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ESSAYS ON EMPLOYMENT INSURANCE, INCOME MOBILITY,
AND FAMILY INCOME DISTRIBUTION

By

Wen-Hao Chen

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ABSTRACT

ESSAYS ON EMPLOYMENT INSURANCE, INCOME MOBILITY, AND FAMILY INCOME DISTRIBUTION

By

Wen-Hao Chen

The Canadian labour market has experienced several changes in the past two decades. Government played a declining role in the labour market during the 1990s in order to cope with huge deficits from the late 1980s and initiated a fundamental restructuring of the unemployment insurance system in the mid-1990s. However, equality and opportunity become important policy issues as family structure changed, and there was a rapid increase in the number of immigrants. The first chapter of this dissertation studies the impact of the new employment insurance repayment provision. The second chapter examines levels of income mobility, while the third chapter discusses changes in the structure of family income distribution.

A stricter repayment policy was introduced in the *Employment Insurance (EI) Act* enacted in 1996. The first chapter examines the impact of this new provision on the probabilities of filing an EI claim for eligible, laid-off workers. Due to a lack of experimental data, this study adopts regression and propensity score matching methods to evaluate policy effects. The results suggest that the new repayment policy has reduced the probabilities of filing a claim among workers whose annual income is equal to or greater than \$48,750. The estimated decline in the claim rate ranges from 6 to 12 percentage points, depending on the datasets and the methods of estimation.

The second chapter uses a recently available Canadian panel survey—the Survey of Labour and Income Dynamics (SLID)—together with the Panel Survey of Income

Dynamics (PSID) from the U.S. to examine the levels of income mobility for the entire population and particular subgroups. The results reveal that there is significant income mobility in both Canada and the U.S. and that poverty or high income is a temporary experience for most people. Mobility also varies across subgroups. Less-educated people and minority groups tend to experience persistent poverty. Immigrants to Canada experienced slightly longer periods of poverty, but they were less likely to fall back into poverty once their income increased. In terms of cross-national comparisons, it was found that Canada's redistributive system significantly increases income stability. In addition, there is evidence that low-income (or high-income) spell beginnings or endings in the U.S. are mostly associated with events concurrent with changes in labour earnings, while demographic events play a relatively important role in spell beginnings or endings in Canada.

The distribution of family income in Canada became more unequal between 1980 and 1997. The third chapter employs a conditional re-weighting procedure developed by DiNardo, Fortin, and Lemieux (1996) to assess the effects of changing family structure and changing characteristics of immigrants on family income distribution. The results show that the increasing trend toward single-adult families had a substantial impact on increasing family income inequality, explaining one-fifth of the increase in the Gini coefficient and one-third of the growth in the low-income rate between 1980 and 1997. Changing characteristics of immigrants also affected income distribution, particularly in the lower half of the distribution. It explained about one-third of the increase in the 50-10 and 90-10 ratios, and it was responsible for \$462 of the decline in median income between 1980 and 1997.

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FOR MY PARENT
Andrew Chen, and in the loving memory
of Judy Cheng

And for Yu-Mei Hsu
The best part of my life

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TABLE OF CONTENTS

LIST OF TABLES	ix
LIST OF FIGURES	xi
INTRODUCTION	1
 CHAPTER 1	
THE IMPACT OF THE EMPLOYMENT INSURANCE REPAYMENT POLICY: NON-EXPERIMENTAL APPROACHES	
1.1 Introduction	6
1.2 Employment Insurance and High-Income Claimants	8
1.3 Identifying Causal Effects in Non-experimental Studies	11
1.3.1 Regression Adjusted Estimators	12
1.3.2 Matching Estimators and Propensity Score Matching	13
1.4 Data Sources	17
1.5 Results	21
1.6 Economic Impacts of Repayment Policy	26
1.7 Conclusion	29
 CHAPTER 2	
HOUSEHOLD INCOME MOBILITY IN CANADA AND THE UNITED STATES	
2.1 Introduction	41
2.2 Literature Review	44
2.3 Data Sources and Cross-sectional Statistics	47
2.4 Income Mobility	50
2.4.1 Persistence of Low Income and High Income	50
2.4.2 Government Transfers and Income Mobility	53
2.4.3 Short-term versus Long-term Mobility	56
2.4.4 Cross-National Comparison	58
2.5 Empirical Hazards of Low-Income and High-Income Transitions	59
2.6 The Correlates of Income Spell Endings and Beginnings	62
2.7 Econometric Model of Income Dynamics	65
2.8 Conclusions	68

CHAPTER 3

EVOLUTION IN THE STRUCTURE OF FAMILY INCOME IN CANADA, 1980-1997: THE EFFECTS OF CHANGING FAMILY STRUCTURE AND CHANGING CHARACTERISTICS OF IMMIGRANTS

3.1 Introduction	94
3.2 Literature Review	96
3.3 Data and Historical Trends	99
3.4 Methodology	104
3.4.1 Estimation of Conditionally Re-weighting Functions	108
3.5 Results	112
3.5.1 Reverse-order Decomposition	116
3.5.2 Decomposition Breakdown by Two Periods: 1980-1989 and 1989-1997	117
3.6 Conclusions	119
CONCLUSION	137
APPENDICES	142
A. Additional Tables for Chapter 1	142
B. Sample Construction for CIE and SLID data	144
C. Stata Output for Propensity Score Matching	147
D. Technical Note for Reverse-order Decomposition	156
BIBLIOGRAPHY	158

LIST OF TABLES

1.1 Summary of Selected EI Studies	31
1.2 Summary (mean) Statistics, Survey of Changes in Employment (CIE)	33
1.3 Distribution of the Treatment and Control Samples	34
1.4 Estimated Distribution of Propensity Score for CIE and SLID	35
1.5 Estimates of Treatment (Policy) Effects	36
1.6 Economic Impacts of Repayment Policy	37
2.1 Summary Statistics for the Household Equivalent Income	73
2.2 Incidence of Low and High Income, by Characteristics	74
2.3.1 Distribution of Income among Longitudinal Sample	76
2.3.2 Income Mobility by Characteristics	77
2.4 Probabilities of Moving Out of the Low- and High-Income Group	78
2.5 Five-Year Earnings Mobility for Wage/Salary Workers, Cross-National Comparison	79
2.6 Kaplan-Meier Estimates of Exiting Low Income	80
2.7 Kaplan-Meier Estimates of Exiting High Income	82
2.8 Low Income Spell Ending Types, by Person's Household Type in the Last Year of Low Income Spell	84
2.9 Low Income Spell Beginning Types, by Person's Household Type in the First Year of Low Income Spell	85
2.10 High Income Spell Ending Types, by Person's Household Type in the Last Year of High Income Spell	86
2.11 High Income Spell Beginning Types, by Person's Household Type in the First Year of High Income Spell	87
2.12 Coefficients of Hazard Model, Canada	88
2.13 Coefficients of Hazard Model, USA	89
3.1 Weight Used in Density Decomposition	123
3.2 Primary-order Decomposition of Changes in the Distribution of Family Equivalent Income, 1980-1997 (1997 as Reference Year)	124
3.3 Primary-order Decomposition of Changes in the Distribution of Family Equivalent Income, 1980-1997 (1980 as Reference Year)	125

3.4 Reverse-order Decomposition of Changes in the Distribution of Family	
Equivalent Income, 1980-1997	124
3.5 Primary-order Decomposition of Changes in the Distribution of Family	
Equivalent Income, 1980-1989	127
3.6 Primary-order Decomposition of Changes in the Distribution of Family	
Equivalent Income, 1989-1997	128
A.1 Major Changes of Legislation from UI to EI	142
A.2 EI Payment: Repayment of Benefits at Income Tax Time	143
A.3 Data Collection Period for CIE data	143

LIST OF FIGURES

1.1 Net Income Schedule before and after the UI/EI Repayment Policy	38
1.2 Histogram of Estimated Propensity Scores, CIE	39
1.3 Histogram of Estimated Propensity Scores, SLID	40
2.1 Incidence of Low Income	90
2.2 Persistence of Low Income by Demographic Groups	91
2.3 Probability of Moving out of Low Income by Length of Income Tracked and Characteristics (pre-transfer income)	92
2.4 Classification of Income and Demographic Events Associated with a Spell Transition between Year t-1 and t	93
3.1 Trends of Inequality and Low Income	129
3.2 Indexed Equivalent Income by Percentile, 1980-1997	129
3.3a Kernel Density for Equivalent Income, 1980 and 1997.....	130
3.3b Kernel Density for Equivalent Income, 1980 and 1989	130
3.3c Kernel Density for Equivalent Income, 1989 and 1997	131
3.4 Inequality Measures for Male Earnings (age 15-64)	131
3.5 Proportion of Working Wives by Husband's Quartile Earnings Distribution, Couple Families	132
3.6 Family Composition	132
3.7 Median Equivalent Market Income (age 15-64)	133
3.8 Full-time Employment Rate (age 15-64)	133
3.9 Proportion of Immigrants whose mother tongue is English or French	134
3.10 1997 Equivalent Income with 1980 Immigrants' Full-time Employment	134
3.11 1997 Equivalent Income with 1980 Immigrants' Full-time Employment Mother Tongue and Duration of Residency Characteristics	135
3.12 1997 Equivalent Income with 1980 Immigration Factors and Family Structure	135
3.13 1997 Equivalent Income with 1980 Immigration Factors, Family Structure, and Other Attributes	136
3.14 Residual	136

INTRODUCTION

During the past few decades, Canadians have experienced substantial social and economic changes. These changes and concerns about government deficits prompted an unprecedented scrutiny of Canada's social programs during the 1980s and 1990s.

Unemployment Insurance—one of the largest Canadian income support programs—has been cut back significantly since the 1980s. A reform of the unemployment insurance program—the *Employment Insurance Act, 1996* (EI Act)—resulted in a fundamental restructuring of the system. The EI Act changed EI from a passive benefits program to a more active labour market program.

Many people became concerned about income inequality and the growing poverty rates in Canada in the 1980s and 1990s. They thought that a situation in which the most fortunate thrive and the poor are left behind could have a detrimental effect on Canadian society. As a result, the extent of income mobility has become a central part of poverty prevention policy discussions.

Canadian demographics also changed during the past few decades. The number of typical “couple-children” families has declined, and there has been an increase in single-parent families. Life for single-parent families tends to be difficult, and single-parent families with women as the head of the household often live in poverty.

The structure of Canada's population also changed substantially during the past few decades. With a declining fertility rate and increasing life expectancy, Canada's population growth now relies largely on immigration. However, patterns of immigration have changed. At one time, most immigrants to Canada had British and French ancestry.

Immigrants today are mostly visible minority groups, especially people with Asian ancestry, whose mother tongue is neither English nor French.

The changes in Canada's economic and social characteristics have affected the Canadian labour market. Therefore, the main objective of this dissertation is to provide empirical research—with particularly attention paid to employment insurance, income mobility, and family income distribution—that documents the patterns, possible causes, and consequences of these changes. This information is used to discuss policy implications.

The first chapter examines the impact of the EI Act. Similar to other evaluation literature, this study was motivated by a quasi-experiment due to the changes in policy parameters. Briefly, a claimant under the old UI system was required to repay 30 percent of the benefits if his or her annual income reached 1.5 times the maximum insurance earnings. With the new EI system, a claimant is required to repay between 30 and 100 percent of the benefits if his or her annual income reaches 1.25 times the maximum insurance earnings. This stricter repayment policy is designed, for equity purposes, to reduce the benefits paid to repeat EI claimants who earn a relatively high income.

In 2000, Human Resource Development Canada (HRDC) investigated the effectiveness of various parts of the new EI legislation using a series of evaluations. However, HRDC did not examine the effect of the stricter repayment policy. Therefore, the main purpose of this study is to fill a gap in the EI evaluation literature by providing an analysis of the impact of the new repayment policy. Specifically, this chapter attempts to answer the following question: “To what extent does the change in the new repayment provision affect an eligible, laid-off worker's decision to file a EI claim?” Estimates of

policy effects are based on two approaches: (1) regression methods and (2) propensity score matching methods.

The second chapter examines the levels of income mobility and their patterns across subgroups. The extent of income mobility has been considered an essential ingredient to be placed with information about the income distribution at a particular point in time. Inequality based on a snapshot of income distribution in a single year is likely to be misleading if people are able to move easily through different levels of income. A high level of inequality is not considered a problem when there is substantial income mobility. As a result, understanding the level of income mobility becomes relevant for policy formation, particularly for creating anti-poverty policies.

This study used data from a newly released Canadian longitudinal survey—the Survey of Labour and Income Dynamics (SLID, 1993–1998). Prior to the SLID, mobility analysis in Canada was very limited because it relied solely on tax-based files that are usually not available to researchers. It was also limited because many important policy variables (e.g., education and minority) were not included in the tax data. This study used the new survey data to analyze the general pattern of income mobility in Canada. The results of this analysis are compared to the tax data. This chapter also provides information about income mobility among groups of interest to policy makers (e.g., less-educated people and immigrants). The information in this chapter complements the existing Canadian literature and addresses questions that cannot be answered from the tax data alone.

Using transition matrices from both pre-transfer and post-transfer income measures and a decomposition analysis that classifies a transition into a mutually

exclusive concurrent event, the second chapter of this dissertation attempts to answer three specific questions: (1) What is the extent of mobility and poverty (and high-income) persistence, and how do these patterns vary across subgroups? (2) To what extent does a nation's redistributive policies affect changes in market-driven income mobility? (3) To what extent does the occurrence of household events (e.g., marriage) as well as changes in other income sources affect entries into and exits from low income and high income?

The final chapter in this dissertation discusses changes in the structure of family income distribution and the factors that contributed to these changes in income distribution. Previous studies have shown that income inequality in Canada has grown rapidly since the mid-1970s. At the same time, various aspects of Canadian society—such as family structure, the labour market, and population—underwent substantial changes. It was assumed that some of these changes had more effect on inequality or poverty rates than other changes. Therefore, understanding the relationship between income distribution in Canada and factors, such as family structure and population, becomes relevant for developing social policies, which is the main purpose of this research.

