod_{t=2}^{T} \frac{exp(X_{it}.\beta_q + ... + \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq})}{\sum_{j=0}^{5} exp(X_{it}.\beta_j + ... + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{3.16}$$

Where $\nu_i$ is a vector of $\nu_{iq}$ for $q_t$= *0, 1, ..., 4, 5.* As earlier mentioned there are $m$ types of individuals with the set of unobserved characteristics, $\nu_q^m$, that is a vector of $(\nu_q^1, \ldots, \nu_q^M)$. Therefore, I can write unconditional log-likelihood function for individual $i$ as:

$$LogL_i(\nu_i) = \log \sum_{m=1}^{M} \pi_m.L_i(\nu_q^m) \tag{3.17}$$

and finally,

$$L_{NT} = \sum_{i=1}^{N} \log \sum_{m=1}^{M} \prod_{t=2}^{T} \pi_m.\frac{exp(X_{it}.\beta_{1q} + ... + Z_{it}.\gamma_q + \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq})}{\sum_{j=0}^{5} exp(X_{it}.\beta_{1j} + ... + Z_{it}.\gamma_j + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{3.18}$$

## 3.4 Empirical Results

In this section, I report estimation results from maximizing the likelihood function of the multinomial logit model, controlling for the endogenous initial conditions

problem and unobserved heterogeneity for immigrants and natives separately (Tables 3.10 and 3.11). To show the efficiency of the model specification, I also report the estimation results of the model when there is no control for the endogenous initial conditions problem and unobserved heterogeneity (Tables 3.8 and 3.9). All estimation results are weighted by the longitudinal weights provided by Statistics Canada.

I experimented with different support points for both immigrants and natives.I found that a model with three support points fitted the data well for immigrants. For natives, number of supports is six. Tables 3.12 and 3.13 report the values of *AIC*, *BIC*, the number of parameters, and the value of the objective function for different model specifications for immigrants and natives. I used *BIC* to choose the number of support points in the estimation of each model.

Assuming that the initial conditions are exogenous and also ignoring unobserved factors generates inflated estimates of the degree of state dependence (the $\gamma's$) for immigrants and natives. When the model ignores the effects of unobserved factors, it erroneously assumes that the correlation between state dependence variables and time-invariant unobserved factors is zero. This invalid assumption overestimates state dependence parameters. This is consistent with many other studies on dynamic analysis frameworks of discrete choice modeling, for example, Brodaty (2007), Stewart (2007), Hansen et al. (2006), and Henley (2000). A recent study by Bonhomme and Robin (2007) uses a different approach (copula approach)[10] to analyze earnings dynamics and transition mobility matrices. Using a representative three-year panel form the French Labour Force Survey and a model of earnings dynamics, they found that ignoring unobserved heterogeneity factors in estimating

[10]Bonhomme and Robin (2007) in their paper, show that how the concept of copula generalizes the usual transition matrix approach to relative earnings mobility to continuous earnings processes. They develop a model of earnings dynamics that combines a flexible specification of marginal earnings distributions (to fit the large cross-sectional dimension of the data) with a tight parametric representation of the dynamics. In fact, they estimate a simple model where both cross-sections and ranks processes are parametric mixtures.

Table 3.8: Dynamic Multinomial Logit Model of Hourly Wage Quintiles, Immigrants, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| | | Estimated Equations | | | | |
|---|---|---|---|---|---|---|
| **Explanatory Variables** | | **$Q_1$** | **$Q_2$** | **$Q_3$** | **$Q_4$** | **$Q_5$** |
| **State Dependence** | $Q_{1(t-1)}$ | 4.332** (0.246) | 3.754** (0.347) | 3.693** (0.474) | 4.769** (0.837) | 3.271** (0.702) |
| | $Q_{2(t-1)}$ | 3.963** (0.391) | 6.471** (0.442) | 5.812** (0.541) | 5.430** (0.903) | 4.938** (0.739) |
| | $Q_{3(t-1)}$ | 3.047** (0.489) | 5.387** (0.508) | 7.549** (0.580) | 7.524** (0.903) | 5.773** (0.760) |
| | $Q_{4(t-1)}$ | 3.163** (0.566) | 4.329** (0.602) | 6.407** (0.644) | 9.425** (0.934) | 7.480** (0.786) |
| | $Q_{5(t-1)}$ | 4.302** (1.117) | 5.230** (1.142) | 6.344** (1.163) | 9.757** (1.334) | 10.641** (1.222) |
| **Observed Covariates** | **Educated** | -0.446* (0.244) | -0.240 (0.266) | 0.160 (0.285) | 0.262 (0.301) | 1.133** (0.346) |
| | **Black** | 0.435 (0.485) | 0.913* (0.496) | 0.674 (0.514) | 0.018 (0.555) | -0.325 (0.613) |
| | **South East Asian and Oceanic** | 0.449* (0.271) | 0.100 (0.286) | 0.023 (0.295) | -0.097 (0.304) | -0.303 (0.314) |
| | **North African and West Asian** | 4.332** (0.246) | 3.754** (0.347) | 3.693** (0.474) | 4.769** (0.837) | 3.271** (0.702) |
| | **Latin American** | -0.567 (0.461) | -0.556 (0.497) | -0.791 (0.545) | -0.889 (0.610) | -2.500** (1.095) |
| | **Age at Arrival** | -0.080** (0.017) | -0.103** (0.019) | -0.080** (0.020) | -0.080** (0.020) | -0.063** (0.021) |
| | **Married** | 0.465* (0.251) | 0.740** (0.270) | 0.854** (0.280) | 0.479* (0.287) | 0.893** (0.308) |
| | **Unemployment Rate** | -0.003 (0.074) | 0.001 (0.079) | -0.009 (0.081) | -0.054 (0.083) | -0.021 (0.087) |
| | **Years Since Immigration** | -0.110** (0.022) | -0.130** (0.025) | -0.089** (0.026) | -0.094** (0.027) | -0.075** (0.028) |
| | **Less Experienced** | -0.956** (0.451) | -1.363** (0.4824) | -1.102** (0.4884) | -0.907* (0.503) | -0.642 (0.523) |
| | **More Experienced** | -0.813** (0.382) | -0.994 (0.4025) | -0.805** (0.4050) | -0.813** (0.414) | -0.831* (0.4291) |
| | **Intercept** | 3.002** | 2.777* | 0.235 | -0.399 | -2.013 |
| | **Number of Observation** | 4536 | | **Log-Likelihood** | | -3674.6 |
| | **Number of Individuals** | 756 | | **AIC** | | 7519.1 |
| | **Number of Parameters** | 85 | | **BIC** | | 7912.5 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5% or 1% level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 3.9: Dynamic Multinomial Logit Model of Hourly Wage Quintiles, Natives, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | Estimated Equations | | | | |
|---|---|---|---|---|---|---|
| | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
| State Dependence | $Q_{1(t-1)}$ | 4.629** (0.089) | 3.954** (0.119) | 3.713** (0.167) | 3.289** (0.178) | 4.451** (0.420) |
| | $Q_{2(t-1)}$ | 4.053** (0.126) | 6.443** (0.143) | 5.841** (0.181) | 4.494** (0.193) | 5.490** (0.426) |
| | $Q_{3(t-1)}$ | 3.121** (0.156) | 5.532** (0.162) | 7.658** (0.193) | 6.263** (0.199) | 6.916** (0.425) |
| | $Q_{4(t-1)}$ | 2.316** (0.160) | 3.568** (0.167) | 6.108** (0.189) | 7.422** (0.192) | 7.934** (0.420) |
| | $Q_{5(t-1)}$ | 2.272** (0.204) | 2.979** (0.217) | 4.494** (0.223) | 6.459** (0.220) | 9.981** (0.431) |
| Observed Covariates | Educated | 0.528** (0.0704) | 0.873** (0.074) | 1.133** (0.077) | 1.408** (0.081) | 2.125** (0.097) |
| | Married | 0.400** (0.0732) | 0.688** (0.077) | 0.760** (0.079) | 0.944** (0.082) | 1.004** (0.090) |
| | Unemployment Rate | 0.249** (0.0210) | 0.265** (0.022) | 0.273** (0.022) | 0.262** (0.023) | 0.261 (0.024) |
| | Less Experienced | -0.638** (0.1006) | -1.047** (0.105) | -0.994** (0.107) | -1.160 (0.111) | -1.057** (0.120) |
| | More Experienced | -0.065 (0.0953) | -0.166* (0.095) | -0.361** (0.097) | -0.396 (0.098) | -0.255 (0.103) |
| | Intercept | -4.191** | -5.501** | -6.584** | -6.809** | -9.498** |
| | Number of Observation | 47514 | | Log-Likelihood | -38911.9 | |
| | Number of Individuals | 7919 | | AIC | 77933.7 | |
| | Number of Parameters | 55 | | BIC | 78317.5 | |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5% or 1% level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 3.10: Dynamic Multinomial Logit Model of Hourly Wage Quintiles, Immigrants, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| | | | Estimated Equations | | | | |
|---|---|---|---|---|---|---|---|
| **Explanatory Variables** | | | **$Q_1$** | **$Q_2$** | **$Q_3$** | **$Q_4$** | **$Q_5$** |
| **State Dependence** | $Q_{1(t-1)}$ | | 3.644** (0.2924) | 2.751** (0.4057) | 3.171** (0.5705) | 4.912** (1.2178) | 3.369** (1.0437) |
| | $Q_{2(t-1)}$ | | 3.335** (0.4666) | 5.246** (0.5173) | 4.757** (0.6478) | 5.418** (1.2750) | 4.840** (1.0730) |
| | $Q_{3(t-1)}$ | | 2.789** (0.6011) | 4.342** (0.6287) | 6.485** (0.7222) | 7.105** (1.2960) | 5.521** (1.1099) |
| | $Q_{4(t-1)}$ | | 2.789** (0.6011) | 4.342** (0.6287) | 6.485** (0.7222) | 7.105** (1.2960) | 5.521** (1.1099) |
| | $Q_{5(t-1)}$ | | 4.967** (2.4648) | 5.460 (2.4760) | 6.514** (2.4892) | 9.7452** (2.7154) | 10.078** (2.5985) |
| **Observed Covariates** | **Educated** | | -0.670** (0.2624) | -0.558* (0.2921) | -0.155 (0.3330) | 0.018 (0.3816) | 0.8647** (0.4009) |
| | **Black** | | 0.492 (0.5014) | 1.158 (0.5169) | 1.070* (0.5498) | 0.740 (0.6516) | 0.3452 (0.6763) |
| | **South East Asian and Oceanic** | | 0.664** (0.293) | 0.352 (0.310) | 0.239 (0.330) | 0.166 (0.367) | -0.1672 (0.363) |
| | **North African and West Asian** | | -0.102 (0.410) | -0.875* (0.464) | -0.980* (0.509) | -0.713 (0.608) | -0.8642 (0.622) |
| | **Latin American** | | -0.283 (0.524) | -0.140 (0.571) | -0.265 (0.659) | -0.149 (0.865) | -2.7455 (1.785) |
| | **Age at Arrival** | | -0.061** (0.017) | -0.087** (0.019) | -0.074** (0.020) | -0.067* (0.023) | -0.049** (0.023) |
| | **Married** | | 1.464** (0.694) | 0.045 (0.763) | 1.111 (0.830) | 0.402 (0.865) | 1.3840 (0.915) |
| | **Unemployment Rate** | | 0.061 (0.0766) | 0.070 (0.0823) | 0.047 (0.0866) | 0.065 (0.0934) | 0.1368 (0.0951) |
| | **Years Since Immigration** | | -0.054 (1.174) | 0.071 (0.199) | 0.284 (0.215) | 0.149 (0.227) | 0.164 (0.224) |
| | **Less Experienced** | | -2.120 (1.394) | -2.695* (1.501) | -1.040 (1.560) | -0.230 (1.646) | -1.690 (1.657) |
| | **More Experienced** | | -2.616** (1.031) | -2.928** (1.084) | -2.083* (1.097) | -1.005 (1.145) | -2.417** (1.1617) |
| **Pr 1** | 84.2% | **Type 1** | 0.478 | -0.851 | -3.352* | -7.394** | -8.748** |
| **Pr 2** | 14.2% | **Type 2** | 1.630 | 3.080* | 2.403 | 0.103 | -2.927 |
| **Pr 3** | 1.6% | **Type 3** | 0.312 | 0.912 | 8.606 | 1.797 | 6.041 |

| | | | |
|---|---|---|---|
| **Number of Observation** | 4536 | **Log-Likelihood** | -3488.8 |
| **Number of Individuals** | 756 | **AIC** | 7260.6 |
| **Number of Parameters** | 142 | **BIC** | 7917.7 |

**Note:** Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5% or 1% level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 3.11: Dynamic Multinomial Logit Model of Hourly Wage Quintiles, Natives, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | | Estimated Equations | | | | |
|---|---|---|---|---|---|---|---|
| | | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
| State Dependence | $Q_{1(t-1)}$ | | 2.521** (0.137) | 2.295** (0.1731) | 3.079** (0.2172) | 3.241** (0.2378) | 3.054** (0.3379) |
| | $Q_{2(t-1)}$ | | 2.510** (0.186) | 4.205** (0.2233) | 4.545** (0.2409) | 3.968** (0.2550) | 4.374** (0.3412) |
| | $Q_{3(t-1)}$ | | 2.432** (0.205) | 4.112** (0.2166) | 5.957** (0.2571) | 5.095** (0.2493) | 5.289** (0.3472) |
| | $Q_{4(t-1)}$ | | 2.235** (0.214) | 3.115** (0.2175) | 4.494** (0.2367) | 5.826** (0.2404) | 5.544** (0.3397) |
| | $Q_{5(t-1)}$ | | 1.922** (0.262) | 2.845** (0.265) | 4.373** (0.284) | 4.961** (0.275) | 6.349** (0.374) |
| Observed Covariates | Educated | | 0.425** (0.1006) | 0.720** (0.0969) | 1.079** (0.0962) | 1.436** (0.1033) | 2.259** (0.1402) |
| | Married | | 0.566** (0.2546) | 0.610** (0.2565) | 0.686** (0.2630) | 0.571** (0.2710) | 0.975** (0.2905) |
| | Unemployment Rate | | 0.252** (0.0293) | 0.275** (0.0286) | 0.293** (0.0282) | 0.301** (0.0291) | 0.324** (0.0323) |
| | Less Experienced | | -0.729** (0.3437) | -0.655* (0.3414) | -0.635* (0.3446) | -0.764** (0.3517) | -0.602 (0.3707) |
| | More Experienced | | -0.306 (0.2541) | -0.226 (0.2498) | -0.308 (0.2490) | -0.204 (0.2519) | 0.040 (0.2635) |
| Pr 1 | 31.2% | Type 1 | -5.579** | -5.920** | -7.752** | -9.034** | -13.619** |
| Pr 2 | 7.7% | Type 2 | 2.092** | -3.188** | -6.876** | -9.594** | -13.046** |
| Pr 3 | 26.5% | Type 3 | -3.100** | -6.024** | -7.777** | -8.720** | -10.505** |
| Pr 4 | 11.4% | Type 4 | -6.397** | -6.644** | -6.199** | -8.654** | -11.897** |
| Pr 5 | 11.7% | Type 5 | -6.659** | -8.615** | -9.566** | -8.467** | -9.466** |
| Pr 6 | 11.5% | Type 6 | -6.916** | -6.809** | -6.235** | -5.783** | -8.864** |

| | | | |
|---|---|---|---|
| Number of Observation | 47514 | Log Likelihood | -36745.8 |
| Number of Individuals | 7919 | AIC | 73741.6 |
| Number of Parameters | 125 | BIC | 74613.7 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5% or 1% level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 3.12: Discrete Factor Model (*DFM*) Specification for Immigrants, Information Criteria (*AIC and BIC*), Number of Parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 7519.1 | 7912.5 | 85 | -3674.6 |
| No | Yes | 1 | 7328.1 | 7929.8 | 130 | -3534.1 |
| Yes | Yes | 2 | 7292 | 7921.5 | 136 | -3510 |
| Yes | Yes | 3 | 7260.6 | 7917.7 | 142 | -3488.3 |
| **Yes** | **Yes** | **4** | 7257.5 | **7942.5*** | 148 | -3480.8 |

**Note:** The figures are based on the estimation results presented in Tables 3.7 and 3.9.

Table 3.13: Discrete Factor Model (*DFM*) Specification for Natives, Information Criteria (*AIC and BIC*), Number of Parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 77933.7 | 78317.5 | 55 | -38911.9 |
| No | Yes | 1 | 75451.3 | 76114.1 | 95 | -37630.6 |
| Yes | Yes | 2 | 74613.6 | 75318.2 | 101 | -37205.8 |
| Yes | Yes | 3 | 74262.2 | 75008.7 | 107 | -37024.1 |
| Yes | Yes | 4 | 73976.0 | 74764.5 | 113 | -36875 |
| Yes | Yes | 5 | 73811.1 | 74641.4 | 119 | -36786.6 |
| **Yes** | **Yes** | **6** | 73741.6 | **74613.7[1]** | 125 | -36745.8 |

**Note:** The figures are based on the estimation results presented in Tables 3.8 and 3.10.

1- I stopped adding more supports points. After 6 numbers of support points, estimation results remained almost unchanged.

transition probability matrices leads to underestimating inequality levels and the importance of inequality responses to macroeconomic shocks.

My attention in this research focuses more on estimated transition probabilities, proportion of spurious and structural state dependence, and type-specific transition matrices (Tables 3.14 to 3.18). The estimated transition matrices are evaluated at the corresponding sample means and are based on the estimates reported in Tables 3.7 to 3.10. Because the models presented in this essay have a non-linear nature, the magnitudes of the coefficient estimates provide little information about the size of the effects of the observable covariates. Therefore, to analyze the effect of these covariates on probability of being in any hourly wage quintiles, I calculate marginal effects of significant parameters.[11][12] I note that education and experience are significant factors determining hourly wage differences between immigrants and natives. This is, to some extent, in line with Bingley and Westergaard-Nielsen (1997). They found that education and experience are important factors determining individuals' position in the wage distribution. My results show that for immigrants, education has a negative significant effect on logit probability of being in the lower parts of the wage distribution (quintiles one and two) and a positive significant effect on logit probability of being in the last quintile (quintile five), all other factors fixed. For natives, education has a positive significant effect on logit probability of being in any hourly wage quintiles. My calculation shows that the marginal effect of having at least 12 years of schooling is negative in the first and second quintiles and positive in the last quintile for both immigrants and natives, indicating that immigrants and natives with higher years of education have greater

[11]Marginal probabilities are calculated based on the estimation results reported in Tables 3.10 and 3.11. I only reported those which are statistically significant. As coefficient estimates of multinomial logit models are difficult to interpret, instead I calculate the marginal probabilities

[12]I discuss the sign and size of marginal effects with respect to their parameter significance in the multinomial logit model. Causality might require a significance test based on standard errors of these probabilities. No such standard errors have been computed for the marginal effects in this paper. However, it seems likely that highly significant parameter estimates will also have statistically significant marginal effects.

chances to work in the uppermost part of the wage distribution. Marginal effect of education is higher among immigrants than among natives. For example, for immigrants marginal effects of education on probability of being in the first and second quintiles are -0.0373 and -0.0361, respectively, while the equivalent figure in quintile five is 0.0787. For natives, marginal effects of education on probability of being in the first and second quintiles are -0.027 and -0.013, respectively, while the similar figure in quintile five is 0.048. Immigrants who have Canadian experience are less likely to be in the lower part of the wage distribution (quintile two), all other factors fixed. For natives, the positive marginal effect of having more Canadian experience is highest in the middle part of the wage distribution (third quintile). Being married (or common-law) increases logit probability of being in the lowest part of the wage distribution (quintile one) among immigrants, all other factors fixed. Being married (or common-law) has a positive significant effect on logit probability of being in any hourly wage quintiles among natives. Unemployment rate at the time of entry to the labour market is not a significant factor determining wage differentials among immigrants. This is not the case for natives. There is some heterogeneity among different groups of immigrants in the probability of being in any hourly wage quintiles. For example, Arabs have a lower logit probability of being in quintiles two and three, while being Latin American has no significant effect on logit probability of being in any hourly wage quintiles, other factors being fixed. Marginal effects of being Arab in quintiles two and three are -0.0335 and -0.0365, respectively. Blacks are more likely to be in the third quintile, while South East Asians are estimated to be in the first part of the wage distribution, all other factors fixed. Age at immigration is a significant factor determining the probability of being in any hourly wage quintiles. Schaafsma and Sweetman (2001) also found a strong negative correlation between age at immigration and earnings. My calculations show that immigrants who are younger at arrival are more likely to be in the middle part of the wage

distribution. In fact, the probability of being in the lowest and uppermost part of the wage distribution is higher for immigrants who are older at arrival. Marginal effects of age when it increases from 20 to 30 are negative in the first and fifth quintiles (-0.042 and -0.0175, respectively) and positive in quintiles two, three, and four (0.0252, 0.081, and 0.062, respectively). Immigrants who are older at arrival are more likely to work at the bottom and uppermost parts of the wage distribution (first and fifth quintiles). There is a possible correlation between age at arrival and education/experience among immigrants in the uppermost part of the wage distribution, which makes immigrants, who are older at arrival, more likely be in the uppermost part of the distribution. State dependence exists in all hourly wage quintiles. All state dependence variables and their initial values are highly statistically significant in all hourly wage quintiles.

Tables 3.14 and 3.15 report estimated conditional probabilities of leaving previous year's quintile with and without controlling for the endogenous initial conditions problem and unobserved heterogeneity for immigrants and natives. As expected, when controls for these factors are incorporated in the model, there is a reduction in estimated stability rates (and an increase in most transition probabilities). Reduction in stability rates is due to the fact that some portion of observed persistence is attributed to unobserved serial correlations (Heckman, 1981b). For the earnings mobility process, Brodaty (2007) found that stability will be reduced when the model controls for these factors. This fact has been confirmed by various studies with different applications. For example, Hansen, Lofstorm, and Zhang (2006) found this pattern in analyzing transitions into and out of social assistance in Canada. Arulampalam et al. (1998) also found the same results for modeling the unemployment incidence of British men.

My overall conclusions from Tables 3.13 and 3.14 are as follows:

- For the model which does not control for spurious effects, persistence in being

Table 3.14: Transition Matrix for Immigrants and Natives, Estimated Conditional Probabilities of Leaving Previous Year's Quintile, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Origin Quartile | Destination Quartile | | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| **Immigrants** | | | | | | | | | |
| $Q_0$ | **0.721** | 0.159 | 0.067 | 0.033 | 0.009 | 0.011 | 0.000 | **0.721** | 0.279 |
| $Q_1$ | 0.054 | **0.657** | 0.144 | 0.071 | 0.052 | 0.023 | 0.054 | **0.657** | 0.290 |
| $Q_2$ | 0.017 | 0.137 | **0.614** | 0.168 | 0.030 | 0.035 | 0.154 | **0.614** | 0.233 |
| $Q_3$ | 0.012 | 0.039 | 0.145 | **0.603** | 0.152 | 0.049 | 0.154 | **0.614** | 0.233 |
| $Q_4$ | 0.009 | 0.031 | 0.034 | 0.127 | **0.637** | 0.162 | 0.201 | **0.637** | 0.162 |
| $Q_5$ | 0.003 | 0.023 | 0.021 | 0.027 | 0.196 | **0.730** | 0.270 | **0.730** | 0.000 |
| **Total** | 0.064 | 0.163 | 0.158 | 0.190 | 0.208 | 0.218 | 0.171 | **0.656** | 0.174 |
| **Natives** | | | | | | | | | |
| $Q_0$ | **0.682** | 0.163 | 0.078 | 0.035 | 0.037 | 0.006 | 0.000 | **0.682** | 0.319 |
| $Q_1$ | 0.036 | **0.693** | 0.161 | 0.056 | 0.038 | 0.017 | 0.036 | **0.693** | 0.272 |
| $Q_2$ | 0.013 | 0.134 | **0.643** | 0.154 | 0.041 | 0.016 | 0.147 | **0.643** | 0.211 |
| $Q_3$ | 0.009 | 0.035 | 0.167 | **0.601** | 0.149 | 0.040 | 0.211 | **0.601** | 0.189 |
| $Q_4$ | 0.014 | 0.022 | 0.032 | 0.171 | **0.621** | 0.141 | 0.239 | **0.621** | 0.141 |
| $Q_5$ | 0.012 | 0.017 | 0.014 | 0.040 | 0.173 | **0.745** | 0.256 | **0.745** | 0.000 |
| **Total** | 0.071 | 0.179 | 0.191 | 0.193 | 0.192 | 0.174 | 0.166 | **0.660** | 0.175 |

Note: Calculations are based on the estimation results presented in Tables 3.8 and 3.9.

Table 3.15: Transition Matrix for Immigrants and Natives, Estimated Conditional Probabilities of Leaving Previous Year's Quintile, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Immigrants | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Origin Quartile** | **Destination Quartile** | | | | | | **Direction** | | |
| | **$Q_0$** | **$Q_1$** | **$Q_2$** | **$Q_3$** | **$Q_4$** | **$Q_5$** | **Down** | **Stable** | **Up** |
| **$Q_0$** | **0.455** | 0.197 | 0.165 | 0.097 | 0.023 | 0.064 | 0.000 | **0.455** | 0.546 |
| **$Q_1$** | 0.039 | **0.449** | 0.149 | 0.131 | 0.153 | 0.080 | 0.039 | **0.449** | 0.513 |
| **$Q_2$** | 0.016 | 0.111 | **0.514** | 0.178 | 0.077 | 0.103 | 0.127 | **0.514** | 0.358 |
| **$Q_3$** | 0.013 | 0.051 | 0.142 | **0.530** | 0.175 | 0.090 | 0.206 | **0.530** | 0.265 |
| **$Q_4$** | 0.020 | 0.091 | 0.090 | 0.199 | **0.390** | 0.211 | 0.400 | **0.390** | 0.211 |
| **$Q_5$** | 0.002 | 0.077 | 0.074 | 0.079 | 0.221 | **0.548** | 0.453 | **0.548** | 0.000 |
| **Total** | 0.011 | 0.019 | 0.010 | 0.085 | 0.180 | 0.694 | 0.406 | **0.514** | 0.080 |
| **Natives** | | | | | | | | | |
| **$Q_0$** | **0.424** | 0.200 | 0.157 | 0.067 | 0.088 | 0.064 | 0.000 | **0.424** | 0.576 |
| **$Q_1$** | 0.075 | **0.284** | 0.173 | 0.155 | 0.206 | 0.108 | 0.075 | **0.284** | 0.641 |
| **$Q_2$** | 0.033 | 0.119 | **0.361** | 0.208 | 0.146 | 0.133 | 0.153 | **0.361** | 0.487 |
| **$Q_3$** | 0.020 | 0.084 | 0.217 | **0.385** | 0.169 | 0.126 | 0.321 | **0.385** | 0.294 |
| **$Q_4$** | 0.028 | 0.117 | 0.147 | 0.222 | **0.359** | 0.127 | 0.514 | **0.359** | 0.127 |
| **$Q_5$** | 0.040 | 0.123 | 0.170 | 0.192 | 0.223 | **0.253** | 0.747 | **0.253** | 0.000 |
| **Total** | **0.067** | **0.164** | **0.284** | **0.165** | **0.133** | **0.188** | **0.317** | **0.336** | **0.347** |

Note: Calculations are based on the estimation results presented in Tables 3.10 and 3.11.

unemployed (or non-employed) is higher for immigrants than for natives. The probability of being unemployed (or non-employed) next year, if one is unemployed (or non-employed) this year, is 72.1 percent for immigrants, higher than that for natives, which is 68.2 percent.[13] Further, transition probabilities from first and middle parts of the wage distribution into the unemployment (or non-employment) state are higher for immigrants than for natives, with the higher structural portions for natives.

- Natives have more chances to be employed next year if they are unemployed (or non-employed) this year, than similar immigrants, when the model does not control for spurious effects. For natives, the probabilities of moving into first and second quintiles from quintile zero are 16.3 and 7.8 percent, respectively, higher than those for immigrants, which are 15.9 percent and 6.7 percent. The same pattern has been obtained in transition from first to second wage quintile. The probability of moving from first to second wage quintile for natives is 16.1 percent, higher than that for immigrants, which is 14.4 percent. When moving from the middle to the uppermost part of the wage distribution, immigrants and natives behave differently. Immigrants in the upper part of the wage distribution are more likely to move up to the next quintiles than comparable natives. For immigrants, the probability of moving into quintiles three, four, and five from their previous quintiles are 16.8, 15.2, and 16.2 percent, respectively. The equivalent figures for natives are 15.4, 14.9, and 14.1 percent, which are lower than those for immigrants. Looking at the structural parts of these transitions in Table 3.14, except in quintile two in which natives have higher probability (20.2 percent) to move up to the next quintile, immigrants always do better in the upper part of the wage distribution.

[13]The differences between estimated transition matrices reported in Table 3.13 and observed transition matrices reported in Table 3.6 are due to the observed explanatory variables.

- The full transition matrices for immigrants and natives show that the vast majority of the movements reach an adjacent quintile. For example, for immigrants, when the model ignores the effect of spurious factors, the probability of moving from first to second quintile is 14.4 percent, higher than that of moving from first to fifth quintile, which is 2.3 percent. The equivalent figures for natives are 16.1 percent and 1.7 percent. The initial quintile has a positive correlation with downward mobility and a negative correlation with upward mobility for immigrants and natives. These results are in line with Brodaty (2007) and are true both when the model controls and ignores the spurious effects.

The transition probabilities that are reported in Tables 3.14 and 3.15 can be used to decompose the estimated state dependence into structural and spurious state dependence. Immigrant-native differences in persistence in any hourly wage quintiles are more apparent when the spurious effects are removed from the estimation. One possible explanation for this is the differences between immigrants and natives in unobserved characteristics such as statistical discrimination, labour market preferences, and unemployment experiences. Table 3.16 shows the proportion of structural and spurious state dependence in hourly wage quintiles for immigrants and natives. This table clearly illustrates the effect of spurious effects in immigrant-native differences in unemployment (or non-employment) state, as well as in any hourly wage quintiles of one to five. As seen, immigrants have higher degrees of structural state dependence in all hourly wage quintiles than natives, except in quintile zero in which immigrants and natives have almost the same proportions of structural and spurious effects. Immigrants and natives have the highest structural persistence in quintiles three (87.9 percent) and four (57.8 percent), respectively. For natives, persistence in the last quintile (quintile five) stems, to a greater extent (66 percent), from unobserved heterogeneity factors, while for immigrants only 24.9

Table 3.16: Percentage of Structural and Spurious State Dependence in Hourly Wage Quintiles by Immigrants and Natives, Canada 1993-2004

| | $Q_0$ | | $Q_1$ | | $Q_2$ | | Q3 | | Q4 | | Q5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious |
| Immigrants | 63.1 | 36.9 | 68.3 | 31.7 | 83.7 | 16.3 | 87.9 | 12.1 | 61.2 | 38.8 | 75.1 | 24.9 |
| Natives | 62.2 | 37.8 | 41 | 59 | 56.1 | 43.9 | 56.1 | 43.9 | 57.8 | 42.2 | 34 | 66 |

Note: Calculations are based on the estimation results presented in Tables 3.8 to 3.11.

percent of the persistence is spurious. In general, persistence in first and last quintiles for natives predominantly stems from unobserved heterogeneity factors, while immigrants have a greater proportion of structural persistence. Differences between immigrants and natives in structural persistence in the lower, middle, and upper parts of the wage distribution reinforce the necessity of having a dynamic model which controls for both spurious and structural factors.

According to Brodaty (2007), individuals with different unobserved characteristics have different tendencies to be stuck in the upper or lower parts of the earnings distribution. As a result, the wage distribution can be highly segmented in the long-run. To analyze how immigrants and natives behave on the basis of their unobserved types, I constructed type-specific transition matrices for immigrants and natives.

Tables 3.17 and 3.18 report the type-specific transition matrices for immigrants and natives. There are three unobserved heterogeneity types for immigrants and each type has a probability mass of 84.2, 14.2, and 1.6 percent of the sample. Type one immigrants have a high persistence in any hourly wage quintiles. There are

Table 3.17: Type Specific Estimated Transition Matrices, Immigrants

**Type 1**

| Origin Quartile | Destination Quartile | | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | **0.563** | 0.221 | 0.124 | 0.049 | 0.010 | 0.034 | 0.000 | 0.563 | 0.438 |
| $Q_1$ | 0.059 | **0.585** | 0.133 | 0.083 | 0.087 | 0.053 | 0.059 | 0.585 | 0.356 |
| $Q_2$ | 0.027 | 0.171 | **0.543** | 0.131 | 0.050 | 0.079 | 0.198 | 0.543 | 0.260 |
| $Q_3$ | 0.024 | 0.092 | 0.181 | **0.479** | 0.140 | 0.084 | 0.297 | 0.479 | 0.224 |
| $Q_4$ | 0.036 | 0.156 | 0.111 | 0.177 | **0.320** | 0.200 | 0.480 | 0.320 | 0.200 |
| $Q_5$ | 0.005 | 0.137 | 0.093 | 0.072 | 0.179 | **0.515** | 0.486 | 0.515 | 0.000 |
| Distribution | 0.061 | 0.165 | 0.180 | 0.223 | 0.149 | 0.222 | 0.291 | **0.497** | 0.212 |

**Type 2**

| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
|---|---|---|---|---|---|---|---|---|---|
| $Q_0$ | 0.040 | 0.030 | 0.196 | **0.346** | 0.256 | 0.132 | 0.000 | 0.040 | 0.960 |
| $Q_1$ | 0.002 | 0.037 | 0.088 | 0.205 | **0.598** | 0.070 | 0.002 | 0.037 | 0.961 |
| $Q_2$ | 0.001 | 0.006 | 0.260 | 0.272 | **0.355** | 0.106 | 0.007 | 0.260 | 0.733 |
| $Q_3$ | 0.001 | 0.001 | 0.033 | 0.436 | **0.475** | 0.054 | 0.035 | 0.436 | 0.529 |
| $Q_4$ | 0.001 | 0.001 | 0.014 | 0.117 | **0.765** | 0.102 | 0.133 | 0.765 | 0.102 |
| $Q_5$ | 0.000 | 0.002 | 0.014 | 0.055 | **0.565** | 0.364 | 0.636 | 0.364 | 0.000 |
| Distribution | 0.011 | 0.012 | 0.091 | 0.283 | 0.448 | 0.155 | 0.169 | **0.547** | 0.284 |

**Type 3**

| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
|---|---|---|---|---|---|---|---|---|---|
| $Q_0$ | 0.000 | 0.000 | 0.000 | 0.263 | 0.002 | **0.735** | 0.000 | 0.000 | 1.000 |
| $Q_1$ | 0.000 | 0.000 | 0.000 | 0.232 | 0.008 | **0.760** | 0.000 | 0.000 | 1.000 |
| $Q_2$ | 0.000 | 0.000 | 0.000 | 0.251 | 0.002 | **0.747** | 0.000 | 0.000 | 1.000 |
| $Q_3$ | 0.000 | 0.000 | 0.000 | 0.430 | 0.006 | **0.564** | 0.000 | 0.430 | 0.570 |
| $Q_4$ | 0.000 | 0.000 | 0.000 | 0.103 | 0.009 | **0.888** | 0.103 | 0.009 | 0.888 |
| $Q_5$ | 0.000 | 0.000 | 0.000 | 0.016 | 0.002 | **0.982** | 0.018 | 0.982 | 0.000 |
| Distribution | 0.000 | 0.000 | 0.000 | 0.271 | 0.005 | 0.724 | 0.014 | **0.828** | 0.159 |

almost equal mobilities into upper and lower parts of the wage distribution from any hourly wage quintiles. This makes upward and downward mobility rates almost the same for type one immigrants. Type two and type three immigrants are attracted towards the quintiles four and five, respectively. This makes wage distribution very segmented in the upper parts of the wage distribution for these types of immigrants. Further, type two immigrants also have a high probability to move into quintile three, if they are initially unemployed (or non-employed).

There are six unobserved heterogeneity types for natives and each type has

Table 3.18: Type Specific Estimated Transition Matrices, Natives

| Type 0 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Origin | Destination Quartile | | | | | | Direction | | |
| Quartile | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | **0.493** | 0.135 | 0.228 | 0.062 | 0.069 | 0.013 | 0.000 | 0.493 | 0.507 |
| $Q_1$ | 0.100 | 0.214 | **0.276** | 0.166 | 0.211 | 0.033 | 0.100 | 0.214 | 0.686 |
| $Q_2$ | 0.039 | 0.072 | **0.489** | 0.206 | 0.149 | 0.045 | 0.111 | 0.489 | 0.401 |
| $Q_3$ | 0.024 | 0.053 | 0.312 | **0.396** | 0.175 | 0.042 | 0.388 | 0.396 | 0.217 |
| $Q_4$ | 0.035 | 0.082 | 0.232 | 0.239 | **0.369** | 0.042 | 0.589 | 0.369 | 0.042 |
| $Q_5$ | 0.051 | 0.087 | **0.268** | 0.215 | 0.259 | 0.120 | 0.880 | 0.120 | 0.000 |
| **Distribution** | 0.080 | 0.119 | **0.286** | **0.211** | **0.223** | 0.081 | 0.328 | **0.380** | 0.292 |
| Type 1 | | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | 0.259 | **0.476** | 0.086 | 0.033 | 0.046 | 0.101 | 0.000 | 0.259 | 0.742 |
| $Q_1$ | 0.033 | **0.567** | 0.082 | 0.067 | 0.101 | 0.150 | 0.033 | 0.567 | 0.400 |
| $Q_2$ | 0.019 | **0.331** | 0.255 | 0.120 | 0.084 | 0.190 | 0.350 | 0.255 | 0.394 |
| Q3 | 0.013 | **0.257** | 0.171 | 0.255 | 0.111 | 0.193 | 0.441 | 0.255 | 0.304 |
| $Q_4$ | 0.017 | **0.305** | 0.102 | 0.136 | 0.236 | 0.205 | 0.560 | 0.236 | 0.205 |
| $Q_5$ | 0.022 | 0.302 | 0.108 | 0.102 | 0.119 | **0.347** | 0.653 | 0.347 | 0.000 |
| **Distribution** | 0.048 | **0.327** | 0.142 | 0.136 | 0.129 | **0.219** | 0.336 | **0.375** | 0.290 |
| Type 2 | | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | 0.134 | **0.432** | 0.386 | 0.029 | 0.011 | 0.008 | 0.000 | 0.134 | 0.866 |
| $Q_1$ | 0.015 | **0.513** | 0.366 | 0.062 | 0.028 | 0.016 | 0.015 | 0.513 | 0.472 |
| $Q_2$ | 0.005 | 0.186 | **0.693** | 0.077 | 0.019 | 0.020 | 0.191 | 0.693 | 0.116 |
| $Q_3$ | 0.004 | 0.157 | **0.550** | 0.220 | 0.037 | 0.032 | 0.711 | 0.220 | 0.069 |
| $Q_4$ | 0.008 | 0.238 | **0.423** | 0.158 | 0.118 | 0.055 | 0.827 | 0.118 | 0.055 |
| $Q_5$ | 0.010 | 0.236 | **0.445** | 0.122 | 0.066 | 0.121 | 0.879 | 0.121 | 0.000 |
| **Distribution** | 0.027 | **0.255** | 0.432 | 0.131 | 0.069 | 0.086 | 0.312 | **0.481** | 0.207 |
| Type 3 | | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | **0.446** | 0.077 | 0.126 | 0.236 | 0.070 | 0.046 | 0.000 | 0.446 | 0.555 |
| $Q_1$ | 0.076 | 0.116 | 0.128 | **0.456** | 0.146 | 0.078 | 0.076 | 0.116 | 0.808 |
| $Q_2$ | 0.028 | 0.036 | 0.226 | **0.532** | 0.089 | 0.090 | 0.064 | 0.226 | 0.711 |
| $Q_3$ | 0.011 | 0.015 | 0.086 | **0.729** | 0.084 | 0.074 | 0.112 | 0.729 | 0.158 |
| $Q_4$ | 0.021 | 0.028 | 0.071 | **0.546** | 0.241 | 0.094 | 0.666 | 0.241 | 0.094 |
| $Q_5$ | 0.032 | 0.033 | 0.091 | **0.498** | 0.152 | 0.194 | 0.806 | 0.194 | 0.000 |
| **Distribution** | 0.077 | 0.071 | 0.131 | **0.460** | 0.132 | 0.129 | 0.257 | **0.464** | 0.278 |
| Type 4 | | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | 0.281 | 0.041 | 0.087 | 0.123 | **0.333** | 0.135 | 0.000 | 0.281 | 0.719 |
| $Q_1$ | 0.043 | 0.054 | 0.073 | 0.190 | **0.495** | 0.145 | 0.043 | 0.054 | 0.903 |
| $Q_2$ | 0.018 | 0.018 | 0.150 | 0.268 | **0.364** | 0.182 | 0.036 | 0.150 | 0.814 |
| $Q_3$ | 0.007 | 0.007 | 0.053 | 0.386 | **0.382** | 0.165 | 0.067 | 0.386 | 0.547 |
| $Q_4$ | 0.007 | 0.006 | 0.023 | 0.152 | **0.659** | 0.153 | 0.188 | 0.659 | 0.153 |
| $Q_5$ | 0.012 | 0.008 | 0.030 | 0.144 | **0.455** | 0.352 | 0.649 | 0.352 | 0.000 |
| **Distribution** | 0.064 | 0.035 | 0.086 | 0.224 | **0.401** | 0.190 | 0.218 | **0.450** | 0.332 |
| Type 5 | | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | Down | Stable | Up |
| $Q_0$ | **0.564** | 0.096 | 0.036 | 0.014 | 0.083 | 0.206 | 0.000 | 0.564 | 0.435 |
| $Q_1$ | 0.140 | 0.209 | 0.059 | 0.045 | 0.231 | **0.316** | 0.140 | 0.209 | 0.651 |
| $Q_2$ | 0.079 | 0.108 | 0.163 | 0.077 | 0.179 | **0.393** | 0.187 | 0.163 | 0.649 |
| $Q_3$ | 0.049 | 0.066 | 0.087 | 0.150 | 0.236 | **0.411** | 0.202 | 0.150 | 0.647 |
| $Q_4$ | 0.047 | 0.057 | 0.034 | 0.053 | 0.398 | **0.413** | 0.191 | 0.398 | 0.413 |
| $Q_5$ | 0.050 | 0.041 | 0.028 | 0.030 | 0.164 | **0.687** | 0.313 | 0.687 | 0.000 |
| **Distribution** | 0.111 | 0.132 | 0.091 | 0.075 | 0.213 | **0.378** | 0.210 | **0.461** | 0.330 |

a probability mass of 31.2, 7.7, 26.5, 11.4, 11.7, and 11.5 percent of the sample. Almost each type is attracted towards a specific quintile. For example, type one individuals have the highest probability to move into the quintile one, if they are initially in any of the first four quintiles and quintile zero. Type two and type three individuals are more attracted towards quintiles two and three, respectively, whereas type four and type five are attracted to quintiles four and five. Type zero natives have a high persistence in the middle part of the wage distribution. With regard to overall upward and downward mobility, type zero, type one, and type two individuals have higher downward than upward mobility; whereas type three, type four, and type five have higher upward than downward mobility.

Overall, Tables 3.14-3.18 suggest that immigrant-native gaps in persistence in, or transitions into and out of, any hourly wage quintiles are due to some measured and unmeasured factors. The results also point to the importance of controlling for the endogenous initial conditions problem and unobserved heterogeneity factors. I also note that individuals with different unobserved types have different tendencies to be accumulated in the lower, middle, or upper parts of the wage distribution.

Finally, Table 3.19 shows the predicted and observed distribution of wage quintiles. The predicted distributions are calculated for each year. Overall, the predicted distributions are almost similar to the observed frequencies, indicating that the empirical models fit the data well. One measure of goodness of fit in discrete choice modeling is the likelihood ratio index. The index ranges from zero (no model) to one (perfect model). Table 3.20 reports the likelihood ratio indices for the final models.

Table 3.19: Predicted and Observed Distribution of Hourly Wage Quintiles by Immigrants and Natives, Canada 1994-2004

| *Immigrants* | Observed | | | | | Predicted | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
| 1994 | 0.223 | 0.183 | 0.142 | 0.183 | 0.150 | **0.211** | **0.183** | **0.183** | **0.189** | **0.162** |
| 1995 | 0.237 | 0.125 | 0.190 | 0.187 | 0.156 | **0.190** | **0.203** | **0.184** | **0.189** | **0.165** |
| 1996 | 0.251 | 0.178 | 0.145 | 0.157 | 0.175 | **0.179** | **0.187** | **0.224** | **0.177** | **0.167** |
| 1997 | 0.228 | 0.186 | 0.164 | 0.149 | 0.173 | **0.192** | **0.190** | **0.197** | **0.174** | **0.185** |
| 1998 | 0.210 | 0.206 | 0.190 | 0.157 | 0.150 | **0.170** | **0.188** | **0.225** | **0.168** | **0.188** |
| 1999 | 0.187 | 0.164 | 0.178 | 0.204 | 0.196 | **0.160** | **0.193** | **0.211** | **0.185** | **0.206** |
| 2000 | 0.184 | 0.184 | 0.143 | 0.222 | 0.203 | **0.137** | **0.165** | **0.206** | **0.215** | **0.230** |
| 2001 | 0.188 | 0.146 | 0.195 | 0.187 | 0.247 | **0.130** | **0.164** | **0.214** | **0.207** | **0.244** |
| 2002 | 0.164 | 0.147 | 0.150 | 0.173 | 0.277 | **0.134** | **0.137** | **0.192** | **0.211** | **0.284** |
| 2003 | 0.149 | 0.127 | 0.177 | 0.216 | 0.236 | **0.116** | **0.139** | **0.220** | **0.194** | **0.286** |
| 2004 | 0.140 | 0.121 | 0.187 | 0.217 | 0.237 | **0.098** | **0.129** | **0.240** | **0.199** | **0.283** |
| *Natives* | Observed | | | | | Predicted | | | | |
| Year | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
| 1994 | 0.168 | 0.215 | 0.221 | 0.192 | 0.146 | **0.178** | **0.217** | **0.213** | **0.190** | **0.136** |
| 1995 | 0.179 | 0.207 | 0.222 | 0.192 | 0.148 | **0.176** | **0.224** | **0.210** | **0.196** | **0.131** |
| 1996 | 0.202 | 0.180 | 0.208 | 0.183 | 0.148 | **0.176** | **0.223** | **0.215** | **0.195** | **0.128** |
| 1997 | 0.185 | 0.191 | 0.193 | 0.202 | 0.149 | **0.190** | **0.210** | **0.199** | **0.188** | **0.142** |
| 1998 | 0.191 | 0.195 | 0.192 | 0.187 | 0.155 | **0.181** | **0.213** | **0.203** | **0.191** | **0.139** |
| 1999 | 0.144 | 0.169 | 0.190 | 0.197 | 0.213 | **0.181** | **0.206** | **0.191** | **0.192** | **0.156** |
| 2000 | 0.145 | 0.166 | 0.182 | 0.200 | 0.227 | **0.150** | **0.199** | **0.195** | **0.198** | **0.183** |
| 2001 | 0.148 | 0.178 | 0.172 | 0.197 | 0.232 | **0.150** | **0.196** | **0.196** | **0.202** | **0.183** |
| 2002 | 0.126 | 0.159 | 0.170 | 0.218 | 0.259 | **0.120** | **0.190** | **0.198** | **0.211** | **0.213** |
| 2003 | 0.130 | 0.158 | 0.171 | 0.210 | 0.265 | **0.122** | **0.188** | **0.201** | **0.212** | **0.209** |
| 2004 | 0.132 | 0.150 | 0.181 | 0.198 | 0.268 | **0.122** | **0.187** | **0.201** | **0.214** | **0.208** |

**Note:** Predicted values are calculated based on the estimation results presented in Tables 3.10 and 3.11.

Table 3.20: Fit of the Model (*Likelihood Ratio Index*)

| | LL[1] (Full Model) | LL (Full Model) | Likelihood Ratio Index |
|---|---|---|---|
| **Immigrants** | -6656.8 | -3488.3 | 0.48 |
| **Natives** | -68592.3 | -36745.8 | 0.46 |

**Note:** 1. Model with all explanatory variables restricted to zero.

# Chapter 4

# Essay III: Immigrant-Native Differences in Earnings Mobility Process: Evidence from Canadian and Danish Data

## 4.1 Co-authorship statements

This essay is taken from the paper written by both Nisar Ahmad and myself (Rayhaneh Esmaeilzadeh), during Nisar Ahmad's visit at Concordia University, Canada from September 1st, 2008 to January 29th, 2009. Both authors have the equal contribution to the paper.

## 4.2 Introduction

Canada and Denmark have experienced high income inequality since the 1980s.[1] In addition, immigrants from less developed countries are over-represented in the lower part of the income distribution in both countries. The study by Blume and Verner (2007) for Denmark shows that first generation immigrants, especially from the less developed countries, were highly over-represented among the receivers of public income transfers during the period 1984-1999, while immigrants from developed countries are moderately over-represented. For Canada, a recent study by Yuri Ostrousky (2008) on dynamics of immigrant earnings inequality reveals that the economic fortunes of immigrants in the recent years have declined.

Immigration in Denmark is dominated through non-labour immigrants (family reunification, refugees, etc.), whereas Canada has a very long history of labour immigrants (skilled workers). Recently, the Danish government has introduced the same immigration policies as the Canadian immigration system for skilled workers.[2] It would be of a great interest to compare the earnings mobility of immigrants and natives between two countries with different immigration histories.

The primary interest in studying earnings mobility is its relation with income inequality. It is believed that higher earnings mobility can reduce long-run income inequality.[3] Gini coefficients for Denmark and Canada in 2007 are 0.247 and 0.326, respectively (World Development Indicators (*WDI*), 2008). Higher Gini

[1] In Denmark, the Gini coefficient increased by 14 percent during the period 1984-2003 (Deding et al., 2002). The equivalent figure for Canada is 11.3 percent for the period 1979-2004 (Heisz, 2007).

[2] For more information on new immigration policies for Denmark visit www.newindenmark.dk and for Canada www.cic.gc.ca.