This chapter assesses the impact of demographic shifts on family income in Canada. Of particular interest are the effects of changing family structure and the characteristics of immigrants. Both of these factors have undergone substantial changes in the past few decades, and economic outcomes vary greatly by family structure and by cohorts of immigrants. The typical Canadian family is harder to find today than it was a few decades ago. Similarly, immigrants have shifted from British and French ancestry to visible minority groups, especially people with Asian ancestry. Therefore, to investigate

the impact of these changes on income distribution, this chapter attempted to answer the following question: “What would the distribution of family income look like if family structure and immigrants characteristics had not changed in the past 20 years?” The counterfactual distributions are constructed through a relatively new re-weighting technique developed by DiNardo, Fortin, and Lemieux (1996).

Chapter 1

The Impact of the Employment Insurance Repayment Policy: Non-experimental Approaches

1.1 Introduction

The research discussed in this chapter examines the impact of the Employment Insurance (EI) system's strengthened repayment policy (also known as clawback) on eligible, laid-off, Canadian workers' decisions to file a claim. The new *Employment Insurance Act* in 1996 introduced a fundamental restructuring of unemployment insurance in Canada and influenced the behaviour of many people in and out of the labour market. A list of legislative changes is presented in Table A1 in Appendix A. Some changes, such as a reduction in benefit level and entitlement, directly apply to all claimants. Some changes affect individuals who are casual workers (e.g., increasing entrance requirements for new entrants and re-entrants). Some changes target repeat users (e.g., the intensity rule), and some changes penalize high-income claimants (e.g., the repayment policy). Furthermore, the new system introduces more active labour market programs to help unemployed people reenter the workforce. For instance, programs such as work sharing offer monetary assistance to employers to avoid layoffs during temporary work slowdowns, and wage subsidies provide incentives for employers to hire workers who lack experience.

Various aspects of the new EI legislation have been intensively evaluated, with most of these studies being conducted for Human Resource Development Canada (HRDC). Table 1.1 contains a summary of selected studies that have evaluated the changes made to EI. For example, Phipps and MacPhail (2000) and Kapsalis (2000)

examined the impact of stricter entrance requirements on new entrants and re-entrants. Green and Riddell (2000) assessed the effect of the switch from a weeks-based to an hours-based system on the length of employment. Kuhn (2000) employed a cost-benefit analysis to investigate the financial outcomes for part-time workers (those working less than 15 hours per week) who were previously excluded from UI benefits but now are covered under the new EI system. Fortin and Audenrode (2000) analyzed the impact of the intensity rule (experience rating on repeated claimants) on unemployed workers' job-searching behaviours.

However, there are no studies that examine the effect of repayment on unemployed workers' job-searching behaviours. Under UI, a claimant was required to repay 30 percent of the benefits if his or her annual income reached 1.5 times the maximum insurance earnings. Under EI, a claimant is required to repay between 30 and 100 percent of the benefits if his or her annual income reaches 1.25 times the maximum insurance earnings (see Appendix A for a detailed schedule). These changes reduce the net income schedule for EI claimants and could affect their decision to file a claim. Therefore, this study contributes to the existing evaluation literature by examining the impact of the strengthened repayment provision.

When evaluating a program, it is difficult to identify the relationship between outcomes and policy parameters. Is it possible to be sure that the changes in an individual's behaviour are the result of a policy and not something else? Experimental evaluation, known as random assignment, is generally viewed as the most reliable method for evaluating a program's effect on behaviour. However, the high operating costs and problems (e.g., ethical issues or losing participants before they enter the

program) associated with experimental studies also concern researchers and policy makers.

Due to the high cost and problems associated with experimental studies, the study discussed in this chapter employed various non-experimental methods, particularly propensity score matching, to evaluate the impact of the Employment Insurance (EI) system's strengthened repayment policy on eligible, laid-off, Canadian workers' decisions to file a claim. The various non-experimental methods are also compared to see whether results are robust under different approaches.

Using data from two different surveys, Survey of Changes in Employment (CIE) 1995–1999 and Survey of Labour and Income Dynamics (SLID) 1994–1998, the results of this study show that the new repayment policy has reduced the probabilities of filing a claim among high-income individuals by about 4.2 to 6.2 percentage points for the CIE sample, and about 9.7 to 12.7 percentage points for the SLID sample. Based on the estimate of a 6.2 percentage-point decline in claim rate, this study suggests that the new rules could have reduced the average monthly number of regular beneficiaries in post-policy period by about 31,482, and reduced total annual regular benefits by about \$629 million.¹

1.2 Employment Insurance and High-Income Claimants

Under the Canadian UI system, a claimant has to pay back some of the benefits if his or her annual income is beyond a certain limit. This repayment policy was first introduced in 1979. Claimants with an annual net income (including benefits) in excess of 1.5 times the annual maximum insurable earnings were required to repay 30 percent of

the benefits. Nevertheless, the threshold was fairly high, and only claimants with very high incomes were affected. For instance, the threshold was \$63,570 in 1995 (one year before EI reform), while the average full time, full-year worker earned about \$41,000. As a result, most high-income people were not penalized for collecting UI benefits.

The repayment policy was revised in July 1996. It places more restrictions on high-income recipients. Figure 1.1 illustrates the net income schedule before (solid line) and after (dash lines) the changes for eligible claimants. Annual income limits dropped 23 percent (from \$63,570 to \$48,750) for occasional claimants—those who had received less than 20 weeks of benefits in the previous 5 years—and 39 percent (from \$63,570 to \$39,000) for frequent claimants—those who had received more than 20 weeks of benefits in the past 5 years. It is likely that the decline in annual income limits affects more people under the revised repayment policy, including high-income claimants and relatively high-income claimants. In addition, the repayment rates also increased, ranging from 30 percent (schedule B) to as much as 100 percent (schedule D), depending on worker's claim history.

What is the expected impact of the change? Intuitively, EI is less attractive to high-income individuals because the replacement rate is too low or because collecting EI benefits is a “stigma.” According to the *1998 Employment Insurance Monitoring and Assessment Report* by the Canadian Employment Insurance Commission (1998), the number of people having to repay benefits increased from 19,000 (0.7% of people receiving UI benefits) in 1995 to 82,000 (3% of people receiving EI benefits) in 1996. Benefit repayments also rose substantially, from about \$20 million in 1995 to about \$70

¹Currency in this chapter is in Canadian dollars.

million in 1996. Why would high-income people collect UI or EI? How do the reforms affect people's decisions to apply for benefits?

Normally, high-income individuals might apply for UI or EI when unexpected job loss occurs and when there are few available jobs. A stricter repayment policy reduces benefits for those claimants, but it does not necessarily stop them from filing a claim. A person who would likely be affected by the new repayment scheme is someone with a full-time, part-year job who still earns an above-average income (e.g., seasonal jobs). Due to a non-experience rated UI tax system in Canada, UI made working in seasonal industries more attractive because it effectively subsidized wages. Seasonal firms or industries received more subsidies through the UI system, which helped them reduce costs (in terms of wages, layoffs, and re-hiring) and therefore create more demand for workers. Workers and employers in such firms or industries often had an "implicit contract" that took advantage of UI's subsidies (see Feldstein, 1976). When the new repayment policy was implemented, real income for seasonal workers declined, and the incentive to stay in unstable industries decreased. This forced seasonal firms to increase wages to keep quality workers, but it reduced demand for new workers due to the decline in "wage subsidy."

In addition, the old UI program encouraged people to stay in relatively high unemployment areas, which helped to stabilize local economies. A stricter repayment policy might force people to migrate from high unemployment regions to low unemployment regions. Similarly, the occupational choices may have changed because people find manual work such as fishing or construction less attractive under the new EI

program. It is possible that the new EI program will result in more demand for higher education, training, or career changing services.

From a policy perspective, the change also creates questions about equity and efficiency. Equity is about helping the least fortunate in society. Nakamura (1996) and Nakamura and Diewert (2000) argue that the old system was not a fair insurance because it allowed high-earning people to repeatedly collect benefits, and these workers did not even pay the EI tax on earnings exceeding the maximum insurance earnings. The experience-rated repayment provision introduced under EI promotes equity since the real benefits are reduced significantly for all high-income EI repeaters. However, as mentioned above, the new repayment policy also distorts an individual's supply and a firm's demand decision, which reduces efficiency. These issues need to be discussed thoroughly when evaluating the true impact of the new repayment policy.

1.3 Identifying Policy Effects

Analysis in this study was conducted using a one-group design, before and after analysis. *One group* refers to unemployed individuals who are eligible for EI benefits and whose potential net income is at least \$48,750 Canadian dollars, the targets of the repayment policy.² People are assigned to the treatment group if they lost jobs in the post-policy period and to the control group if they lost jobs in the pre-policy period. Without randomized data, a simple practice of difference-in-mean comparison between a treatment group and a control group might be misleading because these two groups are

²The sample does not include individuals whose potential income is less than \$39,000 because they are unaffected by the new repayment policy. Individuals whose potential income is between \$39,000 and \$48,750 are also excluded because whether they are affected by the new policy depends on their claim history, which is not available in either dataset.

not selected at random. Two methods were used to evaluate the effects of the new EI policy: (1) regression methods and (2) propensity score matching methods.

1.3.1 Regression Adjusted Estimators

Consider that, for each unemployed worker, there are two potential outcomes, Y_{1i} , denoting individual i 's decision whether to file an EI claim if he or she is exposed to the policy change, and Y_{0i} , denoting individual i 's decision if he or she is not exposed to the policy change. The effect of the policy change on an individual worker is $Y_{1i} - Y_{0i}$, but this is never observed directly since only one potential outcome is ever observed for each individual at any time. The standard way to isolate the effect of policy on outcomes involves controlling for observable differences between treatment and control groups using regression methods. As described in Angrist and Krueger (1999), we can write the two potential outcomes as:

$$Y_{0i} = X_i' \beta + u_i, \quad Y_{1i} = Y_{0i} + \delta \quad (1)$$

where Y_{0i} has been decomposed into a linear function of observed covariates, $X_i' \beta$, and a residual u_i . Using T_i to indicate whether an individual is exposed to the policy change, this leads to the regression equation,

$$Y_i = X_i' \beta + T_i \delta + u_i \quad (2)$$

where Y_i is the observed outcome. An individual is assigned to the treatment group ($T=1$) if he or she is exposed to the policy change, and to the control group ($T=0$) if not exposed to the policy change. The coefficient for the policy indicator, δ , is interpreted as the treatment effect.

The identification assumption for this method is $Y_{1i}, Y_{0i} \perp T_i \mid X_i$, which implies that being assigned to the treatment group is random conditional on X_i . That is, all relevant differences between treatment and control groups are assumed to be captured by their observables, X_i .

1.3.2 Matching Estimators and Propensity Score Matching

More recently, the method of matching has received significant interest as a tool for evaluation. The basic idea is to pair each treated unit with a control unit that shares similar characteristics and interpret the difference in their outcomes as the effect of the program. This can be done when conditioning variables are discrete and the data have many observations so that each cell contains both treated and control units. However, this becomes less practical when the numbers of variables increase or when continuous variables are involved. To reduce the dimensionality problem, Rosebaum and Rubin (1983) suggest a propensity score approach, which is simply the conditional probability of treatment, given the characteristics X_i :

$$p(X_i) = \text{pr}(T_i = 1 \mid X_i). \quad (3)$$

Rosebaum and Rubin also show that if the exposure to treatment is random within cells defined by X_i it is also random within cells defined by the one-dimensional propensity score:

$$\{Y_{1i}, Y_{0i} \perp T_i\} \mid X_i \Rightarrow \{Y_{1i}, Y_{0i} \perp T_i\} \mid p(X_i) \quad (4)$$

The average treatment effect on the treated (ATT) can then be estimated as follows:

$$\tau = E\{E[Y_{1i} \mid T_i = 1, p(X_i)] - E[Y_{0i} \mid T_i = 0, p(X_i)] \mid T_i = 1\} \quad (5)$$

where the outer expectation is over the distribution of $p(X_i)$ in the treated units.

Like regression estimators, the method of matching also assumes that selection can be explained purely in terms of observable characteristics, $Y_{1i}, Y_{0i} \perp T_i | X_i$. However, the matching estimators are different from regression estimators in some ways. Smith (2000) points out that matching avoids the functional form restrictions implicit in running a linear regression with continuous covariates. Incorrect function form assumptions may seriously affect estimate outcomes. Nevertheless, this difference fades when a sufficient number of higher-order and interaction terms are included in the regression. Angrist and Krueger (1999) argue that the essential difference between regression and matching is the weighting scheme used to pool estimates at different values of the covariates: “The matching estimator combines covariate-value-specific estimates to produce an estimate of the effect of treatment on the treated; regression produces a variance-weighted average of these effects” (p. 1317). Using a simple example where there is a single binary covariate, x , and the probability of treatment is positive at both values of x , Angrist and Krueger show that the weights underlying matching estimators are proportional to the probability of treatment at each value of the covariates, while the weights underlying regression estimators are proportional to the variance of treatment at each value of the covariates. Thus, whether regression results will differ from matching results depends on how much treatment effects vary with X . If, for example, the treatment group is much more likely to include non-seasonal workers ($x = 0$), the regression estimators will put more weight on the treatment effect for seasonal workers ($x = 1$) because the variance of treatment is larger for that group.

Matching methods have two other advantages over regression. First, the use of a propensity score ensures that $0 < P(X) < 1$ and rules out any values of X such that $P(X) = 0$ or 1 because we cannot estimate treatment effect by including people who were treated with certainty, conditional on X . Second, a common support restriction can be easily implemented in matching methods. That is, the samples are limited to the observations whose propensity score belongs to the intersection of the supports of the propensity score of treated and controls. Imposing the common support condition in the estimation of the propensity score may improve the quality of the matches used to estimate the ATT.³

Of course, there are drawbacks to the matching methods. In addition to the identification assumption described above, Heckman, Ichimura, Smith, and Todd (1998) show that the estimates produced by matching can be very sensitive to the choice of variables used to construct the propensity score, and there is no existing guide to help researchers choose variables. In addition, Smith (2000) points out that the choice of matching method can make a difference in small samples. Certain methods have properties that make them a better choice in particular contexts.

In this study, three common matching methods—nearest-neighbor matching, radius matching, and kernel matching—are used to estimate the treatment effect on the treated.⁴

In nearest-neighbor matching, treated unit i is matched to the single control unit j with the closest propensity score such that

³It should be noted that although the quality of the matches may be improved by imposing the common support restriction. However, it is possible to lost high quality matches at the boundaries of the common support. Besides, the sample may be considerably reduced, so imposing the common support restriction is not necessarily better (Becker and Ichino 2002).

⁴Propensity scores and matching estimators are estimated through a user-written Stata program designed by Becker and Ichino (2002).

$$|p_i - p_j| = \min_{k \in (T=0)} \{|p_i - p_k|\}. \quad (6)$$

This method is done with “replacement” because a control unit can be a best match for more than one treated unit. Once each treated unit is matched, ATT can be obtained by averaging the difference in means of the outcome between the treatment and control groups. In nearest-neighbor matching, some of these matches are fairly poor because the nearest neighbour may be very far from some treated units, which reduces the quality of the match. This problem can be overcome by using radius matching. In radius matching, the treated unit is matched to all the control units with estimated propensity scores falling within a self-defined radius r from p_i :

$$r > |p_i - p_j| = \min_{k \in (T=0)} \{|p_i - p_k|\}. \quad (7)$$

Let Y_i^T and Y_j^C be the observed outcomes of the treated and control units, N^T be the number of treated individuals, and N_i^C be the number of control units matched with treated unit i . The ATT for radius matching can be expressed as

$$\tau = \frac{1}{N^T} \sum_{i \in T} \left[Y_i^T - \sum_{j \in C(i)} w_{ij} Y_j^C \right], \text{ where } w_{ij} = \frac{1}{N_i^C}. \quad (8)$$

Obviously, the quality of the matches would improve as the size of the radius becomes smaller. However, it should be noted that when the radius is very small some treated units are not matched because the neighbor does not contain comparable controls. If too many treatments are not matched, the results no longer represent the treated population.

Both nearest-neighbor and radius matching use only a subset of the control group. Efficiency may be compromised if some of the available information is not used. An alternative method is kernel matching, described in Heckmen, Ichimura, and Todd

(1997a, 1997b, 1998). It constructs a match for each treated unit using a kernel-weighted average over all individuals in the control group. The weights depend on the distance between each control and treated unit. Control units that are very far away get a very low weight rather than a zero weight. The ATT with kernel matching is

$$\tau = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{j \in C} Y_j^C k\left(\frac{p_i - p_j}{h_n}\right)}{\sum_{j \in C} k\left(\frac{p_i - p_j}{h_n}\right)} \right\} \quad (9)$$

where the second term in the bracket is a consistent estimator of the counterfactual outcome Y_{0i} .

1.4 Data sources

This study used data from two different sources: (1) the Survey of Changes in Employment (CIE) cohorts 2 to 10, 13, and 17 (1995–1999), and (2) the Survey of Labour and Income Dynamics (SLID) 1993–1998. The CIE is a quarterly survey funded by Human Resources Development Canada (HRDC) used to evaluate and monitor government policy. It samples individuals who experienced “job separations” and were issued a Record of Employment (ROE) within a specified 3-month period, regardless of the reason for job separation (see Appendix A).⁵ Survey respondents are asked about their employment history in the 18 months prior to the interview. The survey also collects information about respondents’ dates in and out of employment, reasons for interruptions,

job characteristics, search activities, recall expectations, UI or EI benefits, demographics, household expenditures, and some income information. The advantage of CIE is that it targets the right population for this study, while the disadvantage of CIE is that it contains very limited information about personal incomes.

To compensate for the weakness of CIE data, a nationally representative dataset (SLID) was also used in this study. Briefly, SLID is a panel survey that began in 1993 for multi-dimensional purposes. The main advantage of this survey is its broad coverage of labour market information, including almost every variable in the CIE, plus a large amount of detailed income information. However, SLID is not designed for monitoring the unemployed population. As a result, the identification of unemployed people and their EI eligibility in SLID is not straightforward.

The main challenge of this type of research is to construct samples that only include people who experienced job interruptions and are also eligible for UI or EI benefits. In Canada, the basic requirements for applying UI or EI benefits are based on two criteria: (1) work history and (2) region of residency. To be eligible, an individual must work at least 12 to 20 weeks under UI (or 420–700 hours under EI), depending on the regional unemployment rate at the time of being unemployed. Unfortunately, there is no existing variable in either dataset that can directly identify such a sample. Certain assumptions are, therefore, required. The procedure used to identify the UI/EI eligible sample is described as follows:

⁵The first 10 cohorts were sampled during the period from July 1995 to December 1997. Due to administrative reasons, only two samples were collected between January 1998 and June 2000: cohort 13 (July–September 1998) and cohort 17 (July–September 1999). Beginning in July 2000, the CIE restarted its regular quarterly collection (cohort 21) with redesigned weighting methodology. The CIE is still active, and the most recent available data is cohort 25. For consistency reasons, cohorts 21 and onward that used a redesigned weighting scheme were not used in this study. Cohort 1 was also excluded because it was merely a test, and its target population was different from other cohorts.

1. Select people who experienced job interruptions.
2. Restrict to individuals who ended a job because of layoffs, business slowdowns, or end of contracts.
3. Exclude people who are 65 years of age and over.
4. Exclude people who had been self-employed.
5. Restrict to those who had full-time jobs (30 or more hours worked per week).
6. Exclude people who did not work enough weeks/hours to meet the UI/EI entrance requirement.

Condition 2 excludes individuals whose job separations were associated with quitting, injury, illness, parental leave, other family responsibilities, returning to school, retirement, or dismissal by the employer. These people usually have quite a different pattern of UI or EI behaviour. In many cases, they are not even eligible for benefits.

Conditions 3 and 4 delete people who are not covered by the UI or EI system. Condition 5 removes all part-time workers because their labour market behaviours are quite different, and usually, they do not have enough worked weeks/hours to qualify for benefits. Individuals satisfying conditions 1 through 5 are not necessarily eligible for benefits. In Canada, workers have to work at least 12 to 20 weeks (or 420–700 hours under the new policy), depending on the local unemployment rates, in order to qualify for benefits. As a result, condition 6 further excludes people who did not have enough weeks/hours to qualify for UI/EI benefits.⁶ Because the repayment policy only affects

⁶Identifying this condition is a bit tedious. See Appendix B for details.

high-income individuals, the samples are limited to those who had a potential annual personal income equal to or greater than \$48,750.⁷

The outcome variable used in this study is UI/EI participation (or take-up).⁸ It is a binary variable that equals 1 if unemployed people received benefits and 0 if they did not receive benefits. Eligible people who were re-employed within 2 weeks (waiting period) after the job separation are also included. The resulting samples consist of 2,985 individuals from the CIE data and 1,118 individuals from the SLID data.^{9,10} Distribution of treatment and control groups from both surveys is shown in Table 1.3. Basically, in the CIE sample, the treated and control units are not systematically different from each other in most characteristics (except for the quarter of the year they were unemployed), while the differences are more apparent in the SLID sample. For instance, compared to the control units, the treated units in SLID consist of more blue-collar workers, more childless couples, and fewer immigrants.

⁷Since most people do not know their actual annual income at the time of job separation, an individual's income from the previous year is used as a proxy for potential annual income. Unfortunately, income from the previous year is not available in the CIE data; therefore, two methods are used to calculate an individual's potential annual income. See Appendix B for details.

⁸See Appendix B for details.

⁹For the CIE data, the original sample from cohort 2–10, 13, and 17 consists of 47,964 observations. Sixty-six were dropped from the sample because they did not live in any of the 10 provinces, 613 were eliminated because of age (≥ 65), and 868 were removed due to self-employment. Individuals whose reasons for separation were other than “layoffs” or “contract ended” were excluded (15,706), and those who were not eligible for UI/EI (as defined in Appendix B) were excluded (2,672). The sample included only full-time workers (4,233 were removed), and those who had no information about their previous income and education status were excluded (619). Finally, only high-income workers were selected from the sample (an additional 20,202 were dropped), resulting in 2,985 observations selected from the CIE data.

¹⁰For the SLID data, there were 57,729 job interruptions that occurred during 1993 and 1998 (33,543 were permanently displaced, and 24,186 were temporarily laid off). Among them, 154 were dropped because of age (≥ 65), and 978 were removed due to self-employment. Individuals whose reasons for separation were other than “layoffs” or “contract ended” were excluded (34,767), and those who were not eligible for UI/EI (as defined in Appendix B) were excluded (4,718). The sample included only full-time workers (2,373 were removed), and those who had no information about education and firm size were excluded (471). Finally, only high-income workers were selected for the sample (an additional 13,150 were dropped), resulting in 1,118 observations from the SLID data.

It should be noted that the outcomes of these two datasets are not directly comparable because of survey designs and different systems for imputation of some variables. For instance, the derivation of the potential personal income variable is not the same in both datasets. In SLID, an individual's income from the previous year is used as a proxy for potential income. Due to limited information, wage earnings rather than previous year income is used for the CIE sample, and this could result in an overestimation of true income. Notice that yearly earnings were calculated based on the respondent working the reported number of weeks per month and hours per week over a 12-month period. Obviously, it is overestimated because these people did not work all 12 months during the year. They all experienced a job interruption at some point. As a result, many high-income people who were placed in the treatment group using this definition were actually unaffected by the repayment policy, resulting in a lower estimate of difference in mean participation rate. This can be seen explicitly from the first row of Table 1.3. The change of mean participation rate was only -0.025 (insignificant at the 0.1 level) for the CIE data, while it was -0.08 (significant at the 0.05 level) for the SLID data. Hence, the estimate of difference in participation rate for the CIE sample might be considered the lower limit of the analysis.

1.5 Results

The treatment effect was analyzed using the regression and matching models described above. The balancing test is used to estimate the propensity score, and the common support restriction is used in matching estimators.¹¹ Lists of controls are

¹¹The balancing hypothesis can be written as $T \perp X \mid p(X)$ (see Becker and Ichino, 2002). To satisfy the balancing property, observations with the same propensity score must have the same distribution of characteristics independent of treatment status. In other words, for each covariate, differences in mean

displayed in Table 1.3. Factors such as seasonal fluctuation (as measured by the quarter of the year a worker was unemployed indicator) and local labour market conditions (as measured by regional or provincial unemployment rates) are also included. These variables are very important in this before-after study because they allow for policy effects to be separated from temporal effects.

Table 1.4 displays the distribution of the estimated propensity scores for each dataset. First of all, the balancing property is satisfied in both cases, showing that the means of each characteristic do not differ between treated and control units within each interval. Second, only one out of 920 control units in the CIE sample is excluded under the common support restriction, suggesting the control units are very comparable to the treated units. Therefore, the final size of the control sample is 919 for the purpose of matching. In addition, Figure 1.2 and Figure 1.3 show that each interval contains enough controls to compare with the treated units, suggesting the quality of matches will not deteriorate, even when matching without replacement.

Turning to the estimates of the average treatment effect on the treated (ATT), row 2 of Table 1.5 displays results from the nearest-match method. It shows that all 2,065 treated units were matched with 624 of the 919 controls (with replacement) for the CIE sample. Similarly, 282 of 464 control units were used to match all treatments for the SLID sample. The ATTs for the single best match method are -0.062 and -0.119 for the CIE and SLID samples, respectively, and both are significantly different from zero (0.05). This suggests that the new repayment policy is responsible for a drop of 6.2 to

across treated and control units within each interval are not significantly different from zero. Notice that the individuals are divided into intervals according to the estimated propensity score.

11.9 percent in the EI participation rate among eligible, unemployed workers whose potential annual income is \$48,750 or more.

The next 5 rows show results from the radius matching that allows multiple controls to be matched to a treated unit if they all fall within a tolerance range. When the size of the neighborhood was very small ($r = 0.0001$), many of the treated units were unable to be matched: Only 533 out of 2065 in the CIE (and 92 out of 654 in SLID) samples were matched in this range. Estimated effects were somewhat larger (but with larger standard errors) in both cases compared to the nearest-neighbor estimators. However, this result may not represent the population of treated because only 26 percent and 14 percent of treated units in the CIE and the SLID samples, respectively, were matched. As the radius increased, more control units were used, and the probability of finding a match for all treated units also increased. For a radius of 0.01, all control units were used, and all treated units found matches in the CIE sample. Similarly, nearly all (462 out of 464) control units were used to match 641 (out of 654) treated units in the SLID sample. Estimates of the treatment effect are quite sensitive to the choice of radius. The estimated drop in EI participation rate ranges from 2.5 to 7.6 percentage points for the CIE data and 9.7 to 18.4 percentage points for the SLID data.

The next 2 rows show results from kernel matching that used all control units (through a kernel-weighted average of the outcomes) to match each treated unit. Two sets of kernel matching are reported: one with a bandwidth of 0.001 and the other with a bandwidth of 0.01. Unlike radius matching, kernel matching uses controls that lie outside the “window,” but those controls that were far away have a very small weight. Generally, results from kernel matching are similar to those from radius matching (when radius

equals bandwidth) in the CIE sample; however, there are minor differences (not statistically significant) in the SLID sample.

Finally, a regression adjustment of the full sample is presented on the bottom rows of Table 1.5. Compared with matching estimates, the estimate of the impact of EI repayment from regression adjustment is slightly smaller and statistically insignificant for the CIE sample, but it similar to the kernel estimate, with a bandwidth = 0.001, for the SLID sample. As suggested by Wooldridge (2002, p. 617), a simple estimate from an OLS regression on the estimated propensity score is also reported in the last column. This is estimated in two steps. First, a probit of the treatment on X is estimated, and then an OLS regression of outcomes on the treatment dummy and fitted propensity score is estimated. The estimated propensity score should contain all the information in the covariates that is relevant for estimating the treatment effect. The advantage of using the propensity score as a regressor is that it rules out any values of X such that $p(X) = 1$. However, it ignores the residual error from the first-stage probit estimation. In this study, the estimated treatment effects are very close to those obtained from simple regression, while the uncorrected standard errors seem to be larger.

Variation of the treatment effects across the estimators in Table 1.5 is due to the use of different control samples and the weighting schemes. For instance, the weight on a given control j when compared with treated i is equal to 1 in the nearest-neighbor matching, while it is $1/N^c$ in the radius matching (where N^c is the total control within the radius of treated i). However, Table 1.5 also exhibits two noticeable patterns. First, the estimated policy effects are much greater in SLID than in CIE across all estimators. The different underlying survey designs and sampling schemes are possible reasons for these

differences. These differences might also be due to the type of variables used in CIE. As described in section 1.4, the imputation of the income variable for the CIE sample may overstate the true income value for an individual. Many unrelated unemployed workers—those who were not really subject to repayment—were included in the at-risk population. Since these people were unaffected by the repayment policy, the average claim rate is expected to be higher by including these people. It might explain why the estimates of difference in EI claim rates are always lower for the CIE sample.