[3] For an earliest reference, we quote from Friedman (1962) "Two societies that have the same distribution of annual income. In one there is great mobility and change so that the position of particular families in the income hierarchy varies widely from year to year. In the other, there is great rigidity so that each family stays in the same position year after year. Clearly, in any meaningful sense, the second would be the more unequal society" (p. 171).

coefficient in Canada compared to Denmark might be a result of lower earnings mobility. Furthermore, labour market policies in Denmark provide greater insurance against adverse earnings shocks, in the form of unemployment insurance and social assistance, which make individuals move easily in the income ladders. Hence, one might expect higher earnings mobility in Denmark compared to Canada. Eriksson and Westergaard-Nielson (2007) also argued that institutional setup of the Danish labour market strongly facilitates labour mobility. On the other hand, Canada is a land of immigrants with a higher proportion of skilled immigrants. Skilled workers are more likely to move up into the income ladder (Theodos and Bednarzik, 2006). Higher proportion of skilled immigrants might make Canada a country with a higher earnings mobility compared to Denmark. Due to these contradictory predictions, we do not have a priori expectation about earnings mobility rates in Canada and Denmark. This is an empirical question which will be addressed in this essay.

Measuring earnings dynamics could be very interesting for policy makers and researchers. For example, the optimal design of unemployment insurance, social assistance, and other income support programs depend on a good understanding of earnings dynamics and the distribution of earnings in a longer-term perspective. In particular, if a large number of individuals have shorter low earnings or unemployment spells, then this problem can be addressed with types of unemployment insurance. On the other hand, if smaller numbers of individuals have longer spells then long term structural solutions are required (skill enhancement programs). Similarly, labor market programs, specifically related to human capital development, can be designed and evaluated more accurately with a better understanding of the earnings mobility. For example, if we observe that earnings tend to rise for individuals who stay longer in the labor market then policies should be aimed to get people started in the labor market.[4]

[4]The policy discussion is derived from Ross Finnie's (1997).

Various studies have been carried out to compare the earnings mobility of the United States and other European countries (see for example, Burkhauser et al. (1997), Grodner (2000), Aaberge et al. (2002), Deding (2002), etc.). In our knowledge there is no study that compares Canada's labour earnings mobility with other European countries. This is the first study that compares the earnings mobility of Canada with Denmark. This comparison will be very interesting since the Danish labour market is very different from other countries in many aspects. For example, Denmark has the highest female labour force participation rate in the world, highest replacement ratio of unemployment benefits for low-wage earners, relatively widespread eligibility for unemployment benefit, etc (for more details, see Eriksson and Westergaard-Nielsen, 2007).

Given the content above, our main objective in this essay is to answer the following questions:

1. What are the determinants of the transitions into and out of any of the earnings quartiles?

2. What are the proportions of spurious and structural state dependence in earnings mobility process?

3. What are unobserved type-specific transition matrices and how are they different between immigrants and natives?

4. What are the policy implications of the form of spurious and structural state dependence to improve earnings mobility process and therefore reduce income inequality?

In this essay, we estimate and analyze a dynamic multinomial logit model with random effects which covers significant observable variables affecting earnings mobility process. The observed raw data shows that immigrants in Denmark are

more attracted towards the lower parts of the earnings distribution, while similar natives are evenly distributed. In Canada, immigrants are more observed in the lower and upper parts of earnings distribution, while natives are more attracted to the middle. Moreover, upward mobility is higher than the downward for immigrants in both countries, but with higher magnitude for Danish immigrants. The estimation results show that the extent of state dependence (mobility) is over-estimated (underestimated) if the model does not control for endogenous initial condition and unobserved individual heterogeneity. Almost all state dependence parameters are positive and statistically significant, indicating that labour market flexibility makes transition towards the quartile zero less probable. Immigrants in Denmark have very high structural state dependence compared to natives, whereas immigrants and natives in Canada have very similar pattern of structural and spurious state dependence. The unobserved type-specific transition matrices for immigrants and natives in Denmark and Canada show that each type has a different transitions pattern. As a result, the long-run stationary earning distribution is segmented on the basis of unobserved types.

This essay is organized in the following way. Section 4.3 reviews important literatures on earnings mobility. In section 4.4, we give background information about immigration history of Denmark and Canada. The data and descriptive statistics are described in section 4.5. Section 4.6 presents an empirical specification of the dynamic model. The empirical results are discussed in section 4.7.

## 4.3 Literature Reviews

Considerable literature exists on earnings mobility, especially for the United States. A nice theoretical and empirical review is presented in Atkinson et al. (1992). In this section, we will review and compare some important and recent studies of the

United States, Denmark, and Canada.

### 4.3.1 Studies on the United State

Burkhauser et al. (1997) has compared the labour earnings mobility and inequality of prime-age men and women in the United States and Germany during the growth years of the 1980s. The data for the U.S. is the Panel Study of Income Dynamics (*PSID*) (1982-1988), whereas for Germany, it is the German Socio-Economic Panel (*GSOEP*) (1984-1988). Despite major differences in the labour market institutions between two countries, the descriptive statistics shows a surprisingly similar pattern of quartile-to-quartile mobility in the two countries. Moreover, the study shows somewhat greater overall labour market mobility in the United States, no difference in downward mobility, and small but significantly larger extreme upward mobility in Germany than in the United States over the period studied. The labour earnings dynamics are modeled by Auto Regressive Moving Averages (*ARMA(1,1)*) specification using logarithm of labour earnings. The empirical results show that there are some differences in the dynamic earnings path, however the end result is the similarities of the earnings mobility for the two countries. The study has merits in calculating and comparing earnings mobility and inequality between the United Sates and Germany using a dynamic analysis frame work, however the empirical methodology is purely statistical, in a sense that it does not impose any structure on the earnings profiles and did not control for any observed explanatory variables.

Grodner (2000) extends Burkhauser et al.'s (1997) study to identify the determinants of moving up and down in the earnings distribution for Germany and the United State. The study has used the binomial probit model for the years 1985-1987 using similar data. The results show that changes in self employment status increase the probability of moving both up and down in the two countries, with much higher effects for moving down in Germany. Higher education has both

protective and prospective effects with higher magnitudes for Germany. Grodner modified Burkhauser' approach to control for the observed characteristics, however, the study analyzes earnings mobility only in the short-run, which is not sufficient for explaining the long-run dynamics.

In another study for the United State, Buchinsky and Hunt (1999) using National Longitudinal Survey of Youth (*NLSY*) (1979-1991), present empirical measures of mobility through both hourly wage and annual earnings distribution. Their model is estimated by non-parametric approach. They decomposed summary measures of mobility into within and between group components. The study found that within-group mobility was predominant and it increased most rapidly when the time horizon is extended, thereby it reduced wage inequality (by 12 percent) to 26 percent. Further, they discussed within-group mobility among earnings quartiles, using year to year estimates of transition probabilities. They found that mobility declined over time, especially at the bottom end of the wage and earnings distribution. This study has a comprehensive comparison of mobility for wage and earnings distribution and is a good source of information.

The most recent study by Brodaty (2007) on the dynamics of American earnings reveals that state dependence in the earnings mobility process is statistically significant and its magnitude is upwardly biased if individual unobserved heterogeneity is not considered. State dependence exists in earnings mobility in the United States. For every quintile but the first, it creates more stability than mobility and it favors upward movements rather than downwards. This study also shows that each individual is attracted towards a specific quintile, which makes the quintile distribution very segmented. Moreover, males, white, and the more educated are attracted towards the upper part of the distribution, while females, non-white, and the less educated tend towards the lower. The main contribution of this paper is that it controls for state dependence variables in quintile mobility and calculates

and compares type-specific transition matrices which can be a good reference for any studies on earnings dynamics.

### 4.3.2 Studies on Denmark

Bingley and Westergaard-Nielsen (1997) identify some of the determinants of individual's wage mobility rates over time. Specifically, they looked at decile transition matrices for the period 1980-1990 to discuss mobility of individuals in the wage distribution. They estimated upward and downward mobility rates using a simple probit model. Their model takes attrition and decile of origin into account. They compared the results of probit model with the switching regression model's to simulate the effects of different variables on wage mobility. They found that education and experience are important factors determining individuals' position in the wage distribution. Moreover, unemployment is the single most important obstacle to the upward mobility. The empirical model disregards the state dependence.

Aaberge et al. (2002) measured and compared the earnings mobility of Scandinavian countries and the United State over the period 1980-1990. Instead of transition matrix approach, the study used a modified version of mobility suggested by Shorrocks (1978). The mobility is measured as the relative reduction in the weighted average of single year inequality. The measure incorporates the close relationship between income inequality and mobility. The results suggest that the pattern of mobility turns out to be very similar in all the countries.[5] The study does not talk about upward or downward mobility rates and only looks at overall mobility rates.

[5]The pattern is similar in the sense that the proportionate reduction in inequality from increasing the accounting time of income is much the same. Aaberge et al. measured the mobility as follows:

$$M = 1 - \frac{G}{\sum_{t=1}^{T} \mu_t / \mu G_t} \tag{4.1}$$

Where M is the crude measure of mobility, G is the Gini Coefficient, and $\mu_t$ is the mean of the T-year distribution of income.

The study by Deding (2002) compares the mobility rates out of low wage employment in Denmark, Germany, and the United State. The study compares the mobility rates both at the aggregate level and by applying a micro-econometric framework. At the aggregate level, she constructed transition matrices for three countries, considering three different states i.e. no wage, low wage, and high wage. Deding found that the mobility patterns are similar across the countries especially for the one-year transition rate, while there is more variation across countries for the three-year period. Level of mobility is higher in Denmark than in Germany, whereas the United State appears rather immobile in the short-run, but mobility increases in the long-run. In order to see the effect of different explanatory variables, she modeled the probability of being low paid in 1993, conditional on low pay in 1992. She found similar results for the three countries in the short-run but these results differ in the long-run. The empirical model disregards the dynamic behaviors of individuals over time.

### 4.3.3 Studies on Canada

For Canada, some studies have analyzed earnings mobility and redistribution of income since the 1990s. A study by Finnie (1997) analyzes earning mobility of Canadians over the period 1982-1992. Using the Longitudinal Administrative Database ($LAD$) from Revenue Canada tax files, this paper examines how individuals' earnings mobility varies with the time period considered and starting position in the earnings distribution, as well as by age and sex. Finnie found higher stability in the upper parts of earnings distribution. Moreover, he found higher upward mobility than downward, especially over longer periods of time and particularly for younger workers. The lower end of the earnings distribution was frequently accumulated with new entrants. Long-run upward mobility rates were higher than short-run. Finnie expanded his analysis to comparison of earnings mobility among different age groups

and sexes, as well as different business cycle effects. Based on his results, younger males tended to be less stable (more mobile) than older ones, particularly in an upward direction. Whereas women were normally less likely to move up and to stay at the top once there. Earnings mobility also varied with business cycle changes and across different age-sex groups. Women in their prime working years were actually more likely to move up through the earnings distribution in the later years, right through the recessionary 1990s. Similarly, aged men experienced a moderate increase in their rates of earnings growth, and upward mobility declined substantially amongst the youngest groups of men and women (under 25), especially for those at the lowest earnings levels to begin with. The study did a through investigation on earnings dynamics of individuals over time. However, it lacks a formal econometrics examination of quartile mobility.

One study by Beach and Finnie (2001) using longitudinal income tax-based data examines the cyclical pattern of changes in the earnings distribution and earnings mobility by sex and age groups over the period 1982-1996. Beach and Finnie analyzed the effects of business cycles on short-run transition probability matrices for men and women across different age groups and for the two periods of peak (1988-89) and trough (1991-92). Their results show that the higher unemployment rate decreases the average net probability of moving up for men, significantly more than that for women. Beach and Finnie also found that younger workers (20 to 34 years old) of both genders are more sensitive to business cycle effects than prime and older workers (35 to 64 years old). Moreover, the higher unemployment rate increases polarization rates across all age and sex groups. Men have the highest cyclical sensitivity of the earnings at the lower end of the distribution; while for females, the greatest cyclical sensitivity occurs in the upper end of the earnings distribution. The study looks at only one-year transition matrices and does not calculate the long-run mobility rates for the period studied. This paper also lacks a

formal econometrics assessment of mobility rates.

## 4.4 History of Immigration process in Denmark and Canada

As mentioned earlier, Denmark and Canada have different immigration histories. Denmark has a relatively short history of immigration, whereas a formal immigration policy in Canada started in 1947.

Until the 1950s, Denmark was a country of net emigration. Denmark was characterized by high labour demand at the end of the 1950s, which triggered labour immigration, mainly from Turkey and Yugoslavia. From that time until 1973, Denmark had a steady inflow of labour immigrants. Then a ban was introduced for labour market-oriented immigration from non-European Economic Area (*EEA*) nationals. Immigration continued afterward, but mainly through family reunification. Since 1979, Denmark has accepted refugees on an annual basis for humanitarian migration. In the early 1990s, the number of war refugees and asylum seekers increased from former Yugoslavia and other countries. The peak in asylum seeking was reached in 1992-1993 with the peak in unemployment rate (see Liebig (2007) for more details).

Like most other European countries, Denmark needs more immigrants in the labour market due to aging and lower population growth. Unlike immigration policies in Canada, Australia, and other developed countries, there was no precise skilled immigration process in Denmark to facilitate skilled immigrants into the economy. Most immigrants in Denmark came through family reunification, as refugees, and asylums, especially from non-western countries. Table 4.1 presents classification of immigrants by purpose of entry into Denmark and Canada. The table shows that in 1999, 73.5 percent of all immigrants arrived in Denmark as a family class or refugee.

Table 4.1: Classification of Immigrants by Purpose of Entry into Denmark and Canada

| | | 1999 | 2002 | 2001 | 2002 | 2003 | 2004 | 2005 |
|---|---|---|---|---|---|---|---|---|
| Canada | Economic class | 109247 | 136291 | 155718 | 137864 | 121044 | 133748 | 156312 |
| | Family Class and Refugees | 80690 | 91160 | 94910 | 91182 | 100302 | 102091 | 105925 |
| | Total | 189937 | 227451 | 250629 | 229046 | 221347 | 235839 | 262239 |
| | Percentage of Family Class and Refugees | 42.5 | 40.1 | 37.9 | 39.8 | 45.3 | 43.3 | 40.4 |
| Denmark | Economic class | 1432 | 1425 | 1267 | 1272 | 1311 | 1674 | 2044 |
| | Family class and Refugees | 3980 | 5096 | 5956 | 4150 | 2740 | 1963 | 1586 |
| | Total | 5412 | 6521 | 7223 | 5422 | 4051 | 3637 | 3630 |
| | Percentage of Family Class and Refugees | 73.5 | 78.1 | 82.5 | 76.5 | 67.6 | 54.0 | 43.7 |

Sources: For Denmark, Statistics Denmark, website www.dst.dk
For Canada, Annual Report to Parliament on Immigration, Minister of Public Works and Government Services Canada (2003–2006).

Moreover, the equivalent figure for immigrants of non-western countries was 95.9 percent (Table 4.2). Recently, the Danish Government has introduced green channels to make it easy for educated young professionals to get a place in the Danish labour market. For example, in 2002 Green Card Scheme, like Canadian skilled immigration system, was introduced for professionals of various fields to come and search for a job in Denmark. If these professionals are successful in finding a job on their own, they are initially given work permit for three years. Furthermore, the Danish government has introduced laws to reduce forced marriages. Introducing the new schemes for attracting skilled immigrants to Denmark in 2005, reduced percentage of family class and refugees from non-western countries to 76 percent.

Unlike Denmark, immigration laws in Canada went through major changes many years ago.[6] In 1967, Canada introduced a point system based on the personal characteristics of the applicant to facilitate immigration process for skilled immigrants. In 1992, family class of immigrants was reduced and government was committed to a stable inflow of 1 percent of the current population. In 2002, the

[6]This information is based on a presentation by Genevive Bouchard in Workshop on German and European Migration and Immigration Policy from a Transatlantic Perspective: Challenge for the 21st Century. Website: http://www.irpp.org/miscpubs/archive

Table 4.2: Classification of Danish Immigrants by Purpose of Entry (*Economic, Refugee and Family Class*)

| | | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 |
|---|---|---|---|---|---|---|---|---|
| Western countries | **Quota refugees** | **0** | **0** | **0** | **0** | **0** | **0** | **0** |
| | **Other refugees** | **7** | **5** | **10** | **3** | **1** | **2** | **1** |
| | **Family reunification to refugees** | **6** | **1** | **4** | **1** | **0** | **1** | **1** |
| | **Family reunification to others** | **361** | **302** | **320** | **218** | **140** | **133** | **108** |
| | Wage earner and independent businessmen | 56 | 61 | 54 | 136 | 179 | 171 | 150 |
| | Persons from the new EU Member States | 0 | 0 | 0 | 0 | 0 | 272 | 345 |
| | Job-card scheme | 0 | 0 | 0 | 16 | 29 | 24 | 27 |
| | Employed persons (EC/EEA) | 1223 | 1230 | 1080 | 959 | 880 | 844 | 1056 |
| Non-western countries | **Quota refugees** | **151** | **253** | **242** | **212** | **295** | **220** | **307** |
| | **Other refugees** | **1263** | **1963** | **2628** | **1359** | **890** | **576** | **386** |
| | **Family reunification to refugees** | **686** | **1000** | **1193** | **1033** | **684** | **405** | **188** |
| | **Family reunification to others** | **1506** | **1572** | **1559** | **1324** | **730** | **626** | **595** |
| | Wage earner and independent businessmen | 86 | 61 | 48 | 68 | 101 | 164 | 163 |
| | Persons from the new EU Member States | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| | Job-card scheme | 0 | 0 | 0 | 24 | 54 | 132 | 208 |
| | Employed persons (EC/EEA) | 67 | 73 | 85 | 69 | 68 | 67 | 94 |
| All Immigrants | Total Economic Class | 1432 | 1425 | 1267 | 1272 | 1311 | 1674 | 2044 |
| | Family and Regugees | 3980 | 5096 | 5956 | 4150 | 2740 | 1963 | 1586 |
| | Total immigrants | 5412 | 6521 | 7223 | 5422 | 4051 | 3637 | 3630 |
| | **Percentage of immigrants Family and Refugees** | **73.5** | **78.1** | **82.5** | **76.5** | **67.6** | **54.0** | **43.7** |
| Non-Western Immigrants | Family Class and Refugees Non-Western Countries | 3606 | 4788 | 5622 | 3928 | 2599 | 1827 | 1476 |
| | Total Immigrants from Non-Western countries | 3759 | 4922 | 5755 | 4089 | 2822 | 2190 | 1942 |
| | **Percentage of Family and Refugee Nonwestern** | **95.9** | **97.3** | **97.7** | **96.1** | **92.1** | **83.4** | **76.0** |

**Sources:** Statistics Denmark, website www.dst.dk

immigration act of 1976 was replaced to attract young bilingual and educated workers. For example, more points were allocated to applicants with trade certificates, bilingual skills (French and English), and greater weight on first two years of experience. There are three main categories of immigrants in Canada, i.e. independent immigrants (immigrated on the basis of skills, capital, and labour market abilities), family class (through family reunification), and refugees. About 56.1 percent of immigrants, who arrived in 2005, were skilled workers. According to the Canada's Immigration Program (October 2004), Canada has the highest per capita immigration rate in the world. Unlike transitionary immigration policy in Denmark, Canada has a stable inflow of immigrants.

## 4.5 Data and Descriptive Statistics

Most of the studies on earnings mobility are based on the cross sectional data which are useful in measuring income mobility at the moment in time; however, they are not suited for analyzing movements over time. Our analysis in this study is based on two longitudinal data sets taken from Denmark and Canada. We analyze immigrants and natives separately with in and between Denmark and Canada.[7] For Denmark, we use the administrative registered data supplied by Statistics Denmark to Labour Market Dynamic Growth (*LMDG*). The data contains labour market and demographic information for all immigrants and natives aged 15 to 70 for the years 1980 to 2003. In this study, we only look at the years 1994 to 2003. The information about income and demographic variables are accurate since they originated from the income-tax registers of the government. For Canada, we use micro data of *SLID* for the years 1993 to 2004.

All estimation results and descriptive statistics outputs for Canada are weighted

[7]This is one of the first essays on immigrant-native differences in earnings mobility process. Future work should focus on different immigrant groups and use some information in *SLID*, such as years of arrival and source country.

by longitudinal weight variables provided by Statistics Canada. For Denmark, a random sample of 40,000 individuals per year is drawn from the whole population. The data is restricted to men aged 25 to 55. The self-employed workers are dropped from the sample. We look at men who are paid-employed in their main jobs. To control for business cycle effects, the dynamic model includes aggregate unemployment rates taken from Statistics Denmark and CANSIM, Table 282-0055. In addition to the aggregate unemployment rate, the models also control for the level of education, marital status, age, levels of work experience, and country of origin.[8] For education, we use a dummy variable indicating if a person has at least a high-school degree at the time of entry into the panel.[9] Marital status is defined if a person is legally married or registered partner. Since people in different age groups have different earnings profiles (Beach and Finnie, 2001), we prefer to divide age into three groups, i.e. prime (25-35), middle (36-45), and older (46-55). Similarly, for experience, we have sets of dummy variables for people with at most 8, between 8 and 16, and more then 16 years of experience.[10] To control for the country of origin, immigrants are divided in two main groups, i.e. immigrants from developed countries and those from the less developed countries.[11]

Table 4.3 provides information on earnings[12] quartiles and mean characteristics of immigrants and natives in Denmark and Canada. Immigrants in Denmark are

[8]Years since immigration might be a significant factor in persistence of or transition into (and out of) any earnings quartiles. Unfortunately, Danish administrative data set provides no information about immigrants' years of arrival. Further, estimation results in essay 2 show that years since immigration is not a significant factor in wage mobility process in Canada. To have two models, comparable for Canada and Denmark (and the fact that this variable might have no (or low) significant effect for Canadian immigrants) we ignored the effect of this variable in our estimation.

[9]To compare two countries with different educational system, we use a dummy variable for education instead of years of schooling. We also treat education as a time-invariant variable because there is small variation in education among individuals in this selected age group.

[10]People with lower experience, are expected to have lower earnings profile; moreover, experience more than 16 years is recorded as 16 in Danish data, so we use dummy variables for experience , instead of years of experience.

[11]List of developed countries includes high-income *OECD* countries plus the following relatively smaller countries: Hong Kong, Israel, Singapore, Taiwan, Andorra, Bermuda, Faroe Islands, Liechtenstein, and San Marino (World Development Indicators (*WDI*), 2008).

[12]Earnings are adjusted by Consumer Price Index (*CPI*).

over-represented in quartiles zero and one compared to their Canadian counterparts. About 14.8 and 37 percent of immigrants in Denmark are in quartiles zero and one, respectively. The equivalent figures for Canadian immigrants are 7.8 and 26.8 percent. Unlike immigrants, Danish natives are evenly distributed from quartiles one to four. On the contrary, immigrants in Canada are more accumulated in the second and higher quartiles. Almost 22.3, 18.3, and 24.9 percent of Canadian immigrants are in quartiles two, three, and four, respectively. Similar figures for Danish immigrants are about 19.5, 14.6, and 14 percent.

First, we compare the mean characteristics of Danish and Canadian immigrants. Table 4.3 shows that 68.1 percent of Danish immigrants have at least high-school degrees versus the equivalent figure for Canadian immigrants, which is 80.3 percent. The proportion of married people is much higher for Canadian immigrants. About 82.5 percent of Canadian immigrants are married or registered partner, while for Danish the equivalent figure is 66.8 percent. The percentage of immigrants from developed countries is higher in Canada (48.5 percent) than in Denmark (31.7 percent). One reason is that the immigration policy in Canada before 1962, gave more priority to immigrants from European countries.[13] The proportion of immigrants in prime and middle ages is higher in Denmark than in Canada. Similarly, the proportion of experienced immigrants in Denmark is less than that of in Canada. This could be due to the higher proportion of younger immigrants in Denmark compared to Canada.

Second, we compare mean characteristics of natives in two countries. Compared to Canada, natives in Denmark are less observed in quartile zero. However, quartile earnings distribution is very similar in both countries. Further, the mean characteristics of natives have almost the same pattern in both countries. Third, we compare immigrant-native differences in mean characteristics between Denmark

[13]In 1950s, 84.6 percent of immigrants were European by birth. The government of Canada abandoned this policy in 1962.

Table 4.3: Mean Characteristics of Males by Immigrants and Natives, Denmark and Canada

| Variables | | Denmark | | Canada | |
|---|---|---|---|---|---|
| | | Immigrants | Natives | Immigrants | Natives |
| Quartiles Dummies | $Q_0$: People not working (Quartile Zero)[1] | 0.148 | 0.036 | 0.078 | 0.080 |
| | $Q_1$: People with Earnings in First Quartile | 0.370 | 0.235 | 0.268 | 0.207 |
| | $Q_2$: People with Earnings in Second Quartile | 0.195 | 0.241 | 0.223 | 0.236 |
| | $Q_3$: People with Earnings in Third Quartile | 0.146 | 0.243 | 0.183 | 0.244 |
| | $Q_4$: People with Earnings in Forth Quartile | 0.140 | 0.243 | 0.249 | 0.232 |
| Observed Characteristics | Educated[2] | 0.681 | 0.760 | 0.803 | 0.770 |
| | Married[3] | 0.668 | 0.572 | 0.825 | 0.759 |
| | Origin (Developed Countries)[4] | 0.317 | - | 0.485 | - |
| | Age between 25 – 35 | 0.306 | 0.303 | 0.238 | 0.265 |
| | Age between 35 - 45 | 0.465 | 0.455 | 0.416 | 0.468 |
| | Age between 45 - 55 | 0.229 | 0.242 | 0.349 | 0.266 |
| | Experience less then 8 years | 0.430 | 0.079 | 0.199 | 0.091 |
| | Experience between 8 to 16 years | 0.381 | 0.396 | 0.312 | 0.247 |
| | Experience more then 16 years | 0.189 | 0.525 | 0.491 | 0.661 |
| | Aggregate Unemployment Rate | 7.36 | 7.36 | 8.27 | 8.38 |
| | Number of Observations | 13110 | 386890 | 4236 | 31338 |
| | Number of Individuals | 1311 | 38689 | 706 | 5223 |

Note: Source: For Denmark, Registered Administrative Datasets 1994-2003, supplied by Statistics Denmark to Labor Market Dynamic Growth (LMDG). For Canada, Survey of Labor and Income Dynamics (SLID) 1993-2004, based on a sample of males aged 25 to 55. The figures for Canada are weighted with longitudinal weight variables provided by Statistics Canada. The figures are rounded to three decimal points.