Second, in both datasets, policy effects show a monotonic decline as the radius width increases. The effects were disproportionately large when the radius was very small ($r = 0.0001$). The effects then became smaller at $r = 0.0005$, remained stable when $r = 0.001$, and dropped monotonically as the width increased further. As mentioned above, matching estimators based on a very small radius may not represent the treated population and, therefore, should be excluded from discussion. For the rest of the radius estimators, it is necessary to determine whether the use of more controls improves or worsens the estimation. Dehejia and Wahba (1998) point out that using more controls might increase the precision of the estimators, but it could also adversely affect the quality of the match on the propensity score. Without an experimental benchmark, it is very difficult to determine whether more controls improve or worsen the estimation because the relationship between radius r and the resulting bias is unknown. The interpretation used in this study is rather intuitive.

An increase in radius width may introduce additional “unrelated” controls in the matching for the CIE sample, while an increase in radius width improves the representation of the treated population in the SLID sample. Notice that in the CIE,

treated and control units have closer propensity scores than the SLID. About 93 percent (1926 out of 2065) of the treated units in the CIE were able to find comparable matches within a neighborhood of 0.001. By increasing the radius width, the possibility of including unrelated controls to match a given treated unit also increased. As shown in Table 1.5, the standard errors did not appreciably decline as the width of the radius increased. The declining policy effects suggest that these unrelated controls were likely to be non-EI participants.

The difference between propensity scores of treated and control units is greater in the SLID sample. For example, only 52 percent of the treated units were matched in a radius of 0.0005. The treated population increased to 68 percent and 98 percent as the radius expanded to 0.001 and 0.01, respectively. As a result, the changes in policy effects (through radius widths) in the SLID sample are likely the result of changes in the representation of the treated population.

1.6 Economic Impact of New Repayment Policy

As shown in the previous section, the strengthened repayment policy is responsible for a 6.2 to 12.7 percentage-point decline (depending on dataset used) in EI claim rates among high-income workers. The extent to which the change in claim rates affects economic outcomes is discussed in this section. It focuses on the impact of claim rate changes on the number of beneficiaries and government benefit payments. Table 1.6 shows the average monthly number of new regular claims (column 1), average monthly number of regular beneficiaries (column 3), and average weekly regular benefits (columns 5 and 6)—the data are from the aggregate source Employment Insurance

Statistics (EIS). The estimated results from the previous section are used to fill in column (2), then the results from columns (1) to (3) are used to extrapolate column (4), which would be the average monthly number of regular beneficiaries if the old repayment rules was still in effect. To estimate the budgetary impact, columns (7) and (8) are calculated using the information from (3) to (6) and the difference is compared.

Unfortunately, column (2) cannot be obtained directly because the estimated results of the previous section only apply to eligible workers whose annual income was equal to or greater than \$48,750. Therefore, a regression was employed to model the relationship between the total number of new EI claims and the claim rate among high-income workers:

$$RClaim_t = a + \beta Claimrate_highincome_t + e_t \quad (10)$$

Equation (10) assumes that the number of new regular claims ($RClaim$) is a function of the claim rate from high-income workers ($Claimrate_highincome$), and subscript t is the month from which the data are obtained. The monthly claim rates among high-income workers ($Claimrate_highincome$) are imputed from the microdata CIE, while the number of monthly regular new claims ($RClaim$) can be obtained either from an aggregated source (EIS) or from the microdata CIE. In panel A, Table 1.6, $RClaim$ was taken from EIS, and $Claimrate_highincome$ was derived from CIE. The estimated equation is

$$RClaim_t = 72276.7 + 226638.4 Claimrate_highincome_t, \quad t = 1, 2, \dots, 24, \quad R^2 = .162. \\ (t=0.91) \quad (t=2.06)$$

These estimated coefficients (column 2), together with results from the previous section, answer the question “What would be the number of new claims in the post-policy period

if the old repayment rules were in effect?” For example, based on the nearest-neighbour matching from CIE, the strengthened repayment rules will reduce EI claim rates for high-income workers by 6.2 percentage points. This estimate, applied to equation (10), suggests that the potential average number of new claims would be 247,715 $\{72276.7+226638.4*(0.7120885+0.062)\}$ if the repayment rules had not been changed.¹²

Once the number of new claims was obtained, the potential beneficiaries under the old rules (column 4) were calculated based on an extrapolation of the results from columns (1) to (3). The result suggests that the average monthly number of beneficiaries would have been higher by 31,482 (from 567,958 to a potential 599,440) if the old rules were still in effect. Finally, annual benefits under the new rules and old rules (counterfactual) are calculated in columns (7) and (8), respectively. Assuming that the entire decline in EI claim rates among high-income workers can be attributed to the new repayment rules, government could have saved about \$629 million in benefits paid out annually. Applying a 95% of confidence interval to this underlying estimate (see footnote 1, Table 1.6), the average number of monthly beneficiaries would have been higher: between 11,570 and 78,778. Correspondingly, the government could have saved \$362 million to \$1,264 million a year.

In panel B, Table 1.6, instead of taking values from an aggregate source, the values are derived from CIE for *RClaim*. The estimated equation becomes

$$RClaim_t = 129220.9 + 132075.9 Claimrate_highincome_t \quad t = 1, 2, \dots, 24 \text{ (months)}, R^2 = .06.$$

(t=1.65) (t=1.21)

¹²Predicted number of new claims is evaluated at the mean value of *Claimrate_highincome* (= 0.7120885).

Based on a 6.2 percentage-point decline in EI claim rate, it is shown that the average number of monthly beneficiaries would have been higher: between 7,054 and 48,042. Correspondingly, the annual saving for government could be \$301 million to \$851 million.

1.7 Conclusion

The study discussed in this chapter examines how the new EI repayment policy affects the probability that an eligible, laid-off worker will file an EI claim. Various propensity score matching approaches and regression-adjusted models are used to estimate the policy impact. Both matching and regression methods rely on the crucial assumption that the outcomes are independent of assignment to treatment and control, conditional on X variables.

The results of this study show that the new repayment policy has reduced the probabilities of filing a claim among high-income individuals by about 4.2 to 6.2 percentage points for the CIE sample, and about 9.7 to 12.7 percentage points for the SLID sample. Based on the estimate of a 6.2 percentage-point decline in the claim rate, this study suggests that the new rules could have reduced the average monthly number of regular beneficiaries in the post-policy period by about 31,482 (or 5.3 percent), and reduced total annual regular benefits by about \$629 million (or 8.5 percent).

However, a few caveats must be borne in mind when interpreting the results. First, results from the two samples are difficult to compare because of different underlying survey designs and different controls in each survey. Second, the estimation approaches—regression and propensity score matching—used in this study rely on

observables. It is possible that unobserved heterogeneity in the control and treatment groups exists. If so, the results would be suspect. Third, the decline in the claim rate could be due to employment effects. With the effective reduction in benefits imposed by the repayment policy, many frequent claimants may no longer be willing to accept seasonal jobs and, instead, seek employment in more stable industries. As a result, the claim rate for the remaining at-risk population would be lower because many individuals who were certain to file a claim no longer belonged to the at-risk population in the post-policy period. Additional analysis of employment effects in response to the repayment policy is needed in future research. Furthermore, it must be remembered that the data used in this study only cover the 2 to 3 years after the legislation was passed, and individuals usually take time to adjust to policy changes. The effects might be even larger as people learn more about the new EI regulations.

Table 1.1
Summary of Selected EI Studies

Study	EI parameters	Outcome of interest	Parameter changes from UI to EI	Main findings
Phipps and MacPhail (2000)	1) The impact of the stricter entrance requirement on new and re-entrants 2) The effect of a switch from a weeks-based to an hours-based system	Benefit receipt of new and re-entrants	From 20 weeks to 26 weeks (or 910 hours) worked UI: ineligible if worked <15hrs EI: all hours count	New requirement reduced access to benefits for new/re-entrants, especially youth and returning mothers The net reduction in access to benefits for new/re-entrants resulting from the switch to EI is small
Kapsalis (2000)	The impact of the stricter entrance requirement for new entrants and re-entrants	Benefit receipt of new and re-entrants	From 20 weeks to 26 weeks (or 910 hours) worked	New requirement significantly reduced the number of beneficiaries and the amount of total benefits paid in 1997 (7%)
Green and Riddell (2000)	The effects of the shift to an hours-based entrance requirement	1) Eligibility and entitlement 2) Job duration	UI: ineligible if worked <15hrs EI: all hours count	Overall, the change has no impact on eligibility but has led to an increase in entitlement The change has no impact on job duration, except for the length of seasonal jobs, which tended to be shorter under EI
Kuhn (2000)	The extension of EI coverage to part-time workers	Financial outcomes for part-time workers	UI: ineligible if worked <15hrs EI: all hours count	Part-time workers experienced a small net gain under EI (about \$39 per worker per year)
Fortin and Audenrode (2000)	The impact of the intensity rule on unemployed workers	EI payment and benefit duration	EI: replacement rate is reduced by 1 to 5%, depending on claim history	Data from COEP show that the intensity rule alone could reduce EI payments by 2.5 percent; also, a slight increase in claimants leaving after 19 weeks to avoid future benefit reductions

Table 1.1 (Cont'd)

Study	EI parameters	Outcome of interest	Parameter changes from UI to EI	Main findings
Sweetman (2000)	The impact of EI on those working less than 15 hours per week	Distribution of the hours of jobs	UI: ineligible if worked <15hrs EI: all paid part-time workers are covered	Except for the Atlantic region, there has been a small decrease in jobs under 15 hours per week for men and an increase in the percentage of jobs over 30 hours. No change is observed for women
Jones (2000)	An assessment of EI legislation	Unemployment duration and benefit receipt	Various changes (see text)	The quasi-experimental research suggests small but significant effects on unemployment duration but no change in the length of time a claimant is unemployed
Phipps, MacDonald, and MacPhail (2000)	Impact of switch from dependency rate (DR) under UI to the family supplement (FS) under EI	Family income	UI: 60% replacement rate for claimants with dependents <u>EI: 65 to 80%</u>	FS is more targeted to low-income families than the DR; FS also provides more income to claimants who have dependents

Table 1.2
Summary (mean) Statistics, Survey of Changes in Employment (CIE),* weighted

	Control (income < \$39,000)		Treatment (income > \$48,750)	
	Pre-policy (1)	Post-policy (2)	Pre-policy (3)	Post-policy (4)
EI participation	82.0	75.8	77.6	74.4
Age	36.6	36.4	40.3	41.5
Male (%)	53.9	52.0	93.9	91.1
Education (%)				
Less than HS	30.5	28.4	29.3	27.7
HS graduated	31.2	28.2	30.0	25.4
Some post-secondary	29.1	33.0	30.0	34.4
University	9.1	10.3	10.7	12.4
Household structure (%)				
Single	37.9	38.9	19.5	22.5
Couple w/o kids	30.3	31.3	41.4	41.3
Couple w/ kids	29.0	25.4	37.0	33.4
Single parent	2.8	4.4	2.1	2.7
Region (%)				
Atlantic	13.4	16.1	6.9	6.7
Quebec	34.5	34.4	26.3	27.0
Ontario	29.1	26.2	32.5	32.7
Prairie	13.9	12.8	14.0	13.2
B.C.	9.0	10.5	20.3	20.3
Canadian born (%)	86.9	88.6	86.6	83.7
Seasonal job (%)	38.0	39.5	31.5	31.0
Received advanced notice (%)	43.4	43.7	36.6	33.6
Firm size (%)				
< 20	45.2	45.5	32.0	31.7
20–99	29.4	29.9	26.8	28.9
100–499	17.9	17.8	19.9	21.7
500 +	7.5	6.7	21.3	17.8
Blue collar worker (%)	52.5	49.4	75.3	74.8
Permanent employee (%)	49.6	43.0	51.4	47.0
Recall expectation with date (%)	27.6	26.7	26.0	23.0
Unemployed (%) for				
Jan.–April	32.6	11.1	39.2	12.3
May–August	18.6	36.5	14.0	39.6
Sept.–Dec.	48.8	52.4	46.8	47.7
Unemployment rate **	9.95	10.0	9.45	9.25
Observations	5,073	12,324	920	2,065

*Samples include cohorts 2–10, 13, and 17.

**Combing information from the Monthly Labour Force Survey (LFS), this variable refers to a provincial unemployment rate at the time of an individual's job interruption.

Table 1.3
Distribution of the Treatment and Control Samples, weighted

	Survey of Changes in Employment (CIE)			Survey of Labour and Income Dynamics (SLID)		
	Control Pre-policy	Treatment Post-policy	Difference	Control Pre-policy	Treatment Post-policy	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable						
EI participation rate	77.6	74.4	-3.2	65.1	57.1	-8.0*
Mean personal characteristics						
Age	40.3	41.5	1.2*	41.0	41.8	0.8
Male (%)	93.9	91.1	-2.8	85.8	90.4	4.6
Education (%)						
Less than HS	29.3	27.7	-1.6	24.0	27.2	3.2
HS graduated	30.0	25.4	-4.6	9.5	11.1	1.6
Some post-secondary	30.0	34.4	4.4	49.4	46.5	-2.9
University	10.7	12.4	1.7	17.1	15.1	-2.0
Household structure (%)						
Single	19.5	22.5	3.0	29.2	26.0	-3.2
Couple w/o kids	41.4	41.3	-0.1	15.6	23.1	7.5**
Couple w/ kids	37.0	33.4	-3.6	51.2	49.1	-2.1
Single parent	2.1	2.7	0.6	4.0	1.8	-2.2
Region (%)						
Atlantic	6.9	6.7	-0.2	7.5	9.9	2.4
Quebec	26.3	27.0	1.0	20.5	17.8	-2.7
Ontario	32.5	32.7	0.2	32.3	35.5	3.2
Prairie	14.0	13.2	-0.7	15.2	14.4	-0.8
B.C.	20.3	20.3	0.0	24.4	22.3	-2.1
Canadian born (%)	86.6	83.7	-2.9	82.0	90.1	8.1**
Mean characteristics associated with ROE job						
Seasonal job (%)	31.5	31.0	-0.5		31.7	-0.7
Rec'd advanced notice (%)	36.6	33.6	-3.0	-	-	-
Firm size (%)						
< 20	32.0	31.7	-0.3	33.3	29.3	-4.0
20-99	26.8	28.9	2.1	28.8	24.8	-4.0
100-499	19.9	21.7	1.8	21.3	25.8	4.5
500 +	21.3	17.8	-3.5	16.5	20.0	3.5
Blue collar worker (%)	75.3	74.8	-0.5	63.4	76.6	13.2**
Permanent employee (%)	51.4	47.0	-4.4	-	-	-
Recall expectation (%)	26.0	23.0	-3.0	-	-	-
Unemployed (%) from						
Jan.-April	39.2	12.3	-26.5**	33.5	25.9	-7.6*
May- August	14.0	39.6	25.6**	46.4	35.1	-11.3**
Sept.- Dec.	46.8	47.7	0.9	20.0	39.0	19.0**
Unemployment rate***	9.45	9.25	-0.20*	10.9	10.5	-0.4**
Observations	920	2,065		464	654	

Data: CIE cohorts 2-10, 13, and 17; SLID (1993-1998)

*Difference is significant at the .1 level, two-tailed test.

**Difference is significant at the .05 level, two-tailed test.

***Combining information from the Monthly Labour Force Survey (LFS), this variable refers to provincial unemployment rates at the time of an individual's job interruption for the CIE data, while it refers to a regional (UI/EI) unemployment rate at the time of an individual's job interruption for the SLID data.

Table 1.4
Estimated Distribution of Propensity Score for CIE and SLID, weighted

Propensity score	Survey of Changes in Employment (CIE) ¹		Survey of Labour and Income Dynamics (SLID) ²	
	Control	Treatment	Control	Treatment
0.0–0.2	-	-	59	40
0.2–0.4	124	63	184	181
0.4–0.5	236	176	104	151
0.5–0.6	93	80	63	111
0.6–0.7	133	352	35	99
0.7–0.8	155	542	16	55
0.8–0.9	140	691	3	17
0.9–1.0	38	161	-	-
Total	919 ³	2,065	464	654
Region of common support	[.2864, .9537]		[.0466, .8842]	
Balancing property	Satisfied		Satisfied	

¹The propensity score for the CIE data is estimated using a probit of treatment status on personal characteristics (age, sex, education, household composition, regions, Canadian born), ROE job characteristics (union, seasonal job, recall expectation with date, firm size, received advanced notice, permanent employee, blue-collar worker), and macro conditions (quarter of unemployment, provincial unemployment rate at the time of job separation).

²The propensity score for the SLID data is estimated using a probit of treatment status on personal characteristics (age, sex, education, household composition, regions, Canadian born), interrupted job characteristics (union, seasonal job, firm size, blue-collar worker), and macro conditions (quarter of unemployment, UI/EI regional unemployment rate at the time of job separation).

³One observation was dropped because its estimated propensity score was not in the region of common support.

Table 1.5
Estimates of Treatment (Policy) Effects, weighted

Outcome: Probability of participation in UI/EI program

	Survey of Changes in Employment (CIE)			Survey of Labour and Income Dynamics (SLID)		
	Mean (observations)		ATT ¹ (s.e.)	Mean (observations)		ATT ¹ (s.e.)
	Control	Treatment		Control	Treatment	
Original sample	0.776 (n=920)	0.744 (n=2065)	-0.032 (0.029)	0.651 (n=464)	0.571 (n=654)	-0.080 ⁺ (0.044)
<i>Matching sample (with common support)</i>						
Nearest-neighbor matching	0.816 (n=624)	0.754 (n=2065)	-0.062 ^{**} (0.021)	0.702 (n=282)	0.583 (n=654)	-0.119 ^{**} (0.041)
Radius matching $r=0.0001$	0.809 (n=417)	0.733 (n=533)	-0.076 ^{**} (0.038)	0.684 (n=85)	0.500 (n=92)	-0.184 ⁺ (0.102)
$r=0.0005$	0.802 (n=773)	0.750 (n=1611)	-0.052 ^{**} (0.026)	0.686 (n=292)	0.566 (n=339)	-0.120 ^{**} (0.055)
$r=0.001$	0.804 (n=855)	0.751 (n=1926)	-0.053 ^{**} (0.019)	0.697 (n=378)	0.570 (n=446)	-0.127 ^{**} (0.040)
$r=0.01$	0.797 (n=919)	0.754 (n=2065)	-0.043 ^{**} (0.018)	0.683 (n=462)	0.581 (n=641)	-0.103 ^{**} (0.028)
$r=0.1$	0.779 (n=919)	0.754 (n=2065)	-0.025 (0.019)	0.680 (n=464)	0.583 (n=654)	-0.097 ^{**} (0.028)
Kernel matching Bwidth=0.001	0.807 (n=919)	0.753 (n=2065)	-0.054 ^{**} (0.021)	0.688 (n=464)	0.582 (n=654)	-0.106 ^{**} (0.039)
Kernel matching Bwidth=0.01	0.795 (n=919)	0.753 (n=2065)	-0.042 ^{**} (0.016)	0.700 (n=464)	0.582 (n=654)	-0.118 ^{**} (0.032)
Regression			-0.044 (0.027)			-0.107 ^{**} (0.042)
	(n=920)	(n=2065)		(n=464)	(n=654)	
Regression on Pscore			-0.43 (0.029) ⁺			-0.106 ^{**} (0.046) ⁺

¹The average treatment effect on the treated (ATT). Standard errors (in parentheses) for matching estimates are calculated using the bootstrapping method (50 replications).

*Significant at the .1 level.

**Significant at the .05 level.

+The standard error is not adjusted for the probit first-stage estimation.

Table 1.6
Economic Impacts of New Repayment Policy

If the new repayment policy reduces claim rates of high-income workers by (percentage point)	Post-Policy Period							
	Average monthly number of new regular claims		Average monthly number of regular beneficiaries		Average weekly regular benefit		Annual regular benefits (million)	
	New rules [*]	Old rules ⁺	New rules [*]	Old rules ⁺⁺	New rules [*]	Old rules [*]	New rules ²	Old rules ²
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A.								
6.2	233,663	247,715	567,958	599,440	251	258	7,413	8,042
2.1	233,663	238,423	567,958	579,528	251	258	7,413	7,775
(lower bound) ¹								
14.3	233,663	266,073	567,958	646,736	251	258	7,413	8,677
(upper bound) ¹								
B.								
6.2	223,271	231,459	567,958	588,787	251	258	7,413	7,899
2.1	223,271	226,044	567,958	575,012	251	258	7,413	7,714
(lower bound) ¹								
14.3	223,271	242,157	567,958	616,000	251	258	7,413	8,264
(upper bound) ¹								

Note: In panel A, the values of monthly number of new claims came from an aggregate source (Employment Insurance Statistics). In panel B, the values of monthly number of new claims were derived from microdata CIE.

^{*}Employment Insurance Statistics-Monthly, Statistics Canada

⁺Predicted value using equation (12) evaluated at mean value of Claimrate_highincome.

⁺⁺Value from extrapolation of columns (1) to (3).

¹The 95% confidence interval of the underlying estimate of 6.2 is obtained by $[\hat{\beta} \pm 1.96 \cdot se(\hat{\beta})]$. Since $se(\hat{\beta}) = 0.021$ (see Table 5 or Appendix C), the confidence interval should be $[0.062 - 1.96 \cdot (0.021), 0.062 + 1.96 \cdot (0.021)] = (0.021, 0.143)$.

²Column (7) = column (3) * (5) * 52; and column (8) = column (4) * (6) * 52.

Figure 1.1
Net Income Schedule Before and After the UI/EI Repayment for EI Claimants

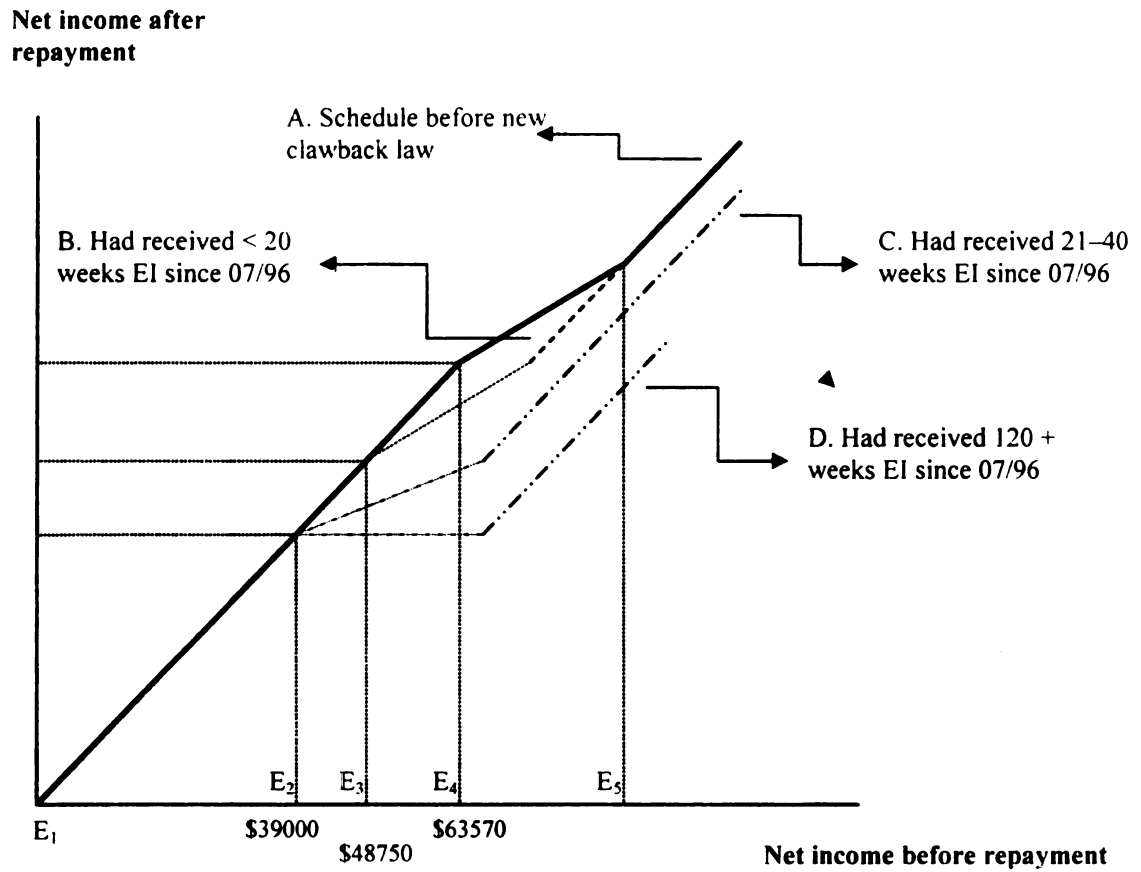


Figure 1.2
Histogram of Estimated Propensity Score, CIE

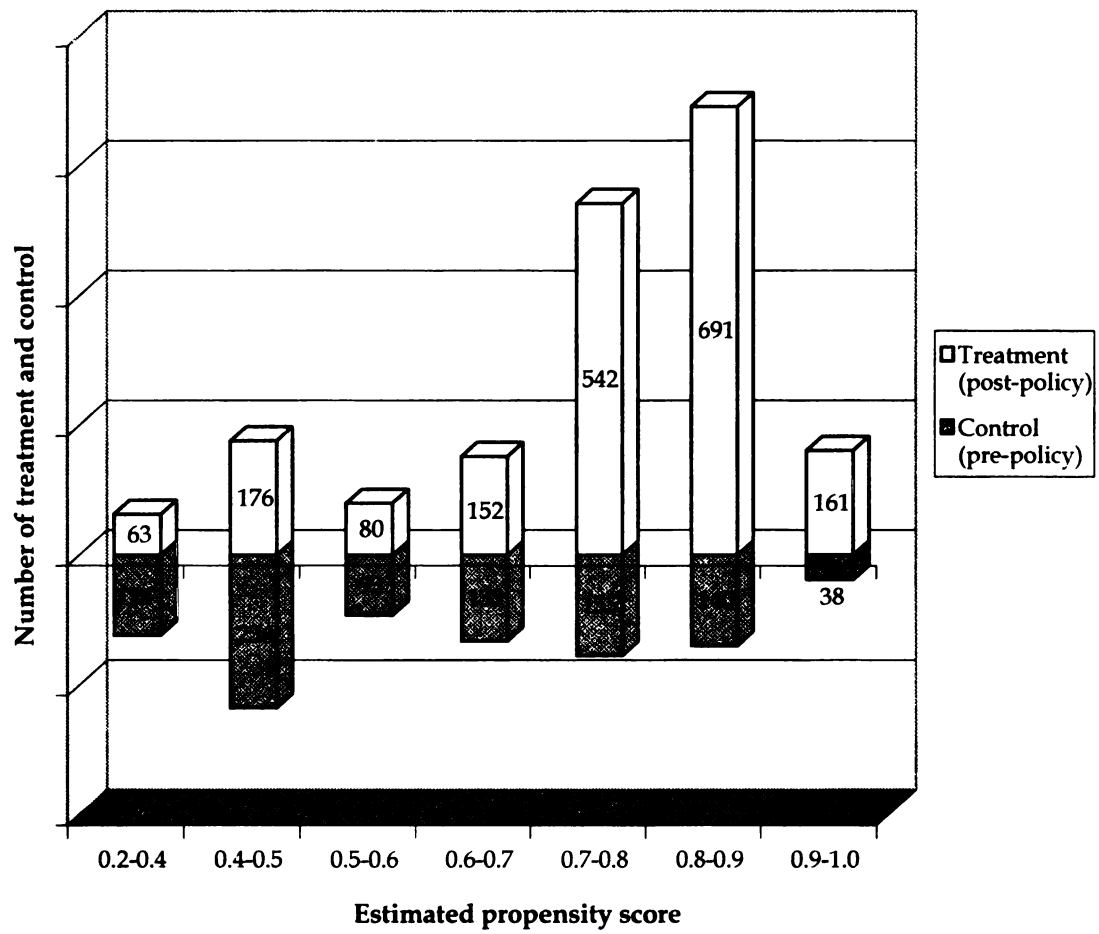
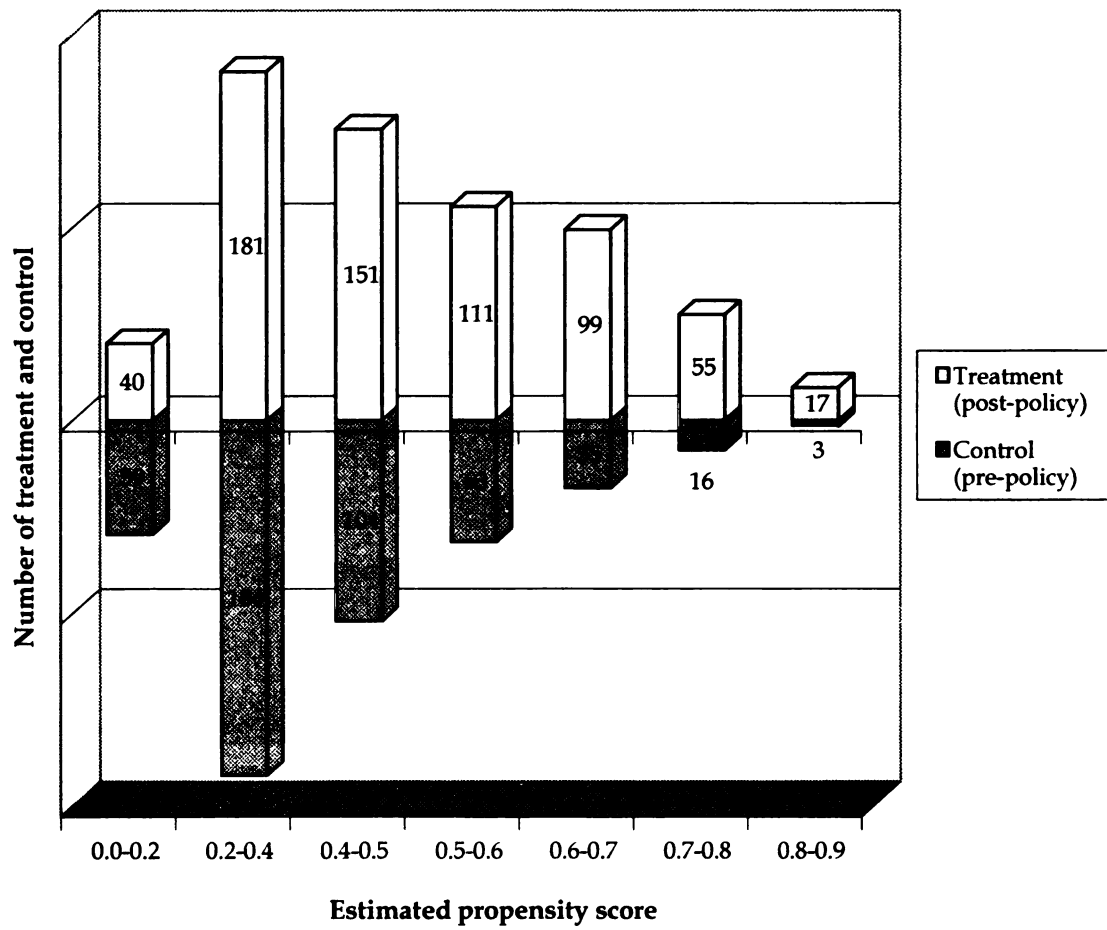