1- This excludes the people who are retired, getting education, or on leaves.

2- Having at least 12 years of formal education.

3- Married or Registered Partner.

4- If an immigrant was born in any High-Income countries i.e. OECD countries or Hong Kong, Israel, Singapore, Taiwan, Andorra, Bermuda, Faroe Islands, Liechtenstein, and San Marino (World Development Indicators, 2008)

and Canada. We observe that in Denmark, immigrants have higher proportions in quartile zero, while in Canada there is no big difference among immigrants and natives. Further, the difference between immigrants and natives in probability of being in quartile one is higher in Denmark than in Canada. Immigrants in Denmark have less proportion of at least high-school diplomas, compared to natives; the opposite is true for Canada.

One of the objectives of this essay is to study the factors affecting transitional rates into and out of the four earnings quartiles and quartile zero (unemployed and non-employed people). To do this, we calculate the mean characteristics of different persistence and transition states among immigrants and natives for both countries. Tables 4.4 and 4.5 provide this information. Persistence in this table refers to individuals' staying in the same quartile one year after, whereas transition refers to individuals' movement from the origin state to any other destinations in the distribution. Looking at these tables, we observe that individuals in any persistence in (or transitions into and out of) any earnings quartiles have different mean characteristics. For example, It is appeared that the proportion of individuals with high-school degree is positively correlated with persistence in the higher quartiles. This is true for immigrants and natives, but with different magnitudes. The same pattern is true for proportion of married people. Further, immigrants from developed countries are more apparent in the higher quartiles. On the other hand, natives and immigrants have the higher proportion of prime age group in the lower quartiles. These examples show that observed characteristics, reported in Tables 4.4 and 4.5, might be significant factors determining differences between immigrants and natives in probability of being in any earnings quartiles.

Mobility and stability in the raw data is examined through transition matrices. A transition matrix is constructed as follows: First, both immigrants and natives, who are working, are ranked together according to their earnings for each year.

Table 4.4: Mean Characteristics of Males by Persistence in Earnings Quartiles, Immigrants and Natives

**Denmark**

| Observed Characteristics | Immigrants | | | | | Natives | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Persistence in Quartiles | | | | | Persistence in Quartiles | | | | |
| | $Q_0$[1] | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| Educated[2] | 0.617 | 0.622 | 0.674 | 0.786 | 0.914 | 0.580 | 0.608 | 0.738 | 0.827 | 0.906 |
| Married[3] | 0.591 | 0.636 | 0.709 | 0.739 | 0.741 | 0.273 | 0.449 | 0.567 | 0.636 | 0.706 |
| Origin (Developed)[4] | 0.269 | 0.284 | 0.288 | 0.399 | 0.585 | - | - | - | - | - |
| Age ( 25 – 35) | 0.449 | 0.333 | 0.250 | 0.239 | 0.169 | 0.378 | 0.349 | 0.328 | 0.288 | 0.230 |
| Age (35 – 45) | 0.395 | 0.466 | 0.504 | 0.494 | 0.485 | 0.410 | 0.417 | 0.456 | 0.467 | 0.510 |
| Age (45 – 55) | 0.156 | 0.200 | 0.245 | 0.267 | 0.347 | 0.212 | 0.235 | 0.216 | 0.245 | 0.259 |
| Experience < 8 years | 0.842 | 0.533 | 0.235 | 0.216 | 0.193 | 0.474 | 0.123 | 0.041 | 0.044 | 0.048 |
| Experience 8 -16 years | 0.140 | 0.374 | 0.445 | 0.463 | 0.455 | 0.413 | 0.435 | 0.403 | 0.368 | 0.391 |
| Experience >16 years | 0.018 | 0.093 | 0.319 | 0.321 | 0.352 | 0.114 | 0.441 | 0.555 | 0.588 | 0.561 |
| Number of Observations | 998 | 2482 | 1338 | 1046 | 1391 | 4976 | 47180 | 53824 | 57191 | 72363 |

**Canada**

| Observed Characteristics | Immigrants | | | | | Natives | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Persistence in Quartiles | | | | | Persistence in Quartiles | | | | |
| | $Q_0$[1] | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| Educated[2] | 0.814 | 0.710 | 0.708 | 0.875 | 0.916 | 0.330 | 0.652 | 0.795 | 0.850 | 0.927 |
| Married[3] | 0.661 | 0.751 | 0.885 | 0.830 | 0.889 | 0.391 | 0.643 | 0.783 | 0.842 | 0.872 |
| Origin (Developed)[4] | 0.340 | 0.333 | 0.405 | 0.594 | 0.678 | - | - | - | - | - |
| Age ( 25 – 35) | 0.339 | 0.335 | 0.259 | 0.222 | 0.148 | 0.244 | 0.387 | 0.301 | 0.263 | 0.181 |
| Age (35 – 45) | 0.210 | 0.420 | 0.444 | 0.418 | 0.405 | 0.372 | 0.421 | 0.489 | 0.469 | 0.532 |
| Age (45 – 55) | 0.451 | 0.245 | 0.297 | 0.360 | 0.447 | 0.284 | 0.192 | 0.210 | 0.268 | 0.287 |
| Experience < 8 years | 0.628 | 0.323 | 0.150 | 0.125 | 0.104 | 0.483 | 0.094 | 0.072 | 0.062 | 0.038 |
| Experience 8 -16 years | 0.196 | 0.339 | 0.393 | 0.264 | 0.260 | 0.184 | 0.324 | 0.261 | 0.252 | 0.215 |
| Experience >16 years | 0.176 | 0.338 | 0.457 | 0.611 | 0.636 | 0.333 | 0.582 | 0.667 | 0.686 | 0.747 |
| Number of Observations | 133 | 708 | 627 | 511 | 822 | 1775 | 5076 | 4775 | 4717 | 4623 |

Note: 1-This excludes the people who are retired, getting education or on leaves.
2- Having at least 12 years of formal education.
3- Married or Registered Partner.
4- If an immigrant was born in any High-Income countries i.e. OECD countries or Hong Kong, Israel, Singapore, Taiwan, Andorra, Bermuda, Faroe Islands, Liechtenstein, and San Marino (World Development Indicators, 2008).

Table 4.5: Mean Characteristics of Males by Transition into and out of the Earnings Quartiles, Immigrants and Natives

**Denmark**

| Observed Characteristics | Immigrants | | | | | | Natives | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Lowest Part of the Earnings Distribution | | Middle of the Earnings Distribution | | Uppermost Part of the Earnings Distribution | | Lowest Part of the Earnings Distribution | | Middle of the Earnings Distribution | | Uppermost Part of the Earnings Distribution | |
| | 0 To 1 | 1 To 0 | 1 To 2 | 2 To 1 | 3 To 4 | 4 To 3 | 0 To 1 | 1 To 0 | 1 To 2 | 2 To 1 | 3 To 4 | 4 To 3 |
| Educated[2] | 0.568 | 0.547 | 0.644 | 0.637 | 0.766 | 0.755 | 0.596 | 0.568 | 0.681 | 0.654 | 0.857 | 0.821 |
| Married[3] | 0.607 | 0.573 | 0.666 | 0.655 | 0.699 | 0.666 | 0.281 | 0.283 | 0.477 | 0.506 | 0.604 | 0.635 |
| Origin (Developed)[4] | 0.317 | 0.197 | 0.232 | 0.238 | 0.398 | 0.403 | - | - | - | - | - | - |
| Age ( 25 – 35) | 0.483 | 0.457 | 0.413 | 0.338 | 0.320 | 0.182 | 0.435 | 0.392 | 0.446 | 0.378 | 0.394 | 0.295 |
| Age (35 – 45) | 0.400 | 0.403 | 0.434 | 0.458 | 0.461 | 0.528 | 0.386 | 0.398 | 0.397 | 0.429 | 0.440 | 0.477 |
| Age (45 – 55) | 0.117 | 0.140 | 0.153 | 0.204 | 0.218 | 0.289 | 0.179 | 0.210 | 0.156 | 0.193 | 0.167 | 0.228 |
| Experience < 8 years | 0.798 | 0.744 | 0.524 | 0.401 | 0.364 | 0.233 | 0.378 | 0.296 | 0.132 | 0.063 | 0.098 | 0.056 |
| Experience 8 -16 years | 0.176 | 0.230 | 0.380 | 0.440 | 0.427 | 0.434 | 0.469 | 0.496 | 0.471 | 0.479 | 0.450 | 0.412 |
| Experience >16 years | 0.024 | 0.026 | 0.097 | 0.159 | 0.209 | 0.333 | 0.153 | 0.208 | 0.397 | 0.458 | 0.452 | 0.532 |
| Number of Observations | 690 | 422 | 590 | 441 | 206 | 159 | 5404 | 3850 | 14474 | 13437 | 10625 | 8837 |

**Canada**

| Observed Characteristics | Immigrants | | | | | | Natives | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Lowest Part of the Earnings Distribution | | Middle of the Earnings Distribution | | Uppermost Part of the Earnings Distribution | | Lowest Part of the Earnings Distribution | | Middle of the Earnings Distribution | | Uppermost Part of the Earnings Distribution | |
| | 0 To 1 | 1 To 0 | 1 To 2 | 2 To 1 | 3 To 4 | 4 To 3 | 0 To 1 | 1 To 0 | 1 To 2 | 2 To 1 | 3 To 4 | 4 To 3 |
| Educated[2] | 0.713 | 0.724 | 0.756 | 0.774 | 0.908 | 0.903 | 0.570 | 0.580 | 0.746 | 0.701 | 0.884 | 0.862 |
| Married[3] | 0.694 | 0.575 | 0.840 | 0.793 | 0.825 | 0.849 | 0.671 | 0.713 | 0.696 | 0.725 | 0.828 | 0.828 |
| Origin (Developed)[4] | 0.383 | 0.503 | 0.389 | 0.402 | 0.477 | 0.518 | - | - | - | - | - | - |
| Age ( 25 – 35) | 0.341 | 0.457 | 0.472 | 0.398 | 0.324 | 0.202 | 0.480 | 0.458 | 0.457 | 0.361 | 0.353 | 0.235 |
| Age (35 – 45) | 0.391 | 0.329 | 0.387 | 0.433 | 0.313 | 0.376 | 0.299 | 0.290 | 0.388 | 0.392 | 0.486 | 0.484 |
| Age (45 – 55) | 0.268 | 0.214 | 0.141 | 0.169 | 0.363 | 0.422 | 0.221 | 0.252 | 0.155 | o.247 | 0.161 | 0.281 |
| Experience < 8 years | 0.588 | 0.401 | 0.258 | 0.182 | 0.278 | 0.166 | 0.192 | 0.089 | 0.097 | 0.054 | 0.076 | 0.033 |
| Experience 8 -16 years | 0.221 | 0.165 | 0.399 | 0.408 | 0.229 | 0.252 | 0.359 | 0.426 | 0.333 | 0.291 | 0.326 | 0.270 |
| Experience >16 years | 0.191 | 0.434 | 0.343 | 0.411 | 0.493 | 0.582 | 0.488 | 0.485 | 0.568 | 0.655 | 0.598 | 0.697 |
| Number of Observations | 25 | 23 | 78 | 95 | 96 | 102 | 94 | 99 | 527 | 683 | 787 | 792 |

On the basis of these ranks each individual belongs to one of the four quartiles. The people who are not working are directly assigned to quartile zero. The same procedure is applied for each year. The transition is recorded by an indicator variable $t^i_{o,d}$ where $t^i_{o,d}$ is equal to 1 if an individual $i$ move from the origin quartile "$o$" to the destination quartile "$d$". If "$d$" is equal to "$o$" then it is recorded as stability. For the whole sample, the transition probabilities and stabilities are calculated by the following formula (for more details, see Burkhauser, et al. (1997)).

$$P_{o,d} = \sum_{i=1}^{N} t^i_{o,d}/N \tag{4.2}$$

Where N is the total number of individual in the origin quartile.[14] Table 4.6 shows transition matrices of immigrants and natives for both countries. This table reveals several interesting relationships and patterns among immigrants and natives. We also examine the issue of state dependence in the raw data.

There are some differences and similarities in transition matrices among Danish and Canadian immigrants. For example, immigrants in Canada have higher stability in any earnings quartiles than their Danish counterparts. Upward mobility is higher than the downward mobility for immigrants in both countries, but with higher magnitude for Danish immigrants.

The full transition matrices show that the vast majority of movements reach adjacent quartiles for both immigrants and natives. For example, for immigrants in Canada, the probability of moving from quartile one to quartile two is 10.4 percent, higher than that of moving from quartile one to quartile four, which is 0.7 percent. The equivalent probabilities for natives are 12.4 and 0.5 percent, respectively. For Denmark, the probability of moving up to quartile two from quartile one is 13.5 percent, higher than that of moving from quartile one to quartile four, which is 0.8 percent. The equivalent figures for natives are 17.6 and 0.6 percent. There

[14]For the Canadian data, this probability is weighted by longitudinal weight variables provided by Statistics Canada.

Table 4.6: Quartile Mobility Rates, Conditional Probability of Leaving Previous Years Quartile by Immigrants and Natives

**Denmark**

**Immigrants**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.554** | 0.383 | 0.034 | 0.018 | 0.009 | 0 | **0.554** | 0.444 |
| $Q_1$ | 0.096 | **0.726** | 0.135 | 0.035 | 0.008 | 0.096 | **0.726** | 0.178 |
| $Q_2$ | 0.036 | 0.195 | **0.592** | 0.164 | 0.013 | 0.231 | **0.592** | 0.177 |
| $Q_3$ | 0.019 | 0.049 | 0.199 | **0.612** | 0.121 | 0.267 | **0.612** | 0.121 |
| $Q_4$ | 0.018 | 0.012 | 0.022 | 0.094 | **0.853** | 0.146 | **0.853** | 0 |
| **Total** | **0.152** | **0.371** | **0.192** | **0.145** | **0.140** | **0.141** | **0.674** | **0.185** |

**Natives**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $Q_0$ | **0.406** | 0.440 | 0.083 | 0.045 | 0.025 | 0 | **0.406** | 0.593 |
| $Q_1$ | 0.047 | **0.738** | 0.176 | 0.032 | 0.006 | 0.047 | **0.738** | 0.214 |
| $Q_2$ | 0.014 | 0.160 | **0.639** | 0.173 | 0.014 | 0.174 | **0.639** | 0.187 |
| $Q_3$ | 0.010 | 0.027 | 0.163 | **0.675** | 0.125 | 0.200 | **0.675** | 0.125 |
| $Q_4$ | 0.009 | 0.007 | 0.013 | 0.108 | **0.863** | 0.137 | **0.863** | 0 |
| **Total** | **0.035** | **0.236** | **0.242** | **0.243** | **0.244** | **0.138** | **0.715** | **0.147** |

**Canada**

**Immigrants**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.848** | 0.125 | 0.026 | 0.006 | 0 | 0 | **0.848** | 0.157 |
| $Q_1$ | 0.030 | **0.840** | 0.104 | 0.019 | 0.007 | 0.030 | **0.840** | 0.130 |
| $Q_2$ | 0.007 | 0.121 | **0.734** | 0.125 | 0.013 | 0.128 | **0.734** | 0.138 |
| $Q_3$ | 0.003 | 0.011 | 0.148 | **0.707** | 0.129 | 0.162 | **0.707** | 0.129 |
| $Q_4$ | 0 | 0.003 | 0.014 | 0.099 | **0.883** | 0.116 | **0.883** | 0 |
| **Total** | **0.079** | **0.268** | **0.223** | **0.179** | **0.249** | **0.095** | **0.804** | **0.101** |

**Natives**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $Q_0$ | **0.930** | 0.043 | 0.012 | 0.008 | 0.006 | 0 | **0.930** | 0.069 |
| $Q_1$ | 0.016 | **0.843** | 0.124 | 0.012 | 0.005 | 0.016 | **0.843** | 0.141 |
| $Q_2$ | 0.005 | 0.106 | **0.748** | 0.131 | 0.009 | 0.111 | **0.748** | 0.140 |
| $Q_3$ | 0.005 | 0.012 | 0.127 | **0.725** | 0.131 | 0.144 | **0.725** | 0.131 |
| $Q_4$ | 0.003 | 0.002 | 0.007 | 0.138 | **0.849** | 0.150 | **0.849** | 0 |
| **Total** | **0.080** | **0.207** | **0.236** | **0.244** | **0.232** | **0.099** | **0.800** | **0.100** |

is a positive correlation between the initial quartile and downward mobility and a negative correlation with upward mobility for immigrants and natives in both countries. Thus the quartile and its lag are not independent, and being in one quartile one year increases the probability to be in the same quartile the year after (state dependence). Our findings confirm Brodaty's (2007).

In Canada, immigrants in lower quartiles this year, are more likely to move down to the quartile zero the year after, compared to natives. In Denmark, the probability of moving down to the quartile zero from any of the four earnings quartiles is higher for immigrants than natives. Moreover, immigrants compared to natives have more chances to move down to their next quartiles next year if they are in the second and third parts of the earnings distribution this year.

To see if there are any differences in earnings dynamics among immigrants with different origin, we calculated transition matrices for immigrants from developed and less-developed countries in Denmark and Canada (Table 4.7). Immigrants in Denmark from less developed countries are over-represented in the first and middle parts of earnings distribution and less observed in the last parts, compared to their counterparts from developed countries. Exactly the same pattern is observed in Canada. In Denmark stability in every quartile is higher for immigrants from developed countries than those from the less developed. Further, in Denmark immigrants from both developed and less developed countries have the higher upward mobility rates than the down-ward. In Canada, upward and downward mobility rates for both types of immigrants are quite similar.

Table 4.7: Quartile Mobility Rates, Conditional Probability of Leaving Previous Years Quartile by Country of Origin (*Developed and Less Developed*)

**Denmark**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| **Country of Origin (Developed)** | | | | | | | | |
| $Q_0$ | **0.625** | 0.301 | 0.042 | 0.016 | 0.016 | 0.000 | **0.625** | 0.375 |
| $Q_1$ | 0.071 | **0.770** | 0.117 | 0.030 | 0.012 | 0.071 | **0.770** | 0.159 |
| $Q_2$ | 0.032 | 0.169 | **0.619** | 0.166 | 0.014 | 0.201 | **0.619** | 0.180 |
| $Q_3$ | 0.013 | 0.036 | 0.125 | **0.690** | 0.135 | 0.175 | **0.690** | 0.135 |
| $Q_4$ | 0.015 | 0.009 | 0.012 | 0.068 | **0.895** | 0.105 | **0.895** | 0.000 |
| **Total** | **0.115** | **0.313** | **0.166** | **0.162** | **0.244** | **0.111** | **0.745** | **0.144** |
| **Country of Origin (Less Developed)** | | | | | | | | |
| $Q_0$ | **0.532** | 0.409 | 0.032 | 0.019 | 0.007 | 0.000 | **0.532** | 0.468 |
| $Q_1$ | 0.106 | **0.710** | 0.141 | 0.037 | 0.006 | 0.106 | **0.710** | 0.184 |
| $Q_2$ | 0.038 | 0.205 | **0.582** | 0.163 | 0.012 | 0.243 | **0.582** | 0.175 |
| $Q_3$ | 0.023 | 0.055 | 0.240 | **0.569** | 0.112 | 0.318 | **0.569** | 0.112 |
| $Q_4$ | 0.022 | 0.017 | 0.035 | 0.127 | **0.799** | 0.201 | **0.799** | 0.000 |
| **Total** | **0.170** | **0.398** | **0.203** | **0.137** | **0.092** | **0.155** | **0.641** | **0.204** |

**Canada**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| **Country of Origin (Developed)** | | | | | | | | |
| $Q_0$ | **0.817** | 0.136 | 0.030 | 0.018 | 0 | 0 | **0.817** | 0.184 |
| $Q_1$ | 0.044 | **0.803** | 0.114 | 0.035 | 0.004 | 0.044 | **0.803** | 0.153 |
| $Q_2$ | 0.007 | 0.114 | **0.699** | 0.159 | 0.020 | 0.121 | **0.699** | 0.179 |
| $Q_3$ | 0.002 | 0.014 | 0.158 | **0.720** | 0.106 | 0.894 | **0.720** | 0.106 |
| $Q_4$ | 0 | ~0 | 0.009 | 0.079 | **0.912** | ~0.088 | **0.912** | 0 |
| **Total** | **0.058** | **0.194** | **0.196** | **0.215** | **0.338** | 0.100 | 0.802 | 0.098 |
| **Country of Origin (Less Developed)** | | | | | | | | |
| $Q_0$ | **0.858** | 0.118 | 0.023 | 0 | 0 | 0 | **0.858** | 0.141 |
| $Q_1$ | 0.023 | **0.860** | 0.098 | 0.010 | 0.009 | 0.023 | **0.860** | 0.117 |
| $Q_2$ | 0.007 | 0.126 | **0.759** | 0.100 | 0.008 | 0.133 | **0.759** | 0.108 |
| $Q_3$ | 0.005 | 0.007 | 0.138 | **0.689** | 0.162 | 0.148 | **0.689** | 0.162 |
| $Q_4$ | 0 | 0.009 | 0.022 | 0.140 | **0.829** | 0.171 | **0.829** | 0 |
| **Total** | **0.100** | **0.34** | **0.249** | **0.145** | **0.166** | **0.091** | **0.805** | **0.104** |

## 4.6 Model and Empirical Specification

To analyze any movements into and out of any earnings quartiles, we choose a dynamic unordered multinomial logit model.[15] We analyze the dynamic structure of the model as a first-order Markov process. Let assume that individual $i$ belongs to alternative $q$ at time $t$. We suppose that utility $V^*_{iqt}$ is the sum of a deterministic component, $U_{iqt}$, that depends on regressors and unknown parameters, and an unobserved random component, $\epsilon_{iqt}$:

$$V^*_{iqt} = U_{iqt} + \epsilon_{iqt} \tag{4.3}$$

This is called an Additive Random-Utility Model ($ARUM$). We observe the outcome $Y_{it}$=$q$ if alternative $q$ has the highest utility of the alternatives. It follows that:

$$Pr(Y_{it} = q) = Pr(V^*_{iqt} \geq V^*_{ijt}) = Pr(V^*_{ijt} - V^*_{iqt} \leq 0), forall j \tag{4.4}$$

and given (4.1),

$$Pr(Y_{it} = q) = Pr(\epsilon_{ijt} - \epsilon_{iqt} \leq U_{iqt} - U_{ijt}), \tag{4.5}$$

Now assume that individuals indexed by $i$ ($i$= $1, 2, \ldots, N$) belong to any of the following five mutually exclusive and exhaustive boundaries (alternatives) of earnings percentiles of $q$ at time $t$ ($t$= $1, 2, \ldots, T$) as below:

- $q_t = 0$ [0] (Individuals who do not work)
- $q_t = 1$ (0,25] (Individuals with earnings in the range from minimum observed value to the 25th percentile)

[15] As discussed in essay two, another alternative in this context would be an ordered probability model. However, it is not clear to what extent this would have changed the estimation results (more discussions in Cameron and Trivedi, 2005)

- $q_t = 2$ (25,50] (Individuals with earnings between the 25th and the 50th percentile)
- $q_t = 3$ (50,75] (Individuals with earnings between the 50th and the 75th percentile)
- $q_t = 4$ (75,100] (Individuals with earnings between the 75th and the 100th percentile)

Let the value, for individual $i$, of belonging to quartile $q$ at time $t$ ($U_{iqt}$) be specified as:

$$U_{iqt} = X_{it}.\beta_q + Z_{it}.\gamma_q + D_i.\delta_q \tag{4.6}$$

and given (4.1), $V^*_{iqt}$ can be written as:

$$V^*_{iqt} = X_{it}.\beta_q + Z_{it}.\gamma_q + D_i.\delta_q + \epsilon_{iqt} \tag{4.7}$$

Where error term, $\epsilon_{iqt}$, is composed of an individual-specific unobserved effect (time-invariant but varying across individuals) and a random error (varying across both time and individuals) as below:

$$\epsilon_{iqt} = \mu_{iq} + \upsilon_{iqt} \tag{4.8}$$

$X_{it}$ is a vector of time varying observed variables, including age dummies, marital status, levels of work experience, and the aggregate unemployment rate. $Z_{it}$ is a vector of dummy variables indicating the previous earnings quartile occupied by the individual $i$ (time state dependence). For Canadian immigrants, we drop observations in extreme transitions from quartiles three and four to one, similarly from quartiles one and two to four. This is due to the fact that there are few moves in these transitions, which make it difficult to get the parameter estimates. For

usual identification purpose, we take quartile zero as the reference quartile. $D_i$ is a vector of time-invariant variables, including dummies for education and the country of origin (developed or less developed).

The assumption regarding the error term, $\epsilon_{iqt}$, can be summarized as follows: $\epsilon_{iqt}$ is composed of two terms: $\upsilon_{iqt}$ and $\mu_{iq}$. Where $\upsilon_{iqt}$ is assumed to follow a Type I extreme value distribution and $\mu_{iq}$ is an unobserved, individual specific factor and independent of $X_{it}$ and $D_i$, but not $Z_{it}$ (endogeneity problem).

Given the distribution assumptions of $\upsilon_{iqt}$, the probability of observing individual $i$ in quartile $q$ at time $t$, conditional on $X_{it}$, $Z_{it}$, $D_i$, and $\mu_{iq}$ can be written as a five-state multinomial logit as:

$$P_{it}(q/X, \mu_{iq}) = \frac{exp(X_{it}.\beta_q + Z_{it}.\gamma_q + D_i.\delta_q + \mu_{iq})}{\sum_{j=0}^{4} exp(X_{it}.\beta_j + Z_{it}.\gamma_j + D_i.\delta_j + \mu_{ij})} \tag{4.9}$$

Where $X$ is a vector of all explanatory variables in the model. To control for the endogeneity problem, we follow Wooldridge's (2005) approach and define the distribution of the unobserved effects, $\mu_{iq}$, conditional on $Z_{i1}$ and the mean values of exogenous time-varying variables over time ($\bar{X}_i$). $Z_{i1}$ is a vector of initial earnings quartiles. [16] $\mu_{iq}$ can be written as:

$$\mu_{iq} = \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq} \tag{4.10}$$

Therefore conditional probability of (4.5) can be modified as:

$$P_{it}(q/X, \bar{X}_i, Z_{i1}, \nu_{iq}) = \frac{exp(X_{it}.\beta_q + ... + \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq})}{\sum_{j=0}^{4} exp(X_{it}.\beta_j + ... + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{4.11}$$

Assuming a discrete distribution for the unobserved factors implies that the cumulative distribution function is approximated by a step function (Mroz, 1999). In particular, the distribution of $\nu_{iq}$ is given by:

[16] As mentioned earlier in this essay, for the usual identification purpose, quartile zero has been taken as the reference group.

$$Pr(\nu_{iq} = \nu_q^m) = \pi_m, m = 1, 2, \ldots, M \tag{4.12}$$

Where,

$$\pi_m > 0 \tag{4.13}$$

$\pi_m$ is the probability that the unobserved factor takes on the values of $\nu_{iq}$, $\nu_q^m$. To be specific, we assume that there are $m$ types of individuals and each individual, $i$, at any quartiles of $q$ is endowed with a set of unobserved characteristics, $\nu_q^m$. To estimate simultaneously the parameters $\beta_q$, $\gamma_q$, $\delta_q$, $\lambda_q$, $\rho_q$, $(\nu_q^1, \ldots, \nu_q^M)$, and $(p_1, \ldots, p_M)$, we use a logistic transformation as:

$$\pi_m = \frac{exp(p_m)}{\sum_{j=1}^{M} exp(p_j)} \tag{4.14}$$

Where,

$$0 < \pi_m < 1 \tag{4.15}$$

and

$$\sum_{m=1}^{M} \pi_m = 1 \tag{4.16}$$

To select the number of support points, we calculate the value of $AIC$ and $BIC$ when an additional point of support is added. We stop adding more support points to the model when either value starts increasing.

The likelihood contribution for individual $i$ with observed quartile states $q_1, \ldots, q_T$ given all observed and unobserved effects can be written as:

$$L_i(\nu_i) = \prod_{t=2}^{T} P_{it}(q/X, \bar{X}_i, Z_{i1}, \nu_{iq}) \tag{4.17}$$

and therefore,

$$L_i(\nu_i) = \prod_{t=2}^{T} \frac{exp(X_{it}.\beta_q + ... + \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq})}{\sum_{j=0}^{4} exp(X_{it}.\beta_j + ... + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{4.18}$$

Where $\nu_i$ is a vector of $\nu_{iq}$ for $q_t$= *0, 1, ..., 4*. As earlier mentioned there are $m$ types of individuals with the set of unobserved characteristics, $\nu_q^m$, that is a vector of $(\nu_q^1, \ldots, \nu_q^M)$. Therefore, I can write unconditional log-likelihood function for individual $i$ as:

$$LogL_i(\nu_i) = \log \sum_{m=1}^{M} \pi_m.L_i(\nu_q^m) \tag{4.19}$$

and finally,

$$L_{NT} = \sum_{i=1}^{N} \log \sum_{m=1}^{M} \prod_{t=2}^{T} \pi_m. \frac{exp(X_{it}.\beta_{1q} + ... + Z_{it}.\gamma_q + \bar{X}_i.\lambda_q + Z_{i1}.\rho_q + \nu_{iq})}{\sum_{j=0}^{4} exp(X_{it}.\beta_{1j} + ... + Z_{it}.\gamma_j + \bar{X}_i.\lambda_j + Z_{i1}.\rho_j + \nu_{ij})} \tag{4.20}$$

## 4.7 Empirical Results

In this section, we report estimation results from maximizing[17] the likelihood function[18] of the multinomial logit model controlling for the endogenous initial conditions problem and unobserved heterogeneity. To show the efficiency of the model specification, as well as to distinguish between spurious and structural state dependence, we estimate the model when there is no control for the endogenous initial conditions problem and unobserved heterogeneity factors.

We experimented with different support points to find the best fitted models. We stopped adding more support points when either the *AIC* or the *BIC* stopped decreasing. The results are presented in Tables 4.8-4.11. For Denmark, we found

[17]We tried with many different starting values to get the converged estimates of the parameters and to avoid multiple local optima

[18]The likelihood function for Canadian data is weighted with weight variables provided by statistics Canada.

Table 4.8: Discrete Factor Model (*DFM*) Specification for Danish Immigrants, Information Criteria (*AIC and BIC*), Number of Parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 20715.1 | 20984.4 | 52 | -10305.5 |
| No | Yes | 1 | 20459.4 | 20915.1 | 88 | -10141.6 |
| Yes | Yes | 2 | 20274.2 | 20755.8 | 93 | -10044.1 |
| Yes | Yes | 3 | 20174.3 | 20681.8 | 98 | -9989.1 |
| Yes | Yes | 4 | 20167.9 | 20701.3* | 103 | -9980.9 |

Note: Figures are based on the estimation results presented in Tables 4.13 and 4.14.

that models with three and four[19] support points (unobserved types) for immigrants and natives, respectively, fit the data quite well. Similarly for Canada, models with three and four support points fit the data well for immigrants and natives, respectively.

As expected, assuming that the initial conditions are exogenous and also ignoring unobserved factors generates inflated estimates of the degree of state dependence. When the model ignores the effects of unobserved factors, it erroneously assumes that the correlation between state dependence variables and time-invariant unobserved factors is zero. This invalid assumption overestimates state dependence parameters. Comparison of parameter estimates of the state dependence variables (the $\gamma's$ ) in the models with and without controlling on these factors confirms the argument (Table 4.12). This is in line with many other studies on dynamic analysis frameworks of discrete choice modeling, for example, Brodaty (2007), Stewart (2007), Hansen et al. (2006), and Henley (2004).

Because the models presented in this paper have a non-linear nature, the

[19]The model with five number of support points for Danish natives did not converge. Hence, we stopped adding more support points after four support points.

Table 4.9: Discrete Factor Model (*DFM*) Specification for Danish Natives, Information Criteria (*AIC and BIC*), Number of Parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 556897.7 | 557308.7 | 48 | -278400.8 |
| No | Yes | 1 | 546534.8 | 547219.9 | 80 | -273187.4 |
| Yes | Yes | 2 | 538787.6 | 539549.7 | 89 | -269304.8 |
| Yes | Yes | 3 | 535851.4 | 536656.3 | 94 | -267831.7 |
| **Yes** | **Yes** | **4**[1] | **534330.5** | **535178.3** | 99 | -267066.2 |

**Note:** Figures are based on the estimation results presented in Tables 4.15 and 4.16.

1- No convergence after number of supports, 4.

Table 4.10: Discrete Factor Model (*DFM*) Specification for Canadian Immigrants, Information Criteria (*AIC and BIC*), Number of Parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 4717.6 | 4936.5 | 48 | -2310.8 |
| No | Yes | 1 | 4539.2 | 4922.2 | 84 | -2185.6 |
| Yes | Yes | 2 | 4485.4 | 4891.2 | 89 | -2153.7 |
| **Yes** | **Yes** | **3** | **4459.5** | **4888.1** | 94 | -2135.7 |
| Yes | Yes | 4 | 4459.9* | 4911.3* | 99 | -2130.9 |

**Note:** Figures are based on the estimation results presented in Tables 4.17 and 4.18.

Table 4.11: Discrete Factor Model (*DFM*) Specification for Canadian Natives, Information Criteria (*AIC and BIC*), Number of Parameters, and Value of Objective Function

| Model Specification | | | AIC | BIC | Number of Parameters | Value of Objective Function |
|---|---|---|---|---|---|---|
| Control for Unobserved Heterogeneity | Control for Endogenous Initial Condition | Number of Support Points | | | | |
| No | No | 1 | 33239.0 | 33553.9 | 48 | -16571.5 |
| No | Yes | 1 | 31745.8 | 32296.9 | 84 | -15788.9 |
| Yes | Yes | 2 | 31385.3 | 31969.2 | 89 | -15603.6 |
| Yes | Yes | 3 | 31192.8 | 31809.5 | 94 | -15502.4 |
| Yes | Yes | 4 | 31010.5 | 31660.5 | 99 | -15406.2 |
| Yes | Yes | 5 | 31048.4* | 31730.7* | 104 | -15420.2 |

**Note: Figures are based on the estimation results presented in Tables 4.19 and 4.20**

magnitudes of the coefficient estimates provide little information about the size of the effects of the observable covariates. Therefore, our attention in this research focuses more on the estimated transition probabilities, downward and upward mobility rates, proportion of spurious and structural state dependence, and type-specific transition matrices. However, before any discussions, we found that all state dependence parameters and their initial values are statistically significant. The comparison of state dependence parameters can be interpreted as a comparison of probabilities for people who have the same characteristics. Moreover, state dependence parameters can be interpreted as a measure of labour market flexibility (Brodaty, 2007). For example, almost all coefficients in Table 4.12 are positive and statistically significant, indicating that labour market flexibility makes the transition towards the quartile zero less probable. The detail estimation results are reported in Tables 4.13-4.20.

Tables 4.21-4.24 report conditional probabilities of leaving previous year's quartile with and without controlling for endogenous initial conditions problem and unobserved heterogeneity factors. As expected, when controls for these factors are incorporated in the model, there is a reduction in estimated stability rates and an

Table 4.12: State Dependence Coefficients, with and without Control for Endogenous Initial Condition and Unobserved Heterogeneity

| | Without Control | | | | With Control | | | |
|---|---|---|---|---|---|---|---|---|
| **Danish Immigrants** | | | | | | | | |
| | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| $Q_{1(t-1)}$ | 2.263 (0.077)** | 3.221 (0.189)** | 2.608 (0.288)** | 1.613 (0.469)** | 1.558 (0.098)** | 2.788 (0.208)** | 2.597 (0.330)** | 1.015 (0.489)** |
| $Q_{2(t-1)}$ | 1.912 (0.164)** | 5.759 (0.230)** | 5.252 (0.311)** | 1.879 (0.680)** | 1.399 (0.190)** | 4.562 (0.259)** | 4.697 (0.352)** | 1.408 (0.771) |
| $Q_{3(t-1)}$ | 0.868 (0.292)** | 5.188 (0.310)** | 7.426 (0.365)** | 6.507 (0.481)** | 1.001 (0.350)** | 4.681 (0.372)** | 7.093 (0.418)** | 6.333 (0.483)** |
| $Q_{4(t-1)}$ | -0.611 (0.412)** | 2.408 (0.420)** | 5.100 (0.391)** | 8.663 (0.483)** | -0.509 (0.485) | 2.779 (0.452)** | 5.094 (0.428)** | 7.535 (0.464)** |
| **Danish Natives** | | | | | | | | |
| $Q_{1(t-1)}$ | 2.408 (0.031)** | 3.062 (0.057)** | 2.026 (0.090)** | 0.472 (0.121)** | 1.588 (0.039)** | 2.356 (0.065)** | 1.930 (0.093)** | 0.856 (0.134)** |
| $Q_{2(t-1)}$ | 2.216 (0.051)** | 5.836 (0.069)** | 5.537 (0.096)** | 2.856 (0.116)** | 1.343 (0.060)** | 4.120 (0.079)** | 4.347 (0.100)** | 2.698 (0.128)** |
| $Q_{3(t-1)}$ | 0.653 (0.077)** | 5.094 (0.086)v | 7.774 (0.107)** | 6.440 (0.119)** | 0.489 (0.082)** | 3.717 (0.093)** | 6.036 (0.110)** | 5.320 (0.131)** |
| $Q_{4(t-1)}$ | -1.299 (0.091)** | 1.526 (0.091)** | 5.486 (0.103)** | 8.150 (0.113)** | -1.102 (0.110)** | 1.292 (0.109)** | 4.180 (0.116)** | 5.999 (0.130)** |
| **Canadian Immigrants** | | | | | | | | |
| $Q_{1(t-1)}$ | 5.144 (0.284)** | 5.268 (0.601)** | 4.085 (0.853)** | - | 2.740 (0.450)** | 2.909 (0.789)** | 2.915 (1.066)** | - |
| $Q_{2(t-1)}$ | 4.975 (0.614)** | 8.983 (0.798)** | 7.976 (0.977)** | - | 1.161 (0.790)** | 3.337 (0.930)** | 4.127 (1.217)** | - |
| $Q_{3(t-1)}$ | - | 10.092 (2.579)** | 12.349 (2.626)** | 13.433 (4.000)** | - | 7.737 (6.853) | 10.316 (6.888)* | 19.141 (8.365)** |
| $Q_{4(t-1)}$ | - | 8.363 (3.677)** | 11.271 (3.712)** | 16.447 (4.563)** | - | 5.665 (11.533) | 10.115 (11.544) | 20.946 (12.271)* |
| **Canadian Natives** | | | | | | | | |
| $Q_{1(t-1)}$ | 6.581 (0.163)** | 5.893 (0.256)** | 4.241 (0.375)** | 2.991 (0.376)** | 3.713 (0.239)** | 3.556 (0.299)** | 2.472 (0.373)** | 1.393 (0.549)** |
| $Q_{2(t-1)}$ | 5.967 (0.253)** | 9.116 (0.314)** | 8.155 (0.400)** | 5.083 (0.389)** | 3.519 (0.296)** | 5.497 (0.345)** | 4.846 (0.385)** | 2.958 (0.502)** |
| $Q_{3(t-1)}$ | 3.725 (0.280)** | 7.373 (0.318)** | 9.902 (0.398)** | 7.816 (0.367)** | 2.649 (0.347)** | 4.895 (0.371)** | 6.387 (0.395)** | 5.150 (0.460)** |
| $Q_{4(t-1)}$ | 2.351 (0.408)** | 4.653 (0.382)** | 8.519 (0.425)** | 9.953 (0.391)** | 1.894 (0.538)** | 3.858 (0.500)** | 6.139 (0.481)** | 6.500 (0.480)** |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.13: Dynamic Multinomial Logit Model of Earnings Quartiles for Danish Immigrants, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | Estimated Equations | | | |
|---|---|---|---|---|---|
| | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| **State Dependence** | $Q_{1(t-1)}$ | 2.263 (0.077)** | 3.221 (0.189)** | 2.608 (0.288)** | 1.613 (0.469)** |
| | $Q_{2(t-1)}$ | 1.912 (0.164)** | 5.759 (0.230)** | 5.252 (0.311)** | 1.879 (0.680)** |
| | $Q_{3(t-1)}$ | 0.868 (0.292)** | 5.188 (0.310)** | 7.426 (0.365)** | 6.507 (0.481)** |
| | $Q_{4(t-1)}$ | -0.611 (0.412)** | 2.408 (0.420)** | 5.100 (0.391)** | 8.663 (0.483)** |
| **Observed Covariates** | **Educated** | 0.124 (0.076) | 0.344 (0.092)** | 0.625 (0.122)** | 1.016 (0.200)** |
| | **Married** | -0.015 (0.076) | 0.055 (0.098) | 0.161 (0.118) | 0.114 (0.167) |
| | **Origin (Developed)** | -0.029 (0.087) | -0.123 (0.109) | 0.116 (0.124) | 0.588 (0.159)** |
| | **Age ( 25 – 35)** | 0.482 (0.112)** | 0.846 (0.146)** | 1.001 (0.174)** | 1.057 (0.247)** |
| | **Age (35 – 45)** | 0.327 (0.101)** | 0.646 (0.126)** | 0.706 (0.145 )** | 0.632 (0.190)** |
| | **Experience < 8 years** | -1.146 (0.185)** | -2.105 (0.198)** | -1.968 (0.217)** | -1.438 (0.275)** |
| | **Experience >16 years** | -0.394 (0.186)** | -1.101 (0.195)** | -0.944 (0.206)** | -0.823 (0.239)** |
| | **Unemployment Rate** | -0.135 (0.021)** | -0.115 (0.027)** | -0.067 (0.124)** | -0.054 (0.045)** |
| | **Intercept** | 1.230 (0.240)** | -1.417 (0.325)** | -3.151 (0.414)** | -4.893 (0.588) |
| | **Number of Observation** | 13110 | | **Log-Likelihood** | -10305.56 |
| | **Number of Individuals** | 1311 | | **AIC** | 20715.1 |
| | **Number of Parameters** | 48 | | **BIC** | 20984.4 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.14: Dynamic Multinomial Logit Model of Earnings Quartiles for Danish Immigrants, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | | Estimated Equations | | | |
|---|---|---|---|---|---|---|
| | | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| **State Dependence** | $Q_{1(t-1)}$ | | 1.558 (0.098)** | 2.788 (0.208)** | 2.597 (0.330)** | 1.015 (0.489)** |
| | $Q_{2(t-1)}$ | | 1.399 (0.190)** | 4.562 (0.259)** | 4.697 (0.352)** | 1.408 (0.771) |
| | $Q_{3(t-1)}$ | | 1.001 (0.350)** | 4.681 (0.372)** | 7.093 (0.418)** | 6.333 (0.483)** |
| | $Q_{4(t-1)}$ | | -0.509 (0.485) | 2.779 (0.452)** | 5.094 (0.428)** | 7.535 (0.464)** |
| **Observed Covariates** | **Educated** | | 0.187 (0.096)** | 0.380 (0.128)** | 0.619 (0.137)** | 1.115 (0.233)** |
| | **Age ( 25 – 35)** | | 0.235 (0.262) | 0.475 (0.326) | 0.446 (0.371)** | 0.511 (0.515) |
| | **Age (35 – 45)** | | 0.227 (0.184) | 0.625 (0.225)** | 0.726 (0.251)** | 0.806 (0.329)** |
| | **Married** | | -0.130 (0.155) | -0.258 (0.204) | -0.339 (0.241) | -0.376 (0.361) |
| | **Experience >16 years** | | 0.457 (0.360) | 0.523 (0.372) | 0.406 (0.391) | 0.535 (0.449) |
| | **Experience < 8 years** | | 0.766 (0.408) | 0.746 (0.438) | 0.649 (0.473) | 0.814 (0.585) |
| | **Unemployment Rate** | | -0.281 (0.029)** | -0.322 (0.038)** | -0.244 (0.045)** | -0.192 (0.062)** |
| | **Origin (Developed)** | | 0.277 (0.123)** | 0.005 (0.149) | 0.352 (0.149)** | 0.948 (0.202)** |
| **Pr 1** | 41.8% | **Type 1** | 3.825 (0.450)** | 0.121 (0.540) | -1.987 (0.662)** | -3.675 (0.848)** |
| **Pr 2** | 45.6% | **Type 2** | 3.615 (0.450)** | 2.200 (0.535)** | -0.894 (0.616) | -5.153 (0.895)** |
| **Pr 3** | 12.6% | **Type 3** | 1.179 (0.463)** | -0.164 (0.547) | -1.572 (0.581)** | -4.301 (0.783)** |
| | | **Number of Observation** | 13110 | | **Log-Likelihood** | -9989.16 |
| | | **Number of Individuals** | 1311 | | **AIC** | 20174.3 |
| | | **Number of Parameters** | 98 | | **BIC** | 20681.8 |