Figure 1.3
Histogram of Estimated Propensity Score, SLID



Chapter 2

Household Income Mobility in Canada and the United States

2.1 Introduction

Levels of poverty and pre-transfer family income inequality have grown rapidly in Canada since the 1980s. Statistics show that the Gini coefficient with respect to pre-transfer family income rose from .37 in 1980 to .43 in 2001 for economic families and from 0.44 to 0.50 for all family units.¹³ Increases in income inequality have created intense public policy debate about the effectiveness of anti-poverty policies and raised concerns about social exclusion. While there is extensive Canadian literature documenting trends and causes of rising inequality,¹⁴ there is relatively little research that examines income mobility.

Understanding the levels of income mobility in Canada is of interest for two reasons. First, this information is essential for understanding the long-term consequences of inequality and poverty and for formulating policies that are appropriate. Inequality of annual income may overstate the problem of low income if people are able to eventually move into a higher income bracket. People will tolerate periods with high levels of income inequality or poverty if there are opportunities for them to improve their incomes. Therefore, it is important to understand the extent of income mobility and poverty persistence in order to develop appropriate social policies, particularly anti-poverty measures.

¹³Source: Statistics Canada, CANSIM Table 202-0705.

¹⁴See Morissette (1995), Morissette, Myles, and Picot (1995), and Zyblock (1996a) for a discussion about the changes in earnings inequality; and Wolfson (1986), Zyblock (1996b), Beach and Slotsve (1996), and Frenette, Green, and Picot (2003) for a discussion about the changes in family income inequality.

Second, income mobility can supply information, although in potentially conflicting ways, about the degree of opportunity in and economic stability of a society. The degree of opportunity shows how the ease or difficulty of upward mobility is related to a person's skill or effort. A high level of market-driven income mobility provides incentives for individuals to work hard, and this productivity makes investments in human capital more rewarding. The latter, however, indicates income movements related to exogenous shocks. Thus, a high level of mobility may also be viewed as a synonym for economic insecurity. Given the integration of the U.S. and Canadian economies, it is important to know whether Canada's upward mobility is similar to the upward mobility in the United States. In addition, given Canada's more progressive government transfer system, Canadian policy makers should know to what extent Canada's redistributive policies contribute to changes in market-driven mobility and to what extent these changes compare to market-driven mobility in the United States.

In this study, short- and long-term mobility and how these types of mobility vary across educational and minority groups are examined using longitudinal data collected over a 6-year period. Both pre-transfer and post-transfer income measures are used to examine how a nation's redistributive system affects the levels of inequality, mobility, and the incidence of persistent poverty (or high income). Also, a decomposition method pioneered by Bane and Ellwood (1986) is used to describe the relation between each income movement and its concurrent event. A parametric hazard model is then employed to examine the role of events and various characteristics in estimating the risks for low- and high-income exits and reentries. To place these estimates in a cross-national context, comparable estimates are computed for the United States.

The results of this study show that significant household income mobility occurred in both Canada and the United States. Although 40 percent of the population in both countries was in the low-income bracket at least once during the survey years, only 10 to 13 percent of the population was in the low-income bracket every year. The results indicate that Canada's redistributive system significantly increased income stability. From any given year ($t-1$ to t), the proportion of people who remained at the two extremes of income distribution decreased from 43.5 percent to 23 percent when post-transfer measures were used, while the proportion who remained in the same middle income groups increased correspondingly (from 21% to 39%). There was considerable income immobility in both countries as well. About 65 percent (70%) of Canadians (Americans) who were living in poverty at the beginning of the survey were still living in poverty after 6 years. Rates of mobility varied greatly across socio-demographic groups. Less-educated and non-white people in both countries tended to experience persistent poverty. Furthermore, there is little evidence in this study that Canadian immigrants whose mother tongue was not one of the two official languages experienced higher risks of continued poverty. A low-income (or high-income) spell beginning or ending in the U.S. was mostly associated with events concurrent with changes in labour earnings, while demographic events, such as family formation or separation, played an equally important role in spell change in Canada.

2.2 Literature Review

The collection of longitudinal data in many countries has produced a vast body of literature on earnings dynamics.¹⁵ Analyses of household income mobility are also well documented (e.g., Gardiner and Hills, 1999; Gittleman and Joyce, 1999; Gottschalk and Danziger, 1997; Jarvis and Jenkins, 1998; McMurrer and Sawhill, 1998), and many of these analyses focus on poverty dynamics (e.g., Band and Ellwood, 1986; Stevens, 1999).

Income mobility has received relatively little attention in Canada. In part, this is due to a lack of longitudinal data. Until recently, Canadian research on income mobility relied on tax-based longitudinal files, which are generally not available to researchers. Among these scarce studies, most of them focus on earnings mobility. Finnie (1997) uses a longitudinal administrative databank (LAD) to conduct a descriptive analysis of earning mobility of Canadians from 1982 to 1992 based on quintile transition matrices. Baker and Solon (1999, 2003) use tax records from 1976 to 1992 to examine changes in earning mobility. They decompose the growth in earnings inequality into transitory (e.g., earnings instability) and permanent (e.g., increase returns in education) components. They found that both components play important roles in explaining the growth in earnings inequality. Beach and Finnie (2001) use LAD from 1982 to 1996 to examine the cyclical pattern of changes in earnings mobility. They measure the short-term mobility (year-to-year) of workers' earnings over the business cycle and find that higher levels of unemployment decrease net earning mobility significantly. Beach and Finnie (2004) further employ a cohort analysis of age-earnings profiles using longitudinal data. Their

results echo Beaudry and Green's (2000) findings and show that the earnings of recent cohorts (between 1990 and 1994) of young workers have slipped considerably. However, they also found that returns to experience have increased for these groups because of steepened profiles.

With respect to income mobility, Laroche (1997) uses LAD from 1982 to 1993 to estimate the persistence of low income in Canada. He employs a hazard model that accounts for multiple spells and finds that about 40 percent of the non-senior, Canadian, low-income population is characterized by relatively low exit rates and high reentry rates. Finnie (2000) uses LAD from 1992 to 1996 to explore the dynamics of low income in Canada. His analyses focus on a variety of issues, including total time spent in the low-income bracket, and he estimates exit and reentry rates. His findings show that while a substantial percentage (40%) of the population experienced low incomes at some point during 1992 to 1996 only 6 percent were poor every year. In addition, his results also show a strong duration dependence: The longer an individual remains in poverty, the less likely that person will be to escape poverty.

The use of administrative data has many advantages in mobility analysis. It is more accurate on income measures. It has longer and generally more consistent series across time, and its enormous sample size enables researchers to explore more flexible models compared to conventional survey data (Baker and Solon, 1999, 2003). However, it is also limited—there is a shortage of personal information—and therefore, it offers fewer opportunities to develop specific policy initiatives. For example, many U.S. studies

¹⁵See, for example, Atkinson, Bourguignon, and Morrison (1992), Gottschalk and Moffitt (1994), Gittleman and Joyce (1996), Gottschalk (1997), Buchinsky and Hunt (1999), Solon (1999b), Haider (2001), Corcoran (2001), and Moffitt and Gottschalk (2002). See also OECD (1996) and Burkhauser, Holtz-Eakin,

(such as Gittleman and Joyce, 1999) consider race to be one of the determining factors of income mobility. Similarly, in Canada, ethnic backgrounds or education level would likely be an important factor influencing income mobility. Nevertheless, these types of questions cannot possibly be answered from tax data alone.

The primary contribution of the present study to the existing Canadian income mobility literature is that it uses the first wave of longitudinal survey data, which became available recently, to examine household income mobility in Canada during the 1990s. The results not only provide a benchmark that can be compared to the results from the tax data, but also further provide information about income mobility among subgroups, particularly in the areas of education and minority status, which are not available in the tax data. This fills a gap in the literature and assesses the influence of education and ethnic backgrounds on an individual's income mobility. Both pre-transfer and post-transfer income measures were used to conduct the mobility analysis. This creates a picture of how a nation's redistributive policies contribute to changes in market-driven mobility. In addition to the conventional focus on changes in the labour market, this study addressed the importance of household decisions and the roles of secondary family members on income mobility. A decomposition method was used to describe the relation between the beginning or ending of a low-income (or high-income) period and its concurrent event (such as family formation). Finally, to see whether Canadian income mobility is different from other countries, U.S. data were also analyzed for cross-national comparison.

and Rhody (1997) for cross-national comparison; and Solon (1999a, 2002) for a survey of cross-national comparison on intergenerational earnings mobility.

2.3 Data Sources and Cross-Sectional Statistics

The analysis uses data from the Cross-National Equivalent Files (CNEF) version of the Panel Study of Income Dynamics (PSID, 1990–1997) for the U.S. sample¹⁶ and the Survey of Labour and Income Dynamics (SLID, 1993–1999) for the Canadian sample. Variables have been defined in a similar manner across the surveys in order to encourage cross-national research.¹⁷ The CNEF data has a key advantage. It provides imputed aggregate income variables and defines them consistently across different datasets. Such variables include pre- and post-transfer household income, estimates of annual labour income, assets, imputed rent, private and public transfers, and taxes paid at the household level. The extensive information available for each household income creates a complete picture of the relative roles of market, family, and state in determining income level.

The analyses of the CNEF data are conducted for both pre- and post-transfer income levels. Pre-transfer income is defined as the sum of household labour income, asset income, imputed rent, and private transfers.¹⁸ Post-transfer income is the amount of pre-transfers plus public transfers, social security pensions, and tax components.¹⁹ The definition of household includes people living in the same dwelling unit, whether related

¹⁶The CNEF version of the PSID does not distinguish between the Survey Research Center (SRC) sample and the Survey of Economic Opportunity (SEO) sample. The former is a nationally representative sample, and the latter is a national sample of low-income families. The PSID core sample combines the SRC and SEO samples. Many U.S. mobility studies use only the SRC sample and exclude SEO from the PSID to avoid overrepresentation of poor individuals (e.g., Haider, 2001). As a result, careful interpretation is needed when comparing results from this study to other U.S. studies. However, it should be noted that although the CNEF version of PSID does not exclude SEO from PSID weights are used to keep the sample nationally representative.

¹⁷See Burkhauser et al. (2000) for a detailed description of the CNEF data.

¹⁸Private transfers include private pensions, annuities, child support, alimony, and income from non-household members.

by blood or marriage or unrelated. To properly measure the well being of each family member, total family incomes are standardized through an equivalence scale in order to take into consideration both monetary and demographic components. The equivalence scale used here is simply a square root of family size. The adjusted income, hereafter called equivalent income, can be regarded as an estimate of potential disposable income for each household member under the assumption of equal sharing.

There is no consensus between Canada and the United States with respect to the definition of poverty or high income. For example, the U.S. has an official “poverty” line, while many cutoffs are used to define low income in Canada.²⁰ In this study, measures of low income and high income are based on the income distribution in each country in a given year. Individuals are considered low income if their equivalent incomes fall below 50 percent of the national median in the first year of the analysis. Similarly, they are considered high income if their equivalent incomes are 150 percent of the national median. In this chapter, the terms “low income” and “poverty” are used interchangeably, although they are not technically the same thing.

The population samples are meant to be representative of all individuals. Table 2.1 offers an overview of cross-sectional statistics for both countries in the 1990s; both pre-transfer and post-transfer income measures are displayed. The data are adjusted for

¹⁹Public transfers in Canada include child tax benefit, employment insurance, workers compensation, social assistance, provincial income supplements, old age security, guaranteed income supplement and spouse allowance, GST credits, and provincial tax credits. Public transfers in the U.S. are the sum of AFDC payments, Supplemental Security Income (SSI), unemployment insurance, worker’s compensation, other welfare income, and the face value of food stamps. Tax components in SLID include federal and provincial income taxes, while in PSID, the tax components cover income taxes as well as payroll taxes.