**Note:** Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.15: Dynamic Multinomial Logit Model of Earnings Quartiles for Danish Natives, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | Estimated Equations | | | |
|---|---|---|---|---|---|
| | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| State Dependence | $Q_{1(t-1)}$ | 2.408 (0.031) ** | 3.062 (0.057) ** | 2.026 (0.090) ** | 0.472 (0.121) ** |
| | $Q_{2(t-1)}$ | 2.216 (0.051) ** | 5.836 (0.069) ** | 5.537 (0.096) ** | 2.856 (0.116) ** |
| | $Q_{3(t-1)}$ | 0.653 (0.077) ** | 5.094 (0.086)v | 7.774 (0.107) ** | 6.440 (0.119) ** |
| | $Q_{4(t-1)}$ | -1.299 (0.091) ** | 1.526 (0.091) ** | 5.486 (0.103) ** | 8.150 (0.113) ** |
| Observed Covariates | Educated[2] | 0.155 (0.027) ** | 0.502 (0.029) ** | 0.831 (0.031) ** | 1.289 (0.037) ** |
| | Age ( 25 – 35) | 0.923 (0.039) ** | 1.261** (0.042) | 1.356 (0.045) ** | 1.383 (0.050) ** |
| | Age (35 – 45) | 0.402 (0.034) ** | 0.566 (0.036) ** | 0.599 (0.038) ** | 0.697 (0.040) ** |
| | Married[3] | 0.416 (0.030) ** | 0.586 (0.031) ** | 0.709 (0.032) ** | 0.853 (0.035) ** |
| | Experience >16 years | -1.028 (0.037) ** | -1.301 (0.038) ** | -1.270 (0.040) ** | -0.998 (0.043) ** |
| | Experience < 8 years | -1.880 (0.044) ** | -2.362 (0.050) ** | -1.742 (0.056) ** | -1.035 (0.066) ** |
| | Unemployment Rate | 0.022 (0.008) ** | 0.053 (0.009) ** | 0.045 (0.009) ** | 0.031 (0.010) ** |
| | Intercept | 0.509 (0.066) ** | -2.246 (0.084) ** | -3.742 (0.109) ** | -4.796 (0.125) ** |
| | Number of Observation | 386890 | | Log Likelihood | -278400.8 |
| | Number of Individuals | 38689 | | AIC | 556897.7 |
| | Number of Parameters | 48 | | BIC | 557308.7 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.16: Dynamic Multinomial Logit Model of Earnings Quartiles for Danish Natives, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | | Estimated Equations | | | |
|---|---|---|---|---|---|---|
| | | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| State Dependence | | $Q_{1(t-1)}$ | 1.588 (0.039)** | 2.356 (0.065)** | 1.930 (0.093)** | 0.856 (0.134)** |
| | | $Q_{2(t-1)}$ | 1.343 (0.060)** | 4.120 (0.079)** | 4.347 (0.100)** | 2.698 (0.128)** |
| | | $Q_{3(t-1)}$ | 0.489 (0.082)** | 3.717 (0.093)** | 6.036 (0.110)** | 5.320 (0.131)** |
| | | $Q_{4(t-1)}$ | -1.102 (0.110)** | 1.292 (0.109)** | 4.180 (0.116)** | 5.999 (0.130)** |
| Observed Covariates | | Educated | 0.059 (0.034)* | 0.554 (0.038)** | 1.032 (0.042)** | 1.577 (0.053)** |
| | | Age ( 25 – 35) | 0.493 (0.088)** | 0.601 (0.093)** | 0.671 (0.098)** | 0.801 (0.108)** |
| | | Age (35 – 45) | 0.283 (0.058)** | 0.498 (0.061)** | 0.650 (0.064)** | 0.944 (0.071)** |
| | | Married | 0.289 (0.065)** | 0.353 (0.068)** | 0.408 (0.071)** | 0.488 (0.077)** |
| | | Experience >16 years | 0.397 (0.060)** | 0.365 (0.062)** | 0.303 (0.065)** | 0.220 (0.702)** |
| | | Experience < 8 years | 0.469 (0.096)** | 0.007 (0.105) | -0.247 (0.114)** | -0.662 (0.127)** |
| | | Unemployment Rate | -0.157 (0.011)** | -0.144 (0.011)** | -0.118 (0.012)** | -0.076 (0.013)** |
| Pr 1 | 26.2% | Type 1 | 3.676 (0.126)** | -0.538 (0.142)** | -4.600 (0.167)** | -7.634 (0.213)** |
| Pr 2 | 25.2% | Type 2 | 3.481 (0.132)** | 1.598 (0.149)** | -2.050 (0.172)** | -8.224 (0.215)** |
| Pr 3 | 27.5% | Type 3 | 1.877 (0.111)** | -1.243 (0.132)** | -3.211 (0.154)** | -7.613 (0.195)** |
| Pr 4 | 21.1% | Type 4 | 3.236 (0.151)** | 1.771 (0.163)** | 0.210 (0.183) | -2.163 (0.211)** |
| | | Number of Observation | 386890 | | Log Likelihood | -267066.2 |
| | | Number of Individuals | 38689 | | AIC | 534330.5 |
| | | Parameters | 99 | | BIC | 535178.3 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.17: Dynamic Multinomial Logit Model of Earnings Quartiles for Canadian Immigrants, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | Estimated Equations | | | |
|---|---|---|---|---|---|
| | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| State Dependence | $Q_{1(t-1)}$ | 5.144 (0.284)** | 5.268 (0.601)** | 4.085 (0.853)** | - |
| | $Q_{2(t-1)}$ | 4.975 (0.614)** | 8.983 (0.798)** | 7.976 (0.977)** | - |
| | $Q_{3(t-1)}$ | - | 10.092 (2.579)** | 12.349 (2.626)** | 13.433 (4.000)** |
| | $Q_{4(t-1)}$ | - | 8.363 (3.677)** | 11.271 (3.712)** | 16.447 (4.563)** |
| Observed Covariates | Educated | -0.256 (0.319) | -0.124 (0.350) | 0.383 (0.390) | 0.705 (0.469) |
| | Married | 0.765 (0.330)** | 1.297 (0.376)** | 0.994 (0.414)** | 1.405 (0.475)** |
| | Origin (Developed) | -0.239 (0.302) | -0.125 (0.330) | 0.240 (0.355) | 0.493 (0.393) |
| | Age ( 25 – 35) | 0.949 (0.388)** | 0.968 (0.430)** | 0.978 (0.469)** | 1.059 (0.542)** |
| | Age (35 – 45) | 0.638 (0.316)** | 0.727 (0.350)** | 0.568 (0.378)** | 0.463 (0.417) |
| | Experience < 8 years | 0.911 (0.324)** | 1.093 (0.372)** | 0.780 (0.432)** | -0.214 (0.527)** |
| | Experience >16 years | 1.697 (0.377)** | 1.947 (0.424)** | 1.845 (0.475)** | 1.104 (0.564)** |
| | Unemployment Rate | 0.119 (0.129) | 0.194 (0.143) | 0.098 (0.156) | 0.043 (0.172) |
| | Intercept | -4.366 (1.281)** | -7.987 (1.516)** | -8.019 (1.708)** | -10.482 (3.453)** |
| | Number of Observation | 4236 | | Log Likelihood | -2310.8 |
| | Number of Individuals | 706 | | AIC | 4717.6 |
| | Number of Parameters | 48 | | BIC | 4936.5 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.18: Dynamic Multinomial Logit Model of Earnings Quartiles for Canadian Immigrants, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | | Estimated Equations | | | |
|---|---|---|---|---|---|---|
| | | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| State Dependence | | $Q_{1(t-1)}$ | 2.740 (0.450)** | 2.909 (0.789)** | 2.915 (1.066)** | - |
| | | $Q_{2(t-1)}$ | 1.161 (0.790)** | 3.337 (0.930)** | 4.127 (1.217)** | - |
| | | $Q_{3(t-1)}$ | - | 7.737 (6.853)** | 10.316 (6.888)** | 19.141 (8.365)** |
| | | $Q_{4(t-1)}$ | - | 5.665 (11.533)* | 10.115 (11.544)* | 20.946 (12.271)* |
| Observed Covariates | | Educated | -0.247 (0.384) | -0.279 (0.452) | 0.351 (0.478) | -0.090 (0.617) |
| | | Age ( 25 – 35) | 0.479 (1.371) | -0.036 (1.494) | 0.867 (1.590) | 0.050 (1.804) |
| | | Age (35 – 45) | 0.137 (1.068) | 0.814 (1.145) | 0.625 (1.208) | 0.771 (1.325) |
| | | Married | -0.412 (1.569) | -0.809 (1.699) | -1.868 (1.784) | -1.361 (1.881) |
| | | 8<Experience >16 years | 2.726 (0.734)** | 2.125 (0.805)** | 2.125 (0.894)** | 1.853 (1.063)** |
| | | Experience > 16 years | 5.802 (0.965)** | 4.872 (1.075)** | 5.429 (1.172)** | 6.161 (1.452)** |
| | | Unemployment Rate | 0.512 (0.173)** | 0.539 (0.190)** | 0.365 (0.201)** | 0.353 (0.227)** |
| | | Origin (Developed) | -0.298 (0.391) | -0.507 (0.470) | 0.244 (0.461) | 0.503 (0.555) |
| Pr 1 | 20% | Type 1 | -6.231 (1.738)** | 12.370 (2.106)** | -8.308 (2.193)** | -14.655 (3.669)** |
| Pr 2 | 28% | Type 2 | -7.476 (1.813)** | -8.735 (2.058)** | -8.991 (2.235)** | 12.199 (3.653)** |
| Pr 3 | 52% | Type 3 | -8.683 (1.763)** | -13.206 (2.101)** | 11.123 (2.181)** | 12.570 (3.548)** |
| Number of Observation | | | 4236 | Log Likelihood | | -2135.8 |
| Number of Individuals | | | 706 | AIC | | 4459.5 |
| Number of Parameters | | | 94 | BIC | | 4888.1 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.19: Dynamic Multinomial Logit Model of Earnings Quartiles for Canadian Natives, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | Estimated Equations | | | |
|---|---|---|---|---|---|
| | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| State Dependence | $Q_{1(t-1)}$ | 6.581 (0.163)** | 5.893 (0.256)** | 4.241 (0.375)** | 2.991 (0.376)** |
| | $Q_{2(t-1)}$ | 5.967 (0.253)** | 9.116 (0.314)** | 8.155 (0.400)** | 5.083 (0.389)** |
| | $Q_{3(t-1)}$ | 3.725 (0.280)** | 7.373 (0.318)** | 9.902 (0.398)** | 7.816 (0.367)** |
| | $Q_{4(t-1)}$ | 2.351 (0.408)** | 4.653 (0.382)** | 8.519 (0.425)** | 9.953 (0.391)** |
| Observed Covariates | Educated | 0.414 (0.135)** | 0.879 (0.139)** | 0.990 (0.146)** | 1.474 (0.159)** |
| | Married | 0.290 (0.141)** | 0.608 (0.145)** | 0.759 (0.151)** | 0.931 (0.161)** |
| | Age ( 25 – 35) | 1.788 (0.225)** | 2.043 (0.232)** | 2.048 (0.239)** | 2.062 (0.250)** |
| | Age (35 – 45) | 1.098 (0.161)** | 1.292 (0.165)** | 1.144 (0.168)** | 1.248 (0.174)** |
| | Experience < 8 years | 0.894 (0.208)** | 0.785 (0.222)** | 0.673 (0.236)** | 0.843 (0.260)** |
| | Experience >16 years | 1.869 (0.226)** | 1.984 (0.240)** | 1.767 (0.254)** | 1.778 (0.280)** |
| | Unemployment Rate | -0.139 (0.062)** | -0.083 (0.064)** | -0.105 (0.065)** | 0.162 (0.068)** |
| | Intercept | -4.242 (0.532)** | -6.704 (0.588)** | -7.270 (0.649)** | 7.101 (0.652)** |
| | Number of Observation | 31338 | | Log Likelihood | -16571.5 |
| | Number of Individuals | 5223 | | AIC | 33239.0 |
| | Number of Parameters | 48 | | BIC | 33553.9 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.20: Dynamic Multinomial Logit Model of Earnings Quartiles for Canadian Natives, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Explanatory Variables | | | Estimated Equations | | | |
|---|---|---|---|---|---|---|
| | | | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| State Dependence | $Q_{1(t-1)}$ | | 3.713 (0.239)** | 3.556 (0.299)** | 2.472 (0.373)** | 1.393 (0.549)** |
| | $Q_{2(t-1)}$ | | 3.519 (0.296)** | 5.497 (0.345)** | 4.846 (0.385)** | 2.958 (0.502)** |
| | $Q_{3(t-1)}$ | | 2.649 (0.347)** | 4.895 (0.371)** | 6.387 (0.395)** | 5.150 (0.460)** |
| | $Q_{4(t-1)}$ | | 1.894 (0.538)** | 3.858 (0.500)** | 6.139 (0.481)** | 6.500 (0.480)** |
| Observed Covariates | Educated | | 0.177 (0.170) | 0.715 (0.174)** | 0.761 (0.174)** | 1.122 (0.215)** |
| | Age ( 25 – 35) | | 0.082 (0.581) | 0.488 (0.588) | 0.268 (0.597) | 0.080 (0.623) |
| | Age (35 – 45) | | 0.031 (0.404) | 0.215 (0.408) | 0.091 (0.411) | 0.054 (0.426) |
| | Married | | -0.070 (0.482)** | -0.131 (0.493)** | 0.008 (0.509)** | 0.058 (0.542)** |
| | Experience >16 years | | 0.395 (0.542) | 1.247 (0.547)** | 1.313 (0.566)** | 2.306 (0.619)** |
| | Experience < 8 years | | 0.672 (0.743) | 1.837 (0.750)** | 1.551 (0.768)** | 2.438 (0.820)** |
| | Unemployment Rate | | -0.016 (0.072) | 0.034 (0.072) | -0.007 (0.073) | -0.079 (0.079) |
| Pr 1 | 52.8% | Type 1 | -9.903 (2.006)** | -15.344 (2.079)** | -14.067 (2.128)** | -14.903 (2.132)** |
| Pr 2 | 18.3% | Type 2 | -3.257 (0.787)** | -5.833 (0.829)** | -6.364 (0.884)** | -9.578 (1.485)** |
| Pr 3 | 17.7% | Type 3 | -11.367 (2.047)** | -14.000 (2.119)** | -11.334 (2.156)** | -15.796 (2.588)** |
| Pr 4 | 52.8% | Type 4 | -9.903 (2.006)** | -15.344 (2.079)** | -14.067 (2.128)** | -14.903 (2.132)** |
| Number of Observation | | | 31338 | Log Likelihood | | -15406.23 |
| Number of Individuals | | | 5223 | AIC | | 31010.5 |
| Number of Parameters | | | 99 | BIC | | 31660.5 |

Note: Figures inside the parentheses are the Standard errors.
** Parameter estimate is significant at 5 % level of significance.
* Parameter estimate is significant at 10% level of significance.

Table 4.21: Transition Matrix, Estimated Conditional Probabilities of Leaving Previous Year's Quartile by immigrants and Natives, Denmark, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Immigrants | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Origin Quartile | Destination Quartile | | | | | Direction | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.486** | 0.459 | 0.034 | 0.015 | 0.006 | 0.000 | **0.486** | 0.514 |
| $Q_1$ | 0.087 | **0.745** | 0.132 | 0.031 | 0.005 | 0.087 | **0.745** | 0.168 |
| $Q_2$ | 0.035 | 0.197 | **0.608** | 0.158 | 0.003 | 0.232 | **0.608** | 0.161 |
| $Q_3$ | 0.020 | 0.035 | 0.178 | **0.667** | 0.100 | 0.233 | **0.667** | 0.100 |
| $Q_4$ | 0.023 | 0.011 | 0.015 | 0.077 | **0.874** | 0.126 | **0.874** | 0.000 |
| **Distribution** | **0.078** | **0.367** | **0.242** | **0.164** | **0.149** | **0.145** | **0.698** | **0.157** |
| **Natives** | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.260** | 0.622 | 0.077 | 0.025 | 0.016 | 0.000 | **0.260** | 0.740 |
| $Q_1$ | 0.031 | **0.767** | 0.178 | 0.021 | 0.003 | 0.031 | **0.767** | 0.202 |
| $Q_2$ | 0.008 | 0.153 | **0.669** | 0.163 | 0.007 | 0.162 | **0.669** | 0.170 |
| $Q_3$ | 0.004 | 0.016 | 0.153 | **0.711** | 0.116 | 0.173 | **0.711** | 0.116 |
| $Q_4$ | 0.006 | 0.004 | 0.007 | 0.105 | **0.879** | 0.121 | **0.879** | 0.000 |
| **Distribution** | **0.023** | **0.246** | **0.245** | **0.242** | **0.244** | **0.119** | **0.745** | **0.136** |

**Note:** Calculations are based on the estimation results presented in Tables 4.13 and 4.15.

increase in the transition probabilities for all earnings quartiles. This reduction in the stability rates is due to the fact that some portion of observed persistence is attributed to unobserved serial correlations (Heckman, 1981b). For earning mobility process Brodaty (2007) found that stability will be reduced when the model controls for these factors. This fact has been confirmed by various studies with different applications. For example, Hansen, Lofstorm, and Zhang (2006) found this pattern in analyzing transitions into and out of social assistance in Canada. Arulampalam et al. (1998) also found the same results for modeling the unemployment incidence of British men.

Table 4.22: Structural Transition Matrix, Estimated Conditional Probabilities of Leaving Previous Year's Quartile by Immigrants and Natives, Denmark, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| **Immigrants** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Origin Quartile** | **Destination Quartile** | | | | | **Direction** | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | **Down** | **Stable** | **Up** |
| $Q_0$ | **0.433** | 0.493 | 0.045 | 0.017 | 0.012 | 0.000 | **0.433** | 0.567 |
| $Q_1$ | 0.139 | **0.626** | 0.164 | 0.060 | 0.011 | 0.139 | **0.626** | 0.235 |
| $Q_2$ | 0.078 | 0.304 | **0.405** | 0.206 | 0.007 | 0.382 | **0.405** | 0.213 |
| $Q_3$ | 0.028 | 0.074 | 0.155 | **0.597** | 0.147 | 0.256 | **0.597** | 0.147 |
| $Q_4$ | 0.053 | 0.037 | 0.062 | 0.162 | **0.687** | 0.313 | **0.687** | 0.000 |
| **Distribution** | **0.100** | **0.378** | **0.199** | **0.176** | **0.147** | **0.220** | **0.566** | **0.214** |
| **Natives** | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | **Down** | **Stable** | **Up** |
| $Q_0$ | **0.153** | 0.517 | 0.170 | 0.080 | 0.081 | 0.000 | **0.153** | 0.847 |
| $Q_1$ | 0.037 | **0.501** | 0.308 | 0.105 | 0.049 | 0.037 | **0.501** | 0.462 |
| $Q_2$ | 0.015 | 0.161 | **0.507** | 0.257 | 0.061 | 0.175 | **0.507** | 0.318 |
| $Q_3$ | 0.010 | 0.060 | 0.232 | **0.542** | 0.157 | 0.302 | **0.542** | 0.157 |
| $Q_4$ | 0.041 | 0.062 | 0.104 | 0.327 | **0.466** | 0.534 | **0.466** | 0.000 |
| **Distribution** | **0.024** | **0.225** | **0.269** | **0.253** | **0.229** | **0.254** | **0.496** | **0.249** |

**Note:** Calculations are based on the estimation results presented in Tables 4.14 and 4.16.

Table 4.23: Transition Matrix, Estimated Conditional Probabilities of Leaving Previous Year's Quartile by Immigrants and Natives, Canada, (*No Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Immigrants | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Origin Quartile | Destination Quartile | | | | | Direction | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.734** | 0.210 | 0.028 | 0.016 | 0.011 | 0.000 | **0.734** | 0.266 |
| $Q_1$ | 0.025 | **0.840** | 0.116 | 0.019 | 0.000 | 0.025 | **0.840** | 0.135 |
| $Q_2$ | 0.005 | 0.119 | **0.731** | 0.144 | 0.000 | 0.124 | **0.731** | 0.144 |
| $Q_3$ | 0.003 | 0.000 | 0.157 | **0.714** | 0.126 | 0.160 | **0.714** | 0.126 |
| $Q_4$ | 0.005 | 0.000 | 0.013 | 0.098 | **0.884** | 0.116 | **0.884** | 0.000 |
| **Distribution** | **0.045** | **0.248** | **0.205** | **0.235** | **0.268** | **0.100** | **0.796** | **0.105** |
| **Natives** | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.848** | 0.086 | 0.031 | 0.014 | 0.021 | 0.000 | **0.848** | 0.152 |
| $Q_1$ | 0.017 | **0.832** | 0.134 | 0.012 | 0.005 | 0.017 | **0.832** | 0.151 |
| $Q_2$ | 0.005 | 0.106 | **0.749** | 0.132 | 0.009 | 0.111 | **0.749** | 0.141 |
| $Q_3$ | 0.005 | 0.011 | 0.129 | **0.730** | 0.125 | 0.145 | **0.730** | 0.125 |
| $Q_4$ | 0.005 | 0.003 | 0.007 | 0.152 | **0.834** | 0.167 | **0.834** | 0.000 |
| **Distribution** | **0.077** | **0.227** | **0.241** | **0.239** | **0.216** | **0.101** | **0.789** | **0.110** |

**Note:** Calculations are based on the estimation results presented in Tables 4.17 and 4.19.

Table 4.24: Structural Transition Matrix, Estimated Conditional Probabilities of Leaving Previous Year's Quartile by Immigrants and Natives, Canada, (*Control for Endogenous Initial Conditions and Unobserved Heterogeneity*)

| Immigrants | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Origin Quartile | Destination Quartile | | | | | Direction | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.158** | 0.382 | 0.375 | 0.085 | 0.000 | 0.000 | **0.158** | 0.842 |
| $Q_1$ | 0.034 | **0.424** | 0.439 | 0.102 | 0.000 | 0.034 | **0.424** | 0.541 |
| $Q_2$ | 0.047 | 0.197 | **0.509** | 0.248 | 0.000 | 0.243 | **0.509** | 0.248 |
| $Q_3$ | 0.000 | 0.000 | 0.211 | **0.491** | 0.298 | 0.211 | **0.491** | 0.298 |
| $Q_4$ | 0.000 | 0.000 | 0.041 | 0.414 | **0.545** | 0.456 | **0.545** | 0.000 |
| Distribution | **0.044** | **0.234** | **0.235** | **0.216** | **0.271** | **0.234** | **0.479** | **0.286** |
| **Natives** | | | | | | | | |
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.223** | 0.263 | 0.200 | 0.153 | 0.161 | 0.000 | **0.223** | 0.777 |
| $Q_1$ | 0.082 | **0.400** | 0.292 | 0.122 | 0.104 | 0.082 | **0.400** | 0.518 |
| $Q_2$ | 0.070 | 0.181 | **0.415** | 0.224 | 0.110 | 0.250 | **0.415** | 0.335 |
| $Q_3$ | 0.065 | 0.119 | 0.219 | **0.426** | 0.171 | 0.403 | **0.426** | 0.171 |
| $Q_4$ | 0.068 | 0.105 | 0.132 | 0.407 | **0.289** | 0.711 | **0.289** | 0.000 |
| Distribution | **0.074** | **0.224** | **0.242** | **0.252** | **0.207** | **0.328** | **0.374** | **0.298** |

**Note:** Calculations are based on the estimation results presented in Tables 4.18 and 4.20.

The differences between estimated transition matrices reported in Tables 4.21 and 4.23 and observed transition matrices reported in Table 4.6 are due to the observed explanatory variables. Table 4.22 reports transition matrices for Danish immigrants and natives after controlling for spurious effects. This table can be interpreted as the structural part of the transition probabilities. Compared to Table 4.21 (transition matrices without controlling for initial conditions and unobserved heterogeneity), structural stability rates are lower and most transition probabilities are higher for immigrants and natives. For example, structural stability rate in quartile zero for immigrants decreased from 48.6 percent in Table 4.21 to 43.3 percent in Table 4.22, a decline of about 10 percent. This reduction is due to the serial correlation of unobserved characteristics with initial observations of state dependence variables.

Structural stability rates for immigrants in Table 4.22 are higher in the lower and upper quartiles (quartiles one and four) compared to the middle quartiles (quartiles two and three). For example, the stability rates in quartiles one and four are 62.6 and 68.7 percent, respectively, whereas the equivalent figures in quartiles two and three are 40.5 and 59.7 percent. Individuals who are in the lowest quartile today could face a deterioration of their human capital (skills and abilities) that would make their rise more difficult in the future (Brodaty, 2007). Unlike immigrants, structural stability rate for natives is higher in the middle two quartiles. Another interesting fact about this table is that immigrants have higher stability rate in quartile zero. The higher persistence of immigrants in quartile zero is consistent with the fact that immigrants in Denmark have higher tendency to stay unemployed (or non-employed) due to the higher unemployment benefits (Pederson and Smith, 2002).

In Table 4.22, we also note that all movements for both immigrants and natives have the higher probabilities to reach the adjacent quartiles. For example, the

probability of moving from quartile one to quartile two for natives is 30.8 percent, higher than that of transition from one to three, which is 10.5 percent. As expected, there is a positive correlation between the initial quartile and downward mobility, whereas there is a negative correlation between the initial quartile with upward mobility. These results are in line with Brodaty (2007). For example for immigrants upward mobility rates in quartile zero is 56.7 percent, which decreases to 14.7 percent in quartile three. Overall upward and downward mobility rates are higher for natives compared to immigrants. However, downward mobility rate is slightly lower than the upward mobility for both immigrants and natives.

Table 4.24 reports the transition matrices for Canadian immigrants and natives after controlling for unobserved heterogeneity factors and endogenous initial conditions problem. The structural state dependence is lower in any earnings quartiles including quartile zero, compared to the equivalent figures in Table 4.23 (estimated transition without controlling the effects). Structural state dependence in quartile zero is 15.8 percent for immigrants and 22.3 percent for natives, much lower than equivalent figures in Table 4.23, which are 73.4 and 84.8 percent. Unlike our findings for Denmark, there are relatively higher proportions of spurious effects in all quartiles.

Like Danish natives, structural stability rates for Canadian natives are lower in the upper and lower quartiles than in the middle part. One reason for this pattern is the higher upward and downward movements in quartiles one and four. Workers in the middle part of the distribution appear to have relatively stable earnings and hence more persistence. Overall stability rates are slightly higher for immigrants than that for natives in every quartile.

Overall upward mobility rate for Canadian immigrants (28.6 percent) is higher than downward mobility rate (23.4 percent). Unlike immigrants, natives have higher downward mobility rate (32.8 percent) than upward mobility rate (29.8 percent).

Immigrants in any earnings quartiles have more chances to move up to the next quartiles, compared to the natives. For example, the probability of moving up from quartile one to quartile two for immigrants is 43.9 percent whereas the equivalent figure for natives is 29.2 percent.

The comparison of stability and mobility between Denmark and Canada shows the following results: natives have higher upward and downward structural mobility compared to immigrants in the respective countries. Furthermore, natives in two countries have higher structural stability in the middle part (quartiles two and three) compared to lower and upper parts (quartiles one and four) of the earnings distribution, which is opposite of what we found in the observed transition matrices for two countries.

Distinction between structural and spurious effects is crucial for economic policy making. Therefore, to find the proportion of structural effects in the observed persistence, we decompose stability rates into two parts: Structural and Spurious. Structural effects are the ratio of state dependence probabilities with and without controlling for unobserved effects. Tables 4.25 and 4.26 report the percentage of structural and spurious state dependence. As seen, in Denmark structural state dependence for immigrants is quite high compared to natives in every earnings quartile except quartile two. Immigrants and natives in Canada have a very low structural state dependence in quartile zero compared to their Danish counterparts. The difference is higher among immigrants. For example, structural state dependence for Danish immigrants in quartile zero is 89.1 percent, whereas the equivalent figure for Canadians is 21.5 percent. Sources of spurious state dependence are due to some unobserved heterogeneity factors that are different between immigrants and natives in either country. Some portions of these spurious effects can be due to the labour market preferences, labour market discrimination, cultural attitudes, and abilities

Table 4.25: Percentage of Structural and Spurious State Dependence in Earnings Quartiles by Immigrants and Natives, Denmark 1994-2003

| | $Q_0$ | | $Q_1$ | | $Q_2$ | | $Q_3$ | | $Q_4$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious |
| **Immigrants** | **89.1** | 10.9 | **84.0** | 16.0 | **66.6** | 33.4 | **89.5** | 10.5 | **78.7** | 21.3 |
| **Natives** | **58.8** | 41.2 | **65.4** | 34.6 | **75.8** | 24.2 | **76.2** | 23.8 | **53.0** | 47.0 |

**Note:** Calculations are based on the estimation results presented in Tables 4.13 to 4.16.

which are not observed in the data. Policies such as changing benefit rules or introducing labour market programs for unemployed immigrants in Denmark can be more effective in pushing immigrants to the earnings distribution or encouraging them to work.

Differences between Canadian immigrants and natives in structural state dependence in the lower parts of the earnings distribution are not that high, compared to their Danish counterparts. This distinction is more prominent in the upper most parts of the earnings quartiles in which Canadian immigrants have dramatically higher proportion of structural state dependence. This indicates that Canadian immigrants in the uppermost part of the earnings quartiles might be more affected by economic policy reforms. For example, modifications in the progressive tax system may encourage immigrants to move down in the earning distribution.

From the above discussion, we note that the immigrant-native differences in proportion of structural and spurious state dependence, as well as upward and downward mobility rates are more prominent in Denmark than in Canada. One reason for such differences can be due to the fact that immigrants in Denmark mostly come through the reasons other than working. In order to reduce these differences Danish government should continue facilitating skilled immigrants to the labour market,

Table 4.26: Percentage of Structural and Spurious State Dependence in Earnings Quartiles by Immigrants and Natives, Canada 1993-2004

| | $Q_0$ | | $Q_1$ | | $Q_2$ | | $Q_3$ | | $Q_4$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious | Structural | Spurious |
| Immigrants | **21.5** | 78.5 | **50.5** | 49.5 | **69.6** | 30.4 | **68.8** | 31.2 | **61.6** | 38.4 |
| Natives | **26.3** | 73.7 | **48.1** | 51.9 | **55.4** | 44.6 | **58.3** | 41.7 | **34.6** | 65.4 |

**Note:** Calculations are based on the estimation results presented in Tables 4.17 to 4.20.

which will reduce the proportion of non-skilled immigrants in Denmark.

Individuals with different unobserved characteristics have different tendency to be in the upper or lower part of the earnings distribution. As a result, the earnings distribution can be highly segmented in the log-run (Brodaty, 2007). To analyze how immigrants and natives behave on the basis of their unobserved types, we constructed type-specific transition matrices for immigrants and natives for both Denmark and Canada.

Table 4.27 reports the type-specific transition matrices for Canadian natives. Patterns of movement for type one, type three, and type four individuals towards a specific quartile are very apparent. Type one individuals are attracted towards quartile one. Type two and three individuals are attracted towards the middle part of the earnings distribution, i.e. quartiles two and three respectively. This makes upward and downward mobility rates similar. Type four has higher probabilities to stay in or move to quartile four from any of the earnings quartiles. As a result, upward mobility (37.3 percent) is higher than downward mobility (12.9 percent).

Type-specific transition matrices for Danish natives are presented in Table 4.28. As seen, type one individuals have relatively higher probabilities to stay in, or to move in quartile one if they are initially in quartiles zero, one, or two. As

Table 4.27: Type Specific Estimated Transition Matrices, Natives, Canada

**Type 1**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.487 | **0.286** | 0.079 | 0.051 | 0.098 | 0.000 | **0.487** | 0.513 |
| $Q_1$ | 0.131 | **0.575** | 0.156 | 0.058 | 0.080 | 0.131 | **0.575** | 0.294 |
| $Q_2$ | 0.095 | **0.294** | 0.328 | 0.156 | 0.128 | 0.389 | **0.328** | 0.284 |
| $Q_3$ | 0.083 | **0.206** | 0.175 | 0.325 | 0.212 | 0.464 | **0.325** | 0.212 |
| $Q_4$ | 0.088 | **0.181** | 0.101 | 0.284 | 0.347 | 0.653 | **0.347** | 0.000 |
| **Distribution** | 0.086 | **0.289** | 0.189 | 0.199 | 0.237 | **0.358** | **0.417** | **0.225** |

**Type 2**

| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
|---|---|---|---|---|---|---|---|---|
| $Q_0$ | 0.056 | 0.207 | **0.533** | 0.107 | 0.097 | 0.000 | **0.056** | 0.945 |
| $Q_1$ | 0.008 | 0.297 | **0.612** | 0.058 | 0.025 | 0.008 | **0.297** | 0.695 |
| $Q_2$ | 0.005 | 0.086 | **0.778** | 0.110 | 0.022 | 0.090 | **0.778** | 0.132 |
| $Q_3$ | 0.005 | 0.051 | **0.541** | 0.331 | 0.073 | 0.596 | **0.331** | 0.073 |
| $Q_4$ | 0.007 | 0.053 | **0.420** | 0.351 | 0.169 | 0.831 | **0.169** | 0.000 |
| **Distribution** | 0.050 | 0.153 | **0.464** | 0.198 | 0.136 | **0.274** | **0.498** | **0.229** |

**Type 3**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.441 | 0.057 | 0.162 | **0.305** | 0.035 | 0.000 | **0.441** | 0.559 |
| $Q_1$ | 0.128 | 0.170 | 0.331 | **0.344** | 0.028 | 0.128 | **0.170** | 0.703 |
| $Q_2$ | 0.080 | 0.046 | 0.389 | **0.468** | 0.017 | 0.126 | **0.389** | 0.485 |
| $Q_3$ | 0.070 | 0.017 | 0.141 | **0.739** | 0.033 | 0.227 | **0.739** | 0.033 |
| $Q_4$ | 0.074 | 0.013 | 0.076 | **0.733** | 0.105 | 0.895 | **0.105** | 0.000 |
| **Distribution** | 0.090 | 0.121 | 0.243 | **0.461** | 0.084 | **0.226** | **0.505** | **0.269** |

**Type 4**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.083 | 0.157 | 0.061 | 0.133 | **0.566** | 0.000 | **0.083** | 0.917 |
| $Q_1$ | 0.057 | 0.258 | 0.136 | 0.160 | **0.389** | 0.057 | **0.258** | 0.685 |
| $Q_2$ | 0.040 | 0.116 | 0.194 | 0.296 | **0.354** | 0.156 | **0.194** | 0.650 |
| $Q_3$ | 0.019 | 0.028 | 0.042 | 0.379 | **0.532** | 0.089 | **0.379** | 0.532 |
| $Q_4$ | 0.012 | 0.007 | 0.009 | 0.164 | **0.808** | 0.192 | **0.808** | 0.000 |
| **Distribution** | 0.066 | 0.184 | 0.117 | 0.209 | **0.425** | **0.129** | **0.498** | **0.373** |

a result, overall downward mobility (29.9 percent) is higher than upward mobility (14.6 percent). Type two individuals are attracted towards quartile two, whereas type three individuals are attracted towards quartile three. Overall downward and upward mobility rates for type two individuals are 26.4 and 20.8 percent, respectively. The equivalent figures for type three individuals are 24.8 and 25.3 percent. Type four individuals have the highest tendency to be in quartile four. As a result, type four individuals have overall higher upward (33.7 percent) than downward (10.8 percent) mobility.

Table 4.29 reports type-specific transition matrices for Canadian immigrants. Similar to Danish immigrants, there are three unobserved individuals' types. The probability mass for these unobserved types are 20, 28, and 52 percent of the sample. Type one individuals have relatively higher probability to stay in quartile one (47.1 percent), or to move to quartile one if they are initially in quartile zero (38.6 percent). Furthermore, these individuals also have higher probability to stay in (74.4 percent), or to move to quartile four if they are initially in quartile three (45.9 percent). Type two individuals have relatively higher probability to move in to the middle part of the distribution. Type three individuals have relatively higher probability to stay in quartile three or, to move in quartile three if they are initially in any of the earnings quartiles. For example, the probability of staying in quartile three is 86.4 percent, whereas the probability of moving to quartile three is 78 percent, if individuals are initially in quartile four. With regard to overall upward and downward mobility, type one and type three individuals have higher upward mobility than downward, whereas type two has higher downward mobility than upward.

Type-specific transition matrices for Danish immigrants are reported in Table 4.30. There are three unobserved types and each type has the probability mass of 41.8, 45.6, and 12.6 percent of the sample. Individuals with different unobserved

Table 4.28: Type Specific Estimated Transition Matrices, Natives, Denmark

**Type 1**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.134 | **0.755** | 0.066 | 0.011 | 0.034 | 0.000 | **0.134** | 0.866 |
| $Q_1$ | 0.034 | **0.791** | 0.139 | 0.016 | 0.021 | 0.034 | **0.791** | 0.176 |
| $Q_2$ | 0.022 | **0.422** | 0.414 | 0.081 | 0.061 | 0.444 | **0.414** | 0.142 |
| $Q_3$ | 0.022 | **0.235** | 0.283 | 0.251 | 0.210 | 0.539 | **0.251** | 0.210 |
| $Q_4$ | 0.071 | **0.210** | 0.107 | 0.118 | 0.494 | 0.506 | **0.494** | 0.000 |
| Distribution | 0.027 | **0.389** | 0.220 | 0.111 | 0.253 | **0.299** | **0.555** | **0.146** |

**Type 2**

| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
|---|---|---|---|---|---|---|---|---|
| $Q_0$ | 0.105 | 0.473 | **0.328** | 0.080 | 0.014 | 0.000 | **0.105** | 0.895 |
| $Q_1$ | 0.021 | 0.389 | **0.499** | 0.085 | 0.006 | 0.021 | **0.389** | 0.591 |
| $Q_2$ | 0.006 | 0.097 | **0.696** | 0.193 | 0.007 | 0.104 | **0.696** | 0.200 |
| $Q_3$ | 0.005 | 0.042 | **0.390** | 0.531 | 0.032 | 0.437 | **0.531** | 0.032 |
| $Q_4$ | 0.031 | 0.061 | **0.250** | 0.468 | 0.191 | 0.809 | **0.191** | 0.000 |
| Distribution | 0.016 | 0.173 | **0.408** | 0.290 | 0.113 | **0.264** | **0.529** | **0.208** |

**Type 3**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.324 | 0.413 | 0.097 | **0.102** | 0.065 | 0.000 | **0.324** | 0.676 |
| $Q_1$ | 0.100 | 0.482 | 0.211 | **0.160** | 0.047 | 0.100 | **0.482** | 0.417 |
| $Q_2$ | 0.042 | 0.165 | 0.358 | **0.380** | 0.055 | 0.207 | **0.358** | 0.436 |
| $Q_3$ | 0.025 | 0.048 | 0.126 | **0.667** | 0.134 | 0.199 | **0.667** | 0.134 |
| $Q_4$ | 0.084 | 0.044 | 0.052 | **0.397** | 0.423 | 0.577 | **0.423** | 0.000 |
| Distribution | 0.058 | 0.216 | 0.183 | **0.329** | 0.214 | **0.248** | **0.498** | **0.253** |

**Type 4**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.050 | 0.247 | 0.192 | 0.174 | **0.338** | 0.000 | **0.050** | 0.951 |
| $Q_1$ | 0.010 | 0.211 | 0.325 | 0.221 | **0.232** | 0.010 | **0.211** | 0.779 |
| $Q_2$ | 0.003 | 0.040 | 0.357 | 0.388 | **0.212** | 0.043 | **0.357** | 0.600 |
| $Q_3$ | 0.001 | 0.007 | 0.086 | 0.536 | **0.370** | 0.094 | **0.536** | 0.370 |
| $Q_4$ | 0.002 | 0.004 | 0.019 | 0.167 | **0.808** | 0.192 | **0.808** | 0.000 |
| Distribution | 0.009 | 0.109 | 0.226 | 0.290 | **0.366** | **0.108** | **0.555** | **0.337** |

Table 4.29: Type Specific Estimated Transition Matrices, Immigrants, Canada

**Type 1**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.295 | **0.386** | 0.250 | 0.069 | 0.000 | 0.000 | **0.295** | 0.705 |
| $Q_1$ | 0.060 | **0.471** | 0.368 | 0.102 | 0.000 | 0.060 | **0.471** | 0.470 |
| $Q_2$ | 0.079 | 0.221 | 0.444 | 0.255 | 0.000 | 0.300 | **0.444** | 0.255 |
| $Q_3$ | 0.000 | 0.000 | 0.148 | 0.394 | **0.459** | 0.148 | **0.394** | 0.459 |
| $Q_4$ | 0.000 | 0.000 | 0.023 | 0.234 | **0.744** | 0.256 | **0.744** | 0.000 |
| **Distribution** | 0.058 | **0.262** | 0.166 | 0.189 | **0.326** | **0.177** | **0.531** | **0.293** |

**Type 2**

| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
|---|---|---|---|---|---|---|---|---|
| $Q_0$ | 0.371 | **0.492** | 0.108 | 0.024 | 0.005 | 0.000 | **0.371** | 0.629 |
| $Q_1$ | 0.103 | **0.518** | **0.312** | 0.064 | 0.004 | 0.103 | **0.518** | 0.380 |
| $Q_2$ | 0.044 | 0.187 | **0.597** | 0.170 | 0.002 | 0.231 | **0.597** | 0.172 |
| $Q_3$ | 0.016 | 0.052 | **0.270** | **0.606** | 0.055 | 0.338 | **0.606** | 0.055 |
| $Q_4$ | 0.052 | 0.043 | 0.174 | **0.292** | 0.439 | 0.561 | **0.439** | 0.000 |
| **Distribution** | 0.035 | 0.138 | **0.452** | 0.140 | 0.235 | **0.240** | **0.560** | **0.200** |

**Type 3**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.101 | 0.548 | 0.141 | **0.210** | 0.000 | 0.000 | **0.101** | 0.899 |
| $Q_1$ | 0.015 | 0.570 | 0.166 | **0.249** | 0.000 | 0.015 | **0.570** | 0.415 |
| $Q_2$ | 0.021 | 0.295 | 0.169 | **0.515** | 0.000 | 0.315 | **0.169** | 0.515 |
| $Q_3$ | 0.000 | 0.000 | 0.054 | **0.864** | 0.082 | 0.054 | **0.864** | 0.082 |
| $Q_4$ | 0.000 | 0.000 | 0.008 | **0.780** | 0.212 | 0.788 | **0.212** | 0.000 |
| **Distribution** | 0.031 | 0.318 | 0.062 | **0.460** | 0.129 | **0.151** | **0.619** | **0.230** |

types have different transition probability matrices. For example, type one individuals have the highest probability to move into the quartile one, if they are initially in any of the first three quartiles. Whereas type three individuals have the highest probability to stay in quartile zero or move down into quartile zero if they are initially in quartile one. Individuals in type two, have the highest probability to stay in or to move to quartiles one and two if they are initially in quartiles zero, one, and two. With regard to overall upward and downward mobility, type one has higher downward than upward, whereas type three has higher upward than downward. For type two individuals upward and downward mobility rates are quite similar.

From the above discussion, we note that each unobserved type has the tendency to move towards a specific quartile. To observe more precisely the zones individuals are attracted to, at stationary equilibrium, it is useful to find the quartile stationary distribution of each type. This distribution helps us understand the segmentation of earnings distribution on the basis of unobserved heterogeneity factors. These stationary distributions are reported in Table 4.31 for immigrants and natives in both countries. The stationary equilibriums of Canadian natives with type one, type two, type three, and type four are in quartiles one, two, three, and four respectively. Similarly, Danish natives with types one, two, three, and four have the highest log-run probabilities to stay in quartiles one, two, three, and four, respectively. Canadian immigrants with types one, two, and three have stationary equilibriums in quartiles one, two, and three, respectively. By looking at the stationary distribution of Danish immigrants, we observe that type three individuals have a higher probability (25.5 percent) to stay in quartile zero, compared to types one and two (8.5 and 7.6 percent, respectively), whereas type one has the stationary equilibrium in quartile one. Unlike immigrants in Denmark, none of the types of Canadian immigrants has a very high probability to be in quartile zero. One reason

Table 4.30: Type Specific Estimated Transition Matrices, Immigrants, Denmark

**Type 1**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | 0.362 | **0.595** | 0.015 | 0.009 | 0.020 | 0.000 | **0.362** | 0.638 |
| $Q_1$ | 0.121 | **0.768** | 0.061 | 0.031 | 0.019 | 0.121 | **0.768** | 0.111 |
| $Q_2$ | 0.093 | **0.517** | 0.217 | 0.153 | 0.020 | 0.610 | **0.217** | 0.173 |
| $Q_3$ | 0.031 | **0.133** | 0.082 | 0.425 | 0.330 | 0.245 | **0.425** | 0.330 |
| $Q_4$ | 0.030 | **0.035** | 0.019 | 0.069 | 0.847 | 0.153 | **0.847** | 0.000 |
| **Distribution** | 0.085 | **0.500** | 0.100 | 0.125 | 0.192 | **0.181** | **0.651** | **0.168** |

**Type 2**

| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
|---|---|---|---|---|---|---|---|---|
| $Q_0$ | 0.371 | **0.492** | 0.108 | 0.024 | 0.005 | 0.000 | **0.371** | 0.629 |
| $Q_1$ | 0.103 | **0.518** | 0.312 | 0.064 | 0.004 | 0.103 | **0.518** | 0.380 |
| $Q_2$ | 0.044 | 0.187 | **0.597** | 0.170 | 0.002 | 0.231 | **0.597** | 0.172 |
| $Q_3$ | 0.016 | 0.052 | **0.270** | 0.606 | 0.055 | 0.338 | **0.606** | 0.055 |
| $Q_4$ | 0.052 | 0.043 | **0.174** | 0.292 | 0.439 | 0.561 | **0.439** | 0.000 |
| **Distribution** | 0.076 | 0.312 | **0.326** | 0.186 | 0.100 | **0.226** | **0.541** | **0.232** |

**Type 3**

| Origin Quartile | Destination Quartile | | | | | Direction | | |
|---|---|---|---|---|---|---|---|---|
| | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | Down | Stable | Up |
| $Q_0$ | **0.787** | 0.128 | 0.033 | 0.032 | 0.021 | 0.000 | **0.787** | 0.214 |
| $Q_1$ | **0.414** | 0.244 | 0.163 | 0.152 | 0.028 | 0.414 | **0.244** | 0.342 |
| $Q_2$ | **0.196** | 0.088 | 0.299 | **0.401** | 0.017 | 0.284 | **0.299** | 0.418 |
| $Q_3$ | **0.037** | 0.011 | 0.062 | **0.679** | 0.211 | 0.109 | **0.679** | 0.211 |
| $Q_4$ | **0.052** | 0.004 | 0.021 | 0.163 | 0.760 | 0.240 | **0.760** | 0.000 |
| **Distribution** | **0.255** | 0.144 | 0.166 | **0.269** | 0.166 | **0.176** | **0.594** | **0.230** |

Table 4.31: Quartile Stationary Distribution, by Unobserved Types

| | Types | Quartile Distribution | | | | |
|---|---|---|---|---|---|---|
| | | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| Canadian Natives | 1 | 0.086 | **0.289** | 0.189 | 0.199 | 0.237 |
| | 2 | 0.050 | 0.153 | **0.464** | 0.198 | 0.136 |
| | 3 | 0.090 | 0.121 | 0.243 | **0.461** | 0.084 |
| | 4 | 0.066 | 0.184 | 0.117 | 0.209 | **0.425** |
| Danish Natives | 1 | 0.027 | **0.389** | 0.220 | 0.111 | 0.253 |
| | 2 | 0.016 | 0.173 | **0.408** | 0.290 | 0.113 |
| | 3 | 0.058 | 0.216 | 0.183 | **0.329** | 0.214 |
| | 4 | 0.009 | 0.109 | 0.226 | 0.290 | **0.366** |
| Canadian Immigrants | 1 | 0.058 | **0.262** | 0.166 | 0.189 | **0.326** |
| | 2 | 0.035 | 0.138 | **0.452** | 0.140 | 0.235 |
| | 3 | 0.031 | 0.318 | 0.062 | **0.460** | 0.129 |
| Danish Immigrants | 1 | 0.085 | **0.500** | 0.100 | 0.125 | 0.192 |
| | 2 | 0.076 | 0.312 | **0.326** | 0.186 | 0.100 |
| | 3 | **0.255** | 0.144 | 0.166 | **0.269** | 0.166 |

can be due to the fact that immigrant workers in Canada are mostly skilled, compared to immigrant workers in Denmark, so they have less chances to be unemployed or out of the labour force.

Overall, Tables 4.27-4.31 suggest that the immigrant-native gaps in persistence of or transitions into or out of, any of the earnings quartiles are due to some measured and unmeasured factors. The results also point to the importance of controlling for the endogenous initial conditions problem and unobserved heterogeneity factors. We also note that individuals with different unobserved types have different tendencies to be accumulated in the lower, middle, or upper parts of the earnings distribution; which makes the earnings distribution segmented.

Finally, Table 4.32 shows the predicted and observed distributions of earnings quartiles. The predicted distributions are calculated for each year for Denmark and Canada. Overall, the predicted distributions are almost similar to the observed

frequencies, indicating that the empirical models fit the data well. One measure of goodness of fit in discrete choice modeling is likelihood ratio test. This measure is defined as, where is the value of the log-likelihood function at the estimated parameters and is the value with all parameters equal to zero. The index ranges from zero (no model) to one (perfect model). Table 4.33 reports the likelihood ratio indices for the final models.

Table 4.32: Yearly Observed and Predicted Probabilities

| *Danish Natives* | Observed | | | | | Predicted | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| 1995 | 0.049 | 0.233 | 0.239 | 0.24 | 0.239 | 0.04 | 0.242 | 0.245 | 0.232 | 0.241 |
| 1996 | 0.039 | 0.234 | 0.242 | 0.242 | 0.242 | 0.032 | 0.238 | 0.255 | 0.237 | 0.238 |
| 1997 | 0.03 | 0.237 | 0.243 | 0.245 | 0.245 | 0.027 | 0.235 | 0.261 | 0.242 | 0.236 |
| 1998 | 0.026 | 0.238 | 0.244 | 0.246 | 0.246 | 0.022 | 0.233 | 0.266 | 0.245 | 0.234 |
| 1999 | 0.028 | 0.237 | 0.244 | 0.245 | 0.246 | 0.019 | 0.232 | 0.269 | 0.248 | 0.232 |
| 2000 | 0.025 | 0.239 | 0.244 | 0.246 | 0.246 | 0.019 | 0.231 | 0.27 | 0.25 | 0.23 |
| 2001 | 0.026 | 0.239 | 0.244 | 0.246 | 0.246 | 0.019 | 0.228 | 0.271 | 0.253 | 0.229 |
| 2002 | 0.034 | 0.237 | 0.241 | 0.244 | 0.244 | 0.02 | 0.227 | 0.271 | 0.254 | 0.229 |
| 2003 | 0.043 | 0.235 | 0.239 | 0.241 | 0.242 | 0.025 | 0.225 | 0.269 | 0.253 | 0.229 |
| *Danish Immigrants* | Observed | | | | | Predicted | | | | |
| Year | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| 1995 | 0.254 | 0.336 | 0.156 | 0.119 | 0.134 | 0.267 | 0.346 | 0.133 | 0.126 | 0.128 |
| 1996 | 0.202 | 0.376 | 0.153 | 0.134 | 0.135 | 0.213 | 0.37 | 0.146 | 0.136 | 0.135 |
| 1997 | 0.16 | 0.374 | 0.184 | 0.146 | 0.137 | 0.169 | 0.396 | 0.155 | 0.145 | 0.136 |
| 1998 | 0.108 | 0.399 | 0.198 | 0.156 | 0.14 | 0.123 | 0.408 | 0.177 | 0.156 | 0.137 |
| 1999 | 0.105 | 0.399 | 0.204 | 0.151 | 0.14 | 0.091 | 0.414 | 0.192 | 0.163 | 0.139 |
| 2000 | 0.087 | 0.38 | 0.218 | 0.164 | 0.151 | 0.087 | 0.415 | 0.198 | 0.161 | 0.14 |
| 2001 | 0.083 | 0.372 | 0.229 | 0.166 | 0.15 | 0.079 | 0.399 | 0.203 | 0.172 | 0.146 |
| 2002 | 0.082 | 0.367 | 0.242 | 0.16 | 0.15 | 0.08 | 0.391 | 0.207 | 0.175 | 0.148 |
| 2003 | 0.111 | 0.362 | 0.225 | 0.158 | 0.143 | 0.1 | 0.378 | 0.199 | 0.176 | 0.147 |
| Canadian Natives | Observed | | | | | Predicted | | | | |
| Year | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| 1994 | 0.051 | 0.218 | 0.258 | 0.260 | 0.214 | 0.060 | 0.231 | 0.256 | 0.265 | 0.188 |
| 1995 | 0.055 | 0.204 | 0.264 | 0.256 | 0.221 | 0.060 | 0.229 | 0.257 | 0.267 | 0.188 |
| 1996 | 0.081 | 0.215 | 0.247 | 0.240 | 0.218 | 0.060 | 0.226 | 0.256 | 0.270 | 0.187 |
| 1997 | 0.081 | 0.215 | 0.243 | 0.248 | 0.213 | 0.071 | 0.231 | 0.245 | 0.255 | 0.199 |
| 1998 | 0.084 | 0.207 | 0.238 | 0.251 | 0.220 | 0.071 | 0.231 | 0.245 | 0.256 | 0.198 |
| 1999 | 0.100 | 0.191 | 0.223 | 0.247 | 0.240 | 0.081 | 0.226 | 0.232 | 0.251 | 0.209 |
| 2000 | 0.087 | 0.209 | 0.223 | 0.229 | 0.253 | 0.082 | 0.229 | 0.228 | 0.252 | 0.211 |
| 2001 | 0.089 | 0.204 | 0.230 | 0.233 | 0.245 | 0.081 | 0.229 | 0.232 | 0.249 | 0.209 |
| 2002 | 0.077 | 0.204 | 0.223 | 0.241 | 0.256 | 0.081 | 0.226 | 0.232 | 0.251 | 0.209 |
| 2003 | 0.082 | 0.208 | 0.222 | 0.238 | 0.250 | 0.084 | 0.226 | 0.224 | 0.254 | 0.212 |
| 2004 | 0.078 | 0.203 | 0.221 | 0.246 | 0.252 | 0.081 | 0.227 | 0.229 | 0.251 | 0.212 |
| Canadian Immigrants | Observed | | | | | Predicted | | | | |
| Year | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_0$ | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
| 1994 | 0.092 | 0.235 | 0.252 | 0.129 | 0.292 | 0.061 | 0.264 | 0.205 | 0.184 | 0.285 |
| 1995 | 0.092 | 0.221 | 0.231 | 0.189 | 0.267 | 0.054 | 0.262 | 0.209 | 0.200 | 0.275 |
| 1996 | 0.077 | 0.293 | 0.223 | 0.180 | 0.227 | 0.056 | 0.252 | 0.217 | 0.203 | 0.273 |
| 1997 | 0.083 | 0.300 | 0.204 | 0.183 | 0.230 | 0.050 | 0.268 | 0.218 | 0.208 | 0.257 |
| 1998 | 0.072 | 0.277 | 0.218 | 0.192 | 0.241 | 0.051 | 0.265 | 0.208 | 0.221 | 0.254 |
| 1999 | 0.082 | 0.267 | 0.216 | 0.192 | 0.243 | 0.040 | 0.273 | 0.201 | 0.239 | 0.248 |
| 2000 | 0.076 | 0.253 | 0.223 | 0.203 | 0.245 | 0.052 | 0.240 | 0.206 | 0.241 | 0.262 |
| 2001 | 0.071 | 0.276 | 0.220 | 0.184 | 0.250 | 0.044 | 0.239 | 0.206 | 0.240 | 0.270 |
| 2002 | 0.069 | 0.257 | 0.229 | 0.176 | 0.269 | 0.044 | 0.229 | 0.221 | 0.223 | 0.283 |
| 2003 | 0.066 | 0.265 | 0.258 | 0.146 | 0.265 | 0.040 | 0.230 | 0.218 | 0.227 | 0.284 |
| 2004 | 0.068 | 0.276 | 0.216 | 0.204 | 0.236 | 0.035 | 0.241 | 0.217 | 0.227 | 0.281 |

Note: Predicted values are calculated based on the estimation results presented in Table 4.14, 4.16, 4.18, and 4.20.