²⁰Instead of a single official poverty line, three different low-income cutoffs are commonly used in Canada. First is the Low Income Cutoffs (LICO), which is calculated according to seven family sizes and five sizes of area of residence to measure low income. Second is the Low Income Measure (LIM), which is defined as half of the median income. The third measure is called market basket measure (MSM), developed by Human Resource Development Canada (HRDC) in 2000. It costs out a basket of necessary goods and services, including food, shelter, clothing and transportation, and a multiplier to cover other essentials.

inflation and expressed in 1997 dollars. To help with interpretation, purchasing power parities (consumption based) are used to convert Canadian dollars to the U.S. equivalent over the sample period.

At first glance, the degree of inequality, as measured by the Gini coefficient and the percentile ratios, was generally higher in the United States. Compared to the Canadian data, the Gini coefficients with respect to pre- and post-transfer income were about 3 and 8 percent higher in the U.S., respectively. Pre-transfer income dispersion was quite substantial in both countries: the 10 to 50 ratios were about one-tenth and one-seventh for Canada and the U.S., respectively. The low-income rates were surprisingly high: Approximately 1 in 4 people in both countries would be low income if there was no tax-transfer system.

The story changed dramatically when transfers were considered. In general, the degree of inequality was reduced significantly in both countries, as indicated by the smaller Gini coefficients and smaller gaps between percentile ratios. Effects of government transfers were relatively significant in Canada: The 10 to 50 ratio increased to 0.47 from 0.1 when transfer incomes were added. The comparable increase for the U.S. data was from 0.15 to 0.35. In terms of low-income rates, the tax-transfer system reduced low-income rates by about 14 percentage points in Canada and about 7 percentage points in the United States. The transfer system in Canada also had a stronger impact on the upper portion of the income distribution: The more progressive tax systems in Canada reduced the high-income rate by an average of 7 percentage points (compared to a 3 to 4 points reduction in the U.S.).

As shown in Table 2.1, pre-transfer income distributions do not differ drastically between Canada and the United States. However, when tax-transfer systems are taken into account, Canada redistributes more income from the two ends of the distribution, and therefore reduces the incidence of poverty. This is consistent with the fact that Canada's social insurance systems—particularly social assistance and public pension benefits—are generally more progressive and more generous for low-income people compared to systems in the U.S. (e.g., Kennedy and Gonzalez, 2003; Turner, 2001).

2.4 Income Mobility

2.4.1 Persistence of Low Income and High Income

Table 2.1 shows the number of people in the low-income bracket in a given year and how government transfers reduced the rate of poverty. However, it does not tell how many people were in poverty on a long-term basis, nor does it provide information about how government transfers reduced the persistence of poverty. Using longitudinal data, Table 2.2 illustrates the incidence of low income and high income. The sample included individuals present in all years during the survey period.

With respect to pre-transfer income, each country had approximately 40 percent of the population in the low-income bracket at least once during the survey period. However, only about 10 and 13 percent of the population in the U.S. and Canada, respectively, experienced low incomes in all survey years. This indicates that low income is likely a temporary experience for most people. Similarly, about 56 percent of Canadians and 48 percent of Americans achieved high-income status at least once during this period, while only 14.4 and 16.3 in Canada and the U.S., respectively, were able to

stay in the high-income bracket on a long-term basis. However, such estimates may be understated because this approach ignores the left- and right-censoring periods at the boundaries. Accordingly, an alternative measure, which is based on average income, is also reported in Table 2.2.²¹ This measure resulted in higher incidences as shown in columns (3) and (6) of Table 2.2. For example, about 21 percent, rather than 11 to 13 percent, of the population in both countries experienced persistent poverty under this measure.

When subgroups are analyzed, patterns of income persistence show differences between countries. Generally, well-educated people (college or more) in the U.S. were less likely to experience a persistence of poverty and tended to stay longer in the high-income bracket: The incidence of persistent poverty and high income among this group was about 2.5 and 29.5 percent, respectively, in the U.S., compared to 6.7 and 19.5 percent in Canada (see Table 2.2, columns [2] and [5]). The stronger high-income stability among well-educated people in the U.S. is likely to increase long-run inequality, which usually is ascribed to a large increase in the returns to education. Consistent with previous findings, this effect is not significant in Canada (Bar-Or et al., 1993).

Minority is another story. No discussion of social policy in Canada or the U.S. would be complete without mentioning minority groups. In the U.S., racial characteristics are seen as barriers to equal opportunity, while ethnic backgrounds and language profiles appear to be a major factor influencing social exclusion in Canada.²² Table 2.2 shows that non-whites in both countries tended to experience poverty and persistent poverty and

²¹ That is, an individual is considered always poor if his or her sum of equivalent incomes across survey years is less (greater) than the sum of the low (high) income thresholds across survey years.

were less likely to attain high-income status. Compared to the average, the chance of experiencing poverty was about 4 and 25.6 percentage points higher for non-whites in Canada and the U.S., respectively, and about 12.7 and 25.2 percentage points lower for experiencing high income. In Canada, Francophone Canadians showed a higher incidence of poverty and a lower chance of high income. However this might be due to the province-specific effect because most Francophone Canadians live in the province of Quebec, and the average family incomes were relatively lower in this province compared to the national average.²³

Immigrants in Canada exhibited two distinct patterns in low- and high-income incidences. Immigrants whose mother tongue was not one of the two official languages experienced about a 5 percentage point higher rate of poverty and experienced about a 15 percentage point lower rate of high income than the national average. On the other hand, immigrants who were proficient in either of Canada's official languages did even better than the average person in Canada: They had fewer risks of being in the low-income bracket and better chances of staying in the high-income bracket. This finding is not surprising because Canada's immigration process involves a points system that favours those who possess talents, including language skills. Immigrants who are proficient in either of Canada's two official languages usually are able to transfer foreign skills successfully.

²²The original CNEF version of SLID does not contain information about mother tongue and immigration status. This information was obtained by linking the SLID_CNEF files to Statistics Canada's SLID Master records.

²³The average pre-transfer family income was \$48,591 in the province of Quebec (compared to the national average \$55,619) over the period of 1993 and 1998 (Statistics Canada, 2003).

2.4.2 Government Transfers and Income Mobility

To look at how redistributive systems affect individuals' mobility through the income distribution, post-transfer income measures are reported in the second and third sections of Table 2.2. The second section defines low income and high income based on relative cutoffs (i.e., below 50% and above 150% of post-transfer median), while the third section applies absolute cutoffs—the same cutoffs used in the pre-transfer income measure—to define low income and high income. By comparing these two measures, it was possible to get a sense of how much change in the incidence of low income or high income is due to transfers or cutoff changes.

Basically, transfer systems in both countries reduced the variations of bad and good income years for an individual and, therefore, increased income stability, particularly in Canada. Compared to the pre-transfer measure, the persistence of low income in Canada dropped from 13 to 2.9 percent. The decline in the low-income rate is mostly due to transfers and not to differences in the cutoff. Using the same poverty cutoff line as a pre-transfer measure would slightly change the low-income rate to 3.8 percent. This suggests that a large proportion of low-income individuals in Canada improved their income level through government transfer systems.

The effect of U.S. transfer systems on low-income incidences was smaller. More interesting, a significant portion of the decline in incidence was caused by a change in the cutoff line, not transfers. For instance, the persistence of poverty in the U.S. dropped 5 percentage points (from 10.7% to 5.7%) with the inclusion of government transfers. However, the decline in persistent poverty shrank to 2.8 points if the same pre-transfer cutoff was used. This suggests that U.S. transfer systems distributed little money to

people living in poverty. Some of these people might rise above the poverty line because of the decline in overall median, but they were still below the average standard of living if a pre-transfer cutoff was used.

The Canadian transfer system also exhibited great impacts on income stability among subgroups. The rates of persistent poverty among less-educated people dropped from 22.4 percent to 4.7 or 6.3 percent and from 18 percent to 2.7 or 4.2 percent for immigrants who did not speak one of the two official languages. On the other hand, the cutoff effect is more salient among subgroups in the U.S., especially for non-whites: About two-thirds of the decline in persistent poverty for this group was caused by a change in the cutoff line.

To further illustrate how the redistributive system affects income mobility, the top section of Table 2.3.1 shows the distribution of individuals across income intervals, and the second section shows the short-term (1-year) mobility rates using both pre-transfer and post-transfer income measures. An absolute cutoff based on pre-transfer income is used throughout this Table. Individuals are placed into income groups according to the size of their incomes relative to the absolute median income. Generally, the population at the two extremes of the income distribution reduced significantly when transfers were considered, suggesting an increase in overall income stability. Prior to transfers, more than 50 percent of individuals in each country had their income located in the two ends of the income distribution. With transfers, the proportion of low-income people dropped from 24 percent to 13 percent in Canada, while it only dropped from 24 percent to 21 percent in the U.S.

The second section of Table 2.3.1 shows 1-year transition rates. With respect to the pre-transfer income, movement at the tails of the distributions was rather rigid in both countries. Roughly four-fifths of individuals in the lowest and the highest income groups were likely to remain in the same group the next year. Of those who moved out of the lowest (or the highest) income group, more than half moved into neighbouring groups. Mobility among individuals not in the two extremes was larger. About 41 to 47 percent (37%–43%) of people in the middle-income groups in Canada (the U.S.) remained in the same income group the next year, while about 12 to 18 percent (12%–24%) of individuals among these groups in Canada (the U.S.) moved up or down more than one income group.

With transfers, the distribution of individuals was more concentrated in the middle-income levels (as shown in the top section), and more people tended to stay in the same income level over time, indicating an increase in income stability. In Canada, for instance, the proportion of individuals located in “0.5–0.75” income category in any given year increased from 11 to 20 percent when transfers were added; the proportion of people staying at this income level over time also increased significantly from 47 to 63 percent. The increase in income stability was more apparent in the lower half of the distribution.

Table 2.3.2 reiterates the impact of a redistributive system on mobility. Instead of the transition rates shown in Table 2.3.1, each entry in Table 2.3.2 represents the percent of individuals from year $t-1$ to year t . There were two main effects of transfers on mobility. First, the percent of individuals who stayed at the two extremes was reduced, while the percent of people who stayed at the same income level other than the two

extremes increased correspondingly. Second, long-range mobility (move of more than two income groups) decreased. If they moved, people were most likely to move into neighbouring groups.

Overall, the redistributive systems in the U.S. play a relatively smaller role in income stability compared to Canadian systems. With transfers, for example, the percent of people who stay at the same income level (not at the two ends) increased by 9.5 percentage points in the U.S. (versus 17.4 in Canada). The cross-national differences are more obvious among subgroups. For individuals with high school or less education, Canadian transfers reduced the risk of staying in the low or high end of the income scale for consecutive years by about 24.8 percentage points (from 44.7% to 19.9%) and increased the chance of staying at the same income level among people in the middle-income range by about 22.2 percentage points (from 21.7% to 43.9%). The comparable numbers for the U.S. are 10.9 and 8.8 percentage points, respectively.

Tables 2.2, 2.3.1, and 2.3.2 provide an analysis of U.S. and Canadian redistributive policies on market-driven income mobility. These Tables show that a redistributive system significantly reduced the incidence of low income and high income and increased income stability for people in the middle of the income spectrum (particularly the lower half). The patterns were more evident in Canada than in the United States.

2.4.3 Short-term versus Long-term Mobility

Using longitudinal data collected over 6 years, it was possible to break down mobility by length of income tracked. Table 2.4 shows mobility rates out of the lowest

and the highest income groups by length of time (1 year, 3 years, and 6 years) and also by characteristics. Only pre-transfer income measures were used. Overall, short-term mobility is slightly higher in the U.S. than in Canada. On average, 22.5 percent of Americans who were observed in low income in the first year of survey left low income the next year (versus 18% for Canadian). However, long-term mobility (6 years) shows an opposite trend: 36 percent of Canadians who were observed in low income in the first year of survey were able to escape low income in 6 years (versus 30% in the U.S.). Upward mobility was even salient in subgroups. Among low-income Canadians who possessed a college education in 1993, 24 percent rose above the poverty line the next year, and only 62.4 (51.7%) percent of the original group remained below the poverty line after 3 (6) years. Compared to the Canadian experience, low-income Americans who possessed a college education tended to rise above the poverty line quickly: About 35 percent of them escaped low income in 1 year. However, the upward mobility rate did not increase proportionately as the length of time increased: About 55.4 percent of the original groups remained in low income after 3 or 6 years. It seems that accumulation of market experience in Canada is a much more important factor than an individual's demographic or ethnic background in the process of income mobility.

This pattern also applied to non-whites and immigrants who did not speak either of Canada's two official languages. For instance, among low-income immigrants in 1993, their upward mobility was modest: about 14.8 percent left low income in next year. However, their upward mobility increased significantly as they gained more experience living in Canada: Nearly 30 percent left low income in 6 years. This has policy implications because this type of immigrant is not considered a benefit to the labour

market because of the language barrier and problem of credential recognition. Some people are afraid that the immobility of income among this type of immigrant may result in welfare dependency and, therefore, create financial and societal problems. The longitudinal data suggest that this problem might be mitigated as the immigrant becomes assimilated into Canadian society.

In the U.S., long-term mobility also increased for minority groups, but the improvement was rather limited. Among low-income non-whites, about 14 percent left low income the next year, while about 82 percent of the original group remained in poverty after 6 years.

Turning to high income mobility, the probability that college-educated people would drop out of the high-income bracket after 1 year was about the same (15%) for Canada and the U.S., but nearly 80 percent of the original group in the U.S. was able to remain in the high-income bracket after 6 years (compared to 72% in Canada).

2.4.4 Cross-National Comparison

Is Canada an outlier in income mobility compared to other OECD countries? Unfortunately, there is no study that can be compared directly with the study discussed in this chapter. Rather than income itself, a few international studies examine earnings mobility. For instance, OECD (1996) examined 5-year earnings mobility for all wage and salary workers for eight OECD countries (Canada not included) between 1986 and 1991, and Burkhauser, Holtz-Eakin, and Rhody (1997) compared earnings mobility in the United States and Germany during the growth years of the 1980s. In order to compare the results of these two studies to the results of the present study, a quantity (based on

household earnings) was calculated for Canada and the U.S. using definitions similar to those used in the two international studies (see Table 2.5). The focus is on 5-year earnings mobility for wage or salary workers. It is, however, still difficult to compare results across countries due to differences in the specific time period analyzed.