Table 4.33: Fit of the Model (*Likelihood Ratio Index*)

| | | $LL^1$ ( No Model ) | LL (Full Model ) | Likelihood Ratio Index |
|---|---|---|---|---|
| **Denmark** | **Immigrants** | -14639.21 | -9989.16 | 0.318 |
| | **Natives** | -455679.04 | -267066.2 | 0.414 |
| **Canada** | **Immigrants** | -5448.5 | -2135.7 | 0.608 |
| | **Natives** | -52829.6 | -15406.2 | 0.708 |

**Note:** 1. Model with all explanatory variables restricted to zero.

# Chapter 5

# Summary and Conclusions

This dissertation studies three essays in labour market mobility as follows:

1. A Dynamic Analysis of Canadian Male Self-Employment.
2. Immigrant-Native Differences in Wage Mobility Process.
3. Immigrant-Native Differences in Earnings Mobility Process: Evidence from Canadian and Danish Data.

All essays employ *SLID* for males aged 25-55. The dynamic process is assumed to follow a first-order Markov process. The empirical model is a multinomial logit which controls for both unobserved factors and endogenous initial conditions problem. All estimation results, as well as descriptive statistics, are weighted with sample longitudinal weights provided by Statistics Canada. In this chapter, I review and summarize my main findings in each essay. Policy implications in the form of structural and spurious state dependence have been discussed.

First essay analyzes transitions into and out of self-employment. Four mutually exclusive and exhaustive labour market states are considered: paid-employment, self-employment, unemployment, and being out of the labour force. Observed raw

data indicates that any persistence in self-employment is associated with being immigrant, being married, being educated, having a remarkably high positive investment income, and living in provinces with relatively low unemployment rates. A man who enters self-employment from paid-employment is likely to be immigrant, be married, be educated, and have educated parents. Regarding the transition from self-employment to paid-employment, it appears to be associated with being married, being highly educated, having educated parents, and living in provinces with relatively low unemployment rates. Further, noticeably low investment incomes have been observed in transition from self-employment into unemployment.

The pattern of self-employment rates among immigrants and natives indicates that immigrants are more responsive to the variation in the unemployment rate than natives. The gap between immigrants' and natives' self-employment rates has been narrowing over the period 1994-2004. Immigrants' self-employment rate was always higher than natives' over the period 1994-2004. Different behaviors of immigrants' and natives' with respect to unemployment rate changes during the period 1994-2004 suggests that cyclical factors alone cannot explain the rise and decline of the self-employment rate.

The observed data shows a high persistence of self-employment and paid-employment for males in Canada. Persistence in unemployment is not that high. A person who is unemployed this year, 53.5 percent is likely to remain unemployed and about 32.2 percent is likely to find a job in the labour market next year. Among individuals who are not in the labour force this year, 14.4 percent are likely to be paid-employed next year and 75.8 percent are still out of the labour force. The high persistence of self-employment and paid-employment has been observed for both immigrants and natives. However, natives have slightly higher persistence in paid-employment (and slightly lower persistence in self-employment) than similar

immigrants. Natives are less likely than immigrants to lose their jobs and be unemployed next year, if they are paid-employed this year. The observed data also show that immigrants are more likely to remain unemployed in the consecutive years than natives. Further, the probability of being self-employed next year, if being in any states of paid-employment, unemployment, or out of the labour force this year is higher among immigrants than among natives. Natives are more likely to find a job (and less likely to be unemployed) next year, if they are out of the labour force this year. Persistence of being out of the labour force is slightly higher among natives than among immigrants for the period 1993-2004. The probability of being self-employed next year, if being out of the labour force this year, is slightly higher among immigrants than among natives.

Estimation results indicate that a model with four support points fitted the data well. The marginal probability of being self-employed among males aged 25 to 55 is negative in times of high unemployment rates, all other factors fixed. This is not the case for immigrants. Immigrants who are residing in provinces with relatively high unemployment rates tend to be self-employed. Immigrants and natives behave differently with respect to unemployment rate changes. Immigrants may feel some uncertainty about labour market conditions when the unemployment rate is high, due to the statistical discrimination they may face in the labour market. Further, the unemployment experience may be very different between immigrants and natives which causes either group to behave differently in times of high unemployment rates. The high unemployment rate pushes immigrants into self-employment more than natives.

Empirical results show that males with positive investment income or wealth tend to be self-employed. However, when the model does not control for the spurious effects, this tendency is more highlighted, indicating that individuals may start up a business because of some unobserved heterogeneity factors or different personal

characteristics. Failure to control for these factors will falsely attribute a highly significant effect of investment income to self-employment decisions.

My estimation results do not show any significant effects of individuals' wage expectation on logit probability of being self-employed or paid-employed. One possible explanation is the non pecuniary benefits that individuals may obtain when they are self-employed or paid-employed. Further, the results show that expectation of having a higher salary in self-employment sectors (versus being a paid-employee) decreases the logit probability of the being unemployed among males age 25 to 55.

My estimation results also reveal that parental background has a significant effect on logit probability of being self-employed, paid-employed, and unemployed, taking all observed and unobserved effects into account. The effects of education and marriage have the expected signs for self-employment and paid-employment equations. As well, all state dependence variables are statistically significant and positive in all equations of self-employment, paid-employment, and unemployment.

Results from the most general specification suggest that the causal effect of past self-employment on current self-employment is relatively weak and much different from what observed data shows. Looking at observed persistence in self-employment for immigrants and natives, no big difference between either group is observed. However, immigrants and natives differ in many unobserved and observed characteristics such as labour market preferences, abilities, and unemployment experiences (which are not observed in the data), as well as observable factors such as level of education and parental background at the time of entry to panel (initial conditions), marital status, and sensitivity to any changes in labour market conditions. Distinguishing between true and spurious state dependence highlights immigrant-native gaps in unobserved characteristics in any labour market states of self-employment, paid-employment, unemployment, and being out of the labour force.

The higher self-employment rate among immigrants than among natives is due to a combination of both higher entry and lower exit rates among immigrants than comparable natives. Higher structural persistence in self-employment among immigrants than among natives is partially due to the lower exit rates from self-employment state. On the other hand, the entry rate to self-employment is higher among immigrants. Comparing estimated entry-exit rates for the model which controls for the spurious effects, and the model which does not, indicates that unobserved factors and initial condition problems play important roles in explaining differences between immigrants and natives in persistence in any labour market states. When the model ignores the effects of spurious factors, it erroneously assumes that the correlation between state dependence variables and time-invariant unobserved factors is zero. This invalid assumption underestimates entry and exit probability rates in all labour market states and therefore does not show the real effect of entry-exit gaps on persistence in any labour market states among immigrants and natives.

My estimation results indicate that structural factors alone can not explain the rise or fall in self-employment participation rates among either immigrants or natives over the period 1993-2004. The structural factors affect the probability of remaining self-employed in consecutive years and consequently affect exit rates from the self-employment state only partially. The probability of entering into the self-employment is also, to some extent, due to unobserved heterogeneity factors such as labour market preferences (labour market discrimination among immigrants which makes them more likely enter and stay in the self-employment state, especially in times of high unemployment rate).

Policies that improve individuals' unobserved heterogeneity (preferences, abilities, and skills) such as public or private training programs for new entrepreneurs, may partially attract immigrants and natives to the self-employment. Furthermore,

government provision of financial supports to the self-employed increases the probability of being self-employed and may encourage individuals to enter and stay in the self-employment state. My results show that labour market discrimination may still exist among immigrants in Canada. When the economic conditions are not good immigrants are pushed into the self-employment due to the statistical discrimination they may face (or feel) in the paid-employment sectors. The results shed light to the importance of Employment Equity Act (*EEA*) of Canada which should apply in all industries and manufacturing companies, not only limited to certain industries which are federally regulated.

The second essay analyzes transitions into and out of any of the five hourly wage quintiles and quintile zero (unemployment and non-employment state). The observed raw data shows that immigrants from visible minority groups on average are accumulated more in the first and second parts of the wage distribution, while comparable natives are mostly evenly distributed. In comparison with other groups of immigrants, Arabs and Latin Americans have a lower mobility rate from the last quintile and a higher mobility rate from the first quintile. This makes the quintile distribution very segmented among Arabs and Latin Americans. Moreover, Asians have more chances to work in the uppermost part of the wage distribution than other groups of immigrants. Moving from the lower part of the wage distribution to the upper part, both immigrants and natives are more likely to be educated and married, more experienced, and face a lower unemployment rate at the time of entry to the labour market. On average, immigrants are more likely to be educated but have less experience than similar natives. Overall upward mobility rate is almost the same between immigrants and natives. However, immigrants compared to natives have lower downward mobility rate.

My estimation results indicate that a model with three and four support points fitted the data well for immigrants and natives, respectively. Empirical results show

immigrants and natives with higher levels of education have greater chances to work in the uppermost part of the wage distribution. The marginal effect of education is higher among immigrants, though. Further, immigrants who are younger at arrival in Canada are more likely to work in the middle part of the wage distribution. State dependence exists in all hourly wage quintiles. All state dependence variables and their initial values are highly statistically significant. Not all observed persistence is structural for immigrants and natives. Some portion is due to the unobservable factors. Immigrants and natives have the highest structural persistence in quintiles three (88 percent) and four (58 percent), respectively. For natives, persistence in the last quintile (quintile five) stems, to a greater extent (66 percent), from unobserved heterogeneity factors, while for immigrants only 25 percent of the persistence is spurious. The source of the unexplained portion is different for immigrants and natives and is difficult to be disentangled. For immigrants, for instance, this may be related to unobserved statistical discrimination, cultural attitudes, and abilities. For natives, this may be due to the unobserved labour market preferences, and skills. My results also show that individuals with different unobserved types have different tendencies to be accumulated in the lower, middle, or upper parts of the wage distribution. This makes the wage distribution segmented. Immigrants and natives have three and six unobserved types, respectively. Each type is attracted towards a specific quintile.

The considerable proportion of spurious effect in persistence in the lower and upper parts of the wage distribution indicates that structural factors alone cannot explain the rise or fall in participation rates of any hourly wage quintile over the period 1993-2004 among immigrants and natives. Public policies that improve unobserved heterogeneity effects (preferences, abilities, or skills) such as public or private job training programs may attract both immigrants and mostly natives to specific wage quintiles and then help reduce income inequality. Policies that lessen

labour market discrimination help capable immigrants to move out of the lower part of the wage distribution to the upper part. Moreover, policies which induce longer unemployment spells such as unemployment insurance or social assistance programs lead to larger skill losses among natives and immigrants, mostly among immigrants, making these policies more costly. Any modifications in unemployment insurance or social assistance programs redistribute the hourly wage pattern among working populations and therefore reduce wage inequality among natives and immigrants.

The final essay studies transitions into and out of any of the four earnings quartiles, and quartile zero (unemployment and non-employment state). The data for Denmark is a random sample of 40,000 individuals, which is taken from administrative registered data of Denmark for the period 1994-2003. The observed raw data show that immigrants in Denmark are more attracted towards the lower parts of the earnings distribution, while natives are evenly distributed. In Canada, immigrants are more observed in the lower and upper parts of the earnings distribution, while natives are more attracted to the middle quartiles. Comparison of natives in two countries reveals that natives in Denmark are less likely to be unemployed (or non-employed). However, earnings distribution for natives is similar in both countries. Immigrants in Canada have higher stability in any earnings quartiles than their Danish counterparts. Upward mobility is higher than the downward mobility for immigrants in both countries, but with higher magnitude for Danish immigrants.

Estimation results show that models with three and four support points fit the data well for immigrants and natives, respectively, in both countries. All state dependence parameters are positive and statistically significant, indicating that labour market flexibility makes the transition towards the quartile zero less probable. Not all observed persistence in earnings quartiles is structural. Some portion of this persistence stems from unobserved heterogeneity factors (spurious effects). Ignoring unobserved effects and endogenous initial conditions problem overestimate the

degree of the state dependence and underestimate mobility. The estimation results confirm this argument. Structural state dependence for Danish immigrants is quite high compared to natives in every quartile except quartile two. Differences in structural state dependence between immigrants and natives in Canada are not that high, in comparison with the differences in Denmark. Unlike immigrants in Canada, immigrants in Denmark have quite high structural state dependence in any earnings quartiles.

The results show that immigrants in Denmark have a very high proportion of structural state dependence (89.1 percent) in quartile zero (unemployed or non-employed) compared to natives (58.8 percent). In this case, as suggested by Hansen et al. (2006), changes in benefit rules or introducing labor market training programs are more likely to meet their objectives. As mentioned earlier, immigration in Denmark is dominated by family class or refugees, especially from non-western countries. As a result, these immigrants are less skilled compared to Danish natives. Therefore, immigrants have fewer prospects to get employed compared to natives.

Sources of spurious state dependence are due to some unobserved heterogeneity factors that are different between immigrants and native in each country. Some portions of these spurious effects can be due to the labour market preferences, labour market discrimination, cultural attitudes, and abilities which are not observed in the data. The results show that immigrant-native differences in proportion of structural and spurious state dependence, as well as upward and downward mobility rates are more prominent in Denmark than in Canada. One reason for such differences can be due to the fact that immigrants in Denmark mostly came through the reasons other than working.

Individuals with different unobserved types have different transition probability matrices. Each unobserved type has the tendency to move towards a specific quartile. Stationary distributions of unobserved types show that individuals are

accumulated in different earnings quartiles. This makes earnings distributions segmented. For example, type three Danish immigrants are more accumulated (25.5 percent) in quartile zero, compared to other types (proportions of type one and three are 8.5 and 7.6 percent, respectively). Unlike immigrants in Denmark, none of the types of Canadian immigrants has a very high probability to be in quartile zero.

In Canada, the huge portion of observed persistence in the state of being unemployed (or non-employed) is due to the factors which are not observed. Labour market policies which improve unobserved heterogeneity factors may lead unemployed people into employment. Sources of spurious effects can be different between immigrants and natives and is difficult to be identified. For immigrants, some portion of this effect can be due to the lack of information on behalf of employers (statistical discrimination), language skills, etc.

Canadian immigrants have a higher structural state dependence in the uppermost part of the earnings quartiles compared to natives. This makes immigrants be more affected by economic policy reforms. For example, modifications in the progressive tax system may encourage immigrants to move down in the earning distribution.

To improve overall mobility (reduce inequality) active labour market programs such as on-job training, apprenticeships, education, labour market information, mobility, and credential recognition could enable individual to move from low-wage jobs into higher paying jobs. This is in contrast to passive income maintenance programs like unemployment insurance, which discourage such mobility and encourage people to stay unemployed (Gunderson, 2007). The effectiveness of these policies is not addressed in this thesis, but is of great interest for future research.

# Bibliography


[1] Aaberge, R., A. Bjorklund, M. Jaantti, M. Palme, P. Pedersen, N. Smith, and T. Wennemo (2002), **Income Inequality and Income Mobility in the Scandinavian Countries Compared to The United States**, Review of Income and Wealth, Series 48, No. 4.

[2] Arulampalam, W., A.L. Booth, and M.P. Taylor (2000), **Unemployment Persistence**, Oxford Economic Papers, 52, P 24-50.

[3] Atkinson, A.B., F. Bourguignon, and C. Morrisson (1992), **Empirical Studies of Earnings Mobility**, Philadelphia, Harwood Academic Publisher.

[4] Beach, C.M. and R. Finnie (2001), **Cyclical Changes in Short-Run Earnings Mobility in Canada, 1982 to 1996**, The State of Economics in Canada: Festschnift in Honour of David Slater, P 453-484.

[5] Bingley, P. and N. Westergaard-Nielsen (1997), **Individual Wage Mobility- The Case of Denmark, 1980-1990**, Working Paper, Centre for Labour Market and Social Research, University of Aarhus and Aarhus School of Business.

[6] Blume, K. and M. Verner (2007), **Welfare Dependency among Danish Immigrants**, European Journal of Political Economy, Elsevier, Vol. 23(2), P 453-471.

[7] Bonhomme, S. and J.M. Robin (2007), **Assessing the Equalizing Force of Mobility Using Short Panels: France, 1990-2002**, Working paper, CEMFI, Paris School of Economics, Universite Paris I Pantheon Sorbonne, University College London.

[8] Brodaty, Thibault (2007), **Earning Mobility, State Dependence and Unobserved Heterogeneity: The Case of the United-States in the 90's**, preliminary version, Universite Paris, Pantheon-Sorbonne and CREST-INSEE.

[9] Brodmann, Stefanie (2006), **The Economic Performance of Immigrants: A Longitudinal Analysis of Earnings Mobility in Denmark and Germany**, Research Paper, Pompeu Fabra University, Barcelona, Spain.

[10] Buchinsky, M. and J. Hunt (1999), **Wage Mobility in the United States**, The Review of Economics and Statistics, Vol. 81, No. 3, P 351-368.

[11] Burkhauser, R.V., D. Holtz-Eakin, and S.E. Rhody (1997), **Labour Earnings Mobility and Inequality in the United-States and Germany during the Growth years of the 1980s**, International Economic Review, Vol. 38(4), P 775-794.

[12] Cameron, A.C. and P.K. Trivedi (2005), **Microeconometrics- Methods and Applications**, Cambridge University Press, NY.

[13] Chamberlain, Gary (1984), **Hand Book of Econometrics**, Vol. II., Elsevier Science Publishers BV.

[14] Chay, K.Y., and D.R., Hyslop (2000), **Identification and Estimation of Dynamic Binary Response Panel Data Models: Empirical Evidence using Alternative Approaches**, UC Berkeley, Working Paper.

[15] Cressy, Robert (1996), **Are Business Startups Debt-Rationed?**, The Economic Journal, Vol. 106, No. 438, p 1253-1270.

[16] Deding, M.C. (2002), **Low Wage Mobility in Denmark, Germany and the United States**, Welfare Distribution Working Paper 33, The Danish National Institute of Social Research, Denmark.

[17] Eriksson, T. and N. Westergaard-Nielsen (2007), **Wage and Labor Mobility in Denmark, 1980-2000**, NBER Working Papers 13064, National Bureau of Economic Research Inc.

[18] Evans, D.S. and B. Jovanovic (1989), **An Estimated Model of Entrepreneurial Choice under Liquidity Constraints**, Journal of Political Economy, 97(4), P 808-827.

[19] Fairlie, R.W. and H.A. Krashinsky (2006), **Liquidity Constraints, Household Wealth, and Entrepreneurship Revisited**, Working paper, University of California, Santa Cruz and University of Toronto

[20] Finnie, Ross (1997), **Earnings Dynamics in Canada: The Earnings Mobility of Canadians 1982-1992**, Applied Research Branch Strategic Policy, Human Resources Development Canada, Working Paper, W-97-3E.a.

[21] Frenette, M. and R. Morissette (2003), **Will They Ever Converge? Earnings of Immigrant and Canadian-born Workers over the Last Two Decades**, Analytical Studies Branch, Research Paper Series, Catalogue no. 11F0019MIE2003215

[22] Frenette, Marc (2002), **Do the Falling Earnings of Immigrants Apply to Self-employed Immigrants?**, Labour Economist, Vol. 18, Issue 2, P 207-232.

[23] Greene, W.H. (2000), **Econometric Analysis**, Fourth Edition, Upper Saddle River, NJ: PrenticeHall.

[24] Grodner, Andrzej (2000), **Factors Influencing Earning Mobility in USA and Germany(1985-1987)- A Bivariate Probit Model**, Center for Policy Research, Syracuse University, Working Paper.

[25] Gunderson, Murley (2007), **Minimum Wages: Issues and Options for Ontario, Toronto**, Ontario Ministry of Finance.

[26] Hamilton, Barton H. (2000), **Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment**, Journal of Political Economy, Vol. 108, No. 3.

[27] Hansen, J., M. Lofstrom, and X. Zhang (2006), **State Dependence in Canadian Welfare Participation**, Working Paper IZA DP, NO. 2260.

[28] Heckman, James J. (1981a), **Heterogeneity and State Dependence**, Studies in Labour Markets, Edited by Sherwin Rosen, Chicago, University of Chicago Press, P 91-139.

[29] Heckman, James J. (1981b), **The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process: In Structural Analysis of Discrete Data with Econometric Applications. eds. Manski. C. and D. McFadden**, MIT Press, London, P 179-195.

[30] Heisz, Andrew (2007), **Income Inequality and Redistribution in Canada: 1976 to 2004**, Business and Labor Market Analysis Division, Working Paper 11F0019MIE, No. 298.

[31] Henley, Andrew (2000), **Self-Employment Choice: State Dependence, Initial Conditions and Unobserved Heterogeneity**, Ysgol Rheolaeth a Busnes, School of Management and Business, Research Paper 7.

[32] Hurst, E. and A. Lusardi (2004), **Liquidity Constraints, Household Wealth, and Entrepreneurship**, Journal of Political Economy, 112(2), P 319-347.

[33] Hyslop, Dean R. (1999), **State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labour Force Participation of Married Women**, Econometrica, Vol. 67, No. 6, P 1255-1294.

[34] Kuhn, P. and H. Schuetze (2001), **Self-Employment Dynamics and Self-Employment Trends: A Study of Canadian Men and Women, 1982-1995**, Canadian Journal of Economics, Vol. 34, No. 3.

[35] Liebig, Thomas (2007), **The Labour Market Integration of Immigrants in Denmark OECD Social Employment and Migration**, Working Papers No. 50.

[36] Lillard, L.A. and R.J. Willis (1978),**Dynamic Aspect of Earning Mobility**, Econometrica, Vol. 46, No. 5, P 985-1012.

[37] Mahler, V.A. and D.K. Jesuit (2005), **Fiscal Redistribution in the Developed Countries: new insights from the Luxembourg and Income Study**, Socio-Economic Review, 10. 1093/ser/mwl003.

[38] Manser, M.E. and G. Picot (1999a), **Self-Employment in Canada and the United States**, Statistics Canada, Catalogue NO. 75-001-XPE, P 37-44.

[39] Manser, M.E. and G. Picot (1999b), **The Role of Self-Employment in U.S. and Canadian Job Growth**, Statistics Canada, Monthly Labour Review, P 10-25.

[40] Moffitt, R. and P. Gottschalk (1998), **Trends in the variances of Permanent and Transitory Earnings in the U.S and their Relation to Earning Mobility**, John Hopkins University and Boston College, Revised Working Paper.

[41] Morissette, Ren (1996), **The Growth of Earnings Inequality in Canada, Business and Labor Market Analysis Division**, Working Paper 75F0002M.

[42] Mroz, Thomas A. (1999), **Discrete Factor Approximations in Simultaneous Equation Models: Estimating the Impact of a Dummy Endogenous Variable on a Continuous Outcome**, Journal of Econometrics, Vol. 92, P 233-274.

[43] Murphy, K.M. and R.H. Topel (1985), **Estimation and inference in two-step econometric models**, Journal of Business and Economic Statistics, 3(4), P 370379.

[44] Nadja, K. and D. Leung (2005), **Recent Developments in Self-Employment in Canada**, Bank of Canada, Working Paper.

[45] Ostrousky, Yuri (2008), **Earnings Inequality and Earnings Instability of Immigrants in Canada**, Business and Labor Market Analysis Division, Working Paper 11F0019MIE, No. 309.

[46] Pedersen, P.J. and N. Smith (2002), **Unemployment Traps: Do Financial Disincentives Matter?**, European Sociological Review, Vol. 18, NO. 3, P 271-288.

[47] Picot, Garnett (1998), **What is Happening to Earning Inequality and Youth Wages in the 1990s?**, Business and Labor Market Analysis Division, Working Paper 11F0019MPE, No. 116.

[48] Prowse, V. (2005), **State Dependence in a Multi-State Model of Employment Dynamics**, IZA Discussion-Paper, 1623.

[49] Schaafsma, J. and A. Sweetman (2001), **Immigrant earnings: Age at immigration matters**, Canadian Journal of Economics, Vol. 34, No.4, P 10661099.

[50] Schuetze, Herbert J. (2000), **Taxes, Economic Conditions and Recent Trends in Male Self-Employment: A Canada-U.S. Comparison**, Labour Economics, Vol. 7, P 507-544.

[51] Schwanen, Daniel (2001), **Trade Liberalization and Inequality in Canada in the 1990s**, The Review of Economic Performance and Social Progress, Working Paper, P 161-182.

[52] Shorrocks, Anthony (1978), **Income Inequality and Income Mobility**, Journal of Economic Theory, 19, P 37693.

[53] Simpson, W. and R. Sproule (1998), **Econometric Analysis of Canadian Self-Employment, using SLID**, Catalogue NO. 98-16, 75F0002M.

[54] Stewart, Mark (2007), **The Interrelated Dynamics of Unemployment and Low-Wage Employment**, Journal of Applied Econometrics, Vol. 22, P 511531.

[55] Theodos, B. and R. Bednarzik (2006), **Earnings Mobility and Low-wage Workers in the United Satates**, Monthly Labor Review, Vol. 129, No. 7, P 34-47.

[56] Wooldridge, Jeffrey M. (2005), **Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models With Unobserved Heterogeneity**, Journal of Applied Econometrics, Vol. 20, No.1, P 39-54.

[57] **World Development Indicators (WDI)** (2008), Washington, DC. World Bank.