Fortunately, the United States appears in all these studies, and it can, therefore, be used as a benchmark. Generally, the results from this present study show that earnings mobility in the U.S. and Canada are very similar. Mobility in the U.S. does not display significant differences from other countries in other two studies; therefore, Canada might also have similar patterns of earnings mobility compared to other countries. Nevertheless, cross-national comparisons of household income mobility remain an issue for future research.

2.5 Empirical Hazards of Low-Income and High-Income Transitions

In the previous section, income mobility was measured as the probability of making income transitions between one year and the next. However, nothing is known about how the length of time being poor affects the probability of leaving poverty. Do the chances of making a transition grow or decline as the time spent in the current income state increases? What are the risks of reentering after escape? This section addresses these questions by offering empirical hazard rates of the associated transitions.

To avoid problems due to left censoring, only individuals who were observed starting a new income level during the survey period are included.²⁴ In the case of the low-income exiting rate, for example, an individual's entry into low income had to be observed over the survey period in order to be included in the calculation. Moreover,

following Jenkins (2000), small income changes around income cutoffs (e.g., earned \$1 dollar above poverty threshold) are not considered a transition.²⁵ Pre-transfer income measure was used in this analysis.

Tables 2.6 and 2.7 show Kaplan-Meier estimates of low- and high-income transition rates, respectively. People entering a new income level were assumed to remain at that level for the rest of the year because only annual data were observed; therefore, there is no hazard rate for the first year of transition. Overall, both Canada and the U.S. displayed very similar patterns in low-income exit rates. About one-third of the poor were able to escape poverty after 1 year. The exit rates then fell as time spent in low income increased, reaching about 0.14 in the fifth year of low income. One exception is Canadian immigrants whose mother tongue is one of the two official languages. Their exit rates from low income remained relatively high even after 5 years. As for poverty reentry, people with a high school diploma or less tended to have higher risks of returning to poverty, particularly in the United States: About 62 percent of this group in the U.S. fell back into poverty in the next 5 years, compared to 48 percent in Canada. The results for Canadian immigrants who do not speak either of the two official languages are somewhat counterintuitive: Their risks of reentry were relatively smaller when compared to other groups.

Information about poverty exit and reentry shows that less-educated people in both countries and non-whites in the U.S. were more likely to experience a persistence of poverty. They had lower chances of leaving poverty, while they faced relatively higher

²⁴The exclusion of left-censored samples may introduce a selection bias (Ham and LaLonde, 1996; Stevens, 1999). For example, individuals who are poor throughout the observed period are excluded from the sample. This may result in an over-estimation of exit rates from poverty.

risks of returning to poverty. Information about immigrants in Canada reveals another story. Immigrants who did not speak either of the two official languages as a mother tongue tended to remain longer in poverty, but they were less likely to fall back once they reached another income level. The possible reason is that skilled immigrants are more likely to be admitted to Canada because of the points system. Immigrants who do not know Canada's official languages but are still admitted usually possess certain skills that are needed in Canada.²⁶ These immigrants may start very slowly, but they are likely to improve their economic status as soon as their skills are transferred and utilized.

High income seems a more permanent fixture than poverty, especially in Canada. Those people who remained in the high-income bracket after 5 years were 49 percent and 40 percent for Canada and the U.S., respectively. Probabilities of exiting high income were roughly the same for college-educated people in both countries. However, high-income reentry rates were relatively greater in the U.S. among this group: About 52 percent of college graduates who left high income were able to re-attain high-income levels in the next 5 years versus only 39 percent in Canada. Although it is not certain whether highly-educated people in the U.S. were better at reentering high income or whether there was simply more demand for skilled workers in the U.S., the results do reveal a relatively better opportunity for well-educated people in the U.S. This finding could have implications for a future "brain drain" from Canada.

²⁵Following Jenkins (2000), post-transition earnings that rise (fall) by not more than 10 percent above (below) the low-income line are not considered an exit (reentry). A similar definition is used for high-income transitions.

2.6 The Correlates of Income Spell Endings and Beginnings

Often, an individual's well being changed as he or she moved into or departed from a household or as a result of an increase (or decline) in income sources from earnings of secondary family members or benefits from welfare programs. In order to examine the importance of household events (e.g., separation) as well as changes in other income sources in relation to entries into and exits from low income and high income for an individual, a decomposition approach was applied to link the occurrence of an income movement and concurrent event. The aim was to assess the roles of market conditions, family, and welfare programs on low-income (or high-income) spell beginnings or endings.

Similar to Bane and Ellwood (1986), and Jenkins (2000), we relate each spell ending or beginning to 1 of 15 mutually exclusive groups (see Figure 2.4). For each entry or exit into a particular state, it was first determined if there was a concurrent change in the head and size of the household²⁷. If there was no change in head and family size, then this was referred to as an "income event." If there was no change in head but a change in family size, two possibilities were allowed. The transition was considered an income event if change in head's earnings accounted for 50% or more of the change in household income. Otherwise, it was considered a demographic event. Similarly, if there was a change in household head, two possibilities were allowed. The transition was considered

²⁶Under Canada's points system, proficiency in official languages accounts for 15 points in the selection for skilled worker; education and occupation-specific factors account for another 34 points. The initial pass mark is 70 points. Note that the selection criteria were revised in 2002, with a shift away from a focus on occupational shortages and towards the human capital indicator of long-term earnings potential (see McHale, 2003).

a demographic event if the change in household income was largely resulted from the variation in earnings due to head changes. That is, a transition was referred to as a demographic event if the difference in earnings between the new head and the old head accounted for 50% or more of the change in household income. Otherwise, it was considered an income event.

Tables 2.8 and 2.9 display events associated with low-income phenomena. Post-transfer income measures were used in this section. Overall, the majority of low-income episodes ended or began because of an income event, particularly due to a change in household head's earnings. An increase in income from a social security pension had a substantial impact on raising senior citizens in Canadians out of poverty: About 37 percent of senior households ended their poverty spells because of an increase in social security pensions. Assets and private transfers, on the other hand, were relatively important in helping senior citizens escape poverty in the U.S. It is noteworthy that public benefits in both countries provided little support in helping single-parent households move out of poverty. Rather, about 40 percent and 30 percent of single-parent households in the U.S. and Canada, respectively, relied on their own efforts to escape poverty. However, the effect of public transfers might be understated because some of the benefits were actually embedded in the form of earnings (e.g., U.S. earned income tax credit, EITC, and the Canadian National Child Benefit Supplement²⁸) because these benefits are only available to people with earned income.

²⁷In both surveys the male partner was always identified as the household head. Notice that in the general SLID database, the household head is defined as the person with the greatest individual income (total from all sources before taxes) for the year. However, a modification to this concept has been made for the purposes of the equivalence file. In CNEF, if the major income earner is a female living with a spouse, the male partner is identified as the household head.

²⁸The Canadian National Child Tax Benefit provides a refundable tax credit to assist low-income workers.

Demographic events were more frequently observed in Canada, particularly among subgroups. In Canada, about 29 percent of single-parent households ended their poverty spells because of events associated with marriage or partnership, and about 40 percent of single-parent households began poverty spells with events related to family separation. The corresponding figures were about 18 and 31 percent in the U.S. It is also noteworthy that, in Canada, only 27 percent of low-income spell endings among single-unattached families were associated with a rise of income from own labour earnings, while about 47 percent of the spell endings among this family type were associated with a demographic event. If young adults comprised most of the population in this family type, it may suggest a great hardship faced by young Canadians who became independent. Thus how to provide immediate social assistance or how to establish an access to labour market or education may be very important.

Tables 2.10 and 2.11 show the events coinciding with high-income transitions. About 83 percent (87 percent) of high-income spell endings (beginnings) in the U.S. were associated with an income event, compared to 63 percent (78 percent) in Canada. Basically, changes in earnings were the main reason for achieving or forfeiting high-income status. However, the U.S. and Canada do exhibit quite different patterns, particularly among traditional households (couple with children). In Canada, 33 percent of high-income spell beginnings in this group were associated with a rise in secondary earnings compared to only 17 percent in the U.S. Instead, in the U.S., 53 percent of beginnings among couple/children households were the result of an increase in the household head's earnings. This suggests that double earners in a household are an

important factor in attaining high-income in Canada, while it is high-paying jobs, rather than double earners, that propel U.S. families into wealth.

2.7 Econometric Model of Income Dynamics

The above section highlights the importance of household events on the transition probabilities. However, such arithmetic is not modeling, and it does not provide a means for predicting future risks of income transitions. In this section, a discrete-time hazard model is used to incorporate these events as regressors alongside other personal and household characteristics. Estimated coefficients are also used to predict the transition probabilities.

Event variables are defined in a hierarchical fashion (see section 2.6). Each event is summarized by a binary variable that is equal to 1 in the interval the event occurred and 0 for all other intervals.²⁹ The other covariates include duration, calendar year indicators, female-head indicator, dummies for age groups, family compositions, regions, minority status, and level of education for household head (defined as the primary wage earner).³⁰ Mother tongue and immigrants status are also included as regressors in the Canadian data.

Analyses cover individuals who had fresh spells (non-left censored), and those individuals had a nonzero cross-sectional weight.³¹ Income transitions were based on the definition of pre-transfer incomes throughout this section. Pre-transfer income was used to provide a picture of income mobility prior to interventions.

²⁹By doing this, it is assumed that the effects of events are entirely contemporaneous. The impact of an event that persists over time is ignored.

³⁰In case of equal earnings within a household, the characteristics of the oldest male in the household are used.

Tables 2.12 and 2.13 show the estimated parameters for four transitions: (1) leaving low income, (2) reentering low income, (3) leaving high income, and (4) reentering high income. The predicted transition probabilities for the reference person are also provided at the bottom of the Tables. In SLID, a *reference person* was defined as an 18- to 34-year-old adult (in 1997), living in an Ontario household containing a couple with children who had not experienced any demographic events within a year and whose household head is a native-born white male with 12 years of education who speaks English as a first language. In PSID, a *reference person* was defined as an 18- to 34-year-old adult (in 1996), living in a northeastern U.S. household containing a couple with children who had not experienced any demographic events within a year and whose household head is a male with 12 years of education and does not belong to a minority group.

Basically, the econometric results echo descriptive findings from the previous sections. With respect to the role of events, marriage and household merge (e.g., two families move into one house) were found to have a strong effect on leaving poverty in both countries, while events such as divorce or newly established family (e.g., child becomes head or spouse) significantly affect the probabilities of poverty reentry. For example, compared to the reference person, the predicted poverty exit rates for Canadians (Americans) whose household underwent a marriage event were about 31 (24) percentage points higher. Events of addition or subtraction to household (other than head and spouse) exhibited mixed results. Child-birth events tended to reduce the chance of leaving poverty and increased the risks of poverty reentry in Canada, while the effects were not

³¹ Also see footnote 24 for possible bias by exclusion of left-censored samples.

significant in the U.S. data. Addition of adults to household increased the probabilities of leaving poverty in the Canadian data, while it showed an opposite effect in the U.S. data.

For high-income transitions, demographic events—despite being observed less frequently in a hierarchical fashion of spell ending and beginning (see Tables 2.10 and 2.11)—had a strong impact on the probabilities of ending or beginning a high-income spell. Generally, events such as newly established family, divorce, and household merge led to the end of a high-income spell, while marriage, household merge, and subtraction to family (needs fall) events resulted in the start of a high-income spell.

As for the role of other characteristics, both countries exhibit strong duration dependence in low income transition: The longer an individual stays in low income (non-low income), the more difficult it is for him or her to escape (reenter). Parameter estimates show that seniors, single-parent families, those less educated, and individuals in households headed by a minority or a female tended to stay longer in poverty and experienced higher risks of reentry. One exception is non-white people in Canada. They tended to stay longer in poverty; however, they were less likely to reenter poverty once they escaped it. After controlling for regions and other characteristics, the poverty exit rates for Canadians who speak French as a mother tongue was no different from their Anglophone counterparts. However, their poverty reentry rates were significantly higher. The other interesting finding is that poverty exit or reentry rates show no difference between immigrants who had little knowledge of Canada's two official language and native-born Canadians once all other observed factors were controlled.

The effect of education on an individual's transition into and out of poverty was substantial. In Canada, the predicted poverty exit rate (reentry rate) for less-educated

people was about 8.0 (5.0) percentage points lower (higher), compared to the reference person. The effect seems stronger in the United States: The predicted poverty exit and reentry rate for less-educated group was about 12.0 points lower and 7.9 points higher, respectively, compared to the reference person.

In the case of high-income transitions, the role of the covariates shows some different patterns between Canada and the U.S. First, duration dependence becomes less apparent in Canada but still shows a strong effect in the U.S. data. In the U.S., for example, the high-income exit rate was fairly high for the reference person (about 0.40), and the rate declined significantly to about 0.18 in the fourth year. Second, it is noteworthy that obtaining a college or above education is especially helpful in remaining at the high-income level, particularly in the U.S. Compared to the reference person, people with a college education in the U.S. were estimated to have about 38 percent (or 15 percentage points) lower high-income exit rates, and about 37 percent (or 7.5 percentage points) higher reentry rates. The comparable figures are about 33 and 16 percent, respectively, in Canada. This finding shows that returns to skills is more rewarding in the U.S.

2.8 Conclusion

This study used longitudinal survey data from the 1990s to look at patterns of household income mobility in Canada. The approach involved examining levels of inequality and mobility from both pre-transfer and post-transfer income measures and short-term and long-term income mobility through transition matrices and conducting a decomposition analysis to examine the relationship between income transitions and

concurrent events. Furthermore, using longitudinal survey data also revealed income mobility across different demographic groups, particularly in the areas of education and minority status. This type of information is not available in the tax data that was used in previous studies. To assess how the Canadian experience differs from other countries, similar U.S. and Canadian data were compared. Based on the 1990s' longitudinal data from Canada and the United States, six conclusions can be drawn from the results of the study discussed in this chapter:

1. There is evidence that significant household income mobility occurred in both Canada and the U.S. Although 40 percent of the population in both countries experienced low income at least once during the survey years, only 10 to 13 percent of them were in low income every year (see Figure 2.1). Mobility rates also vary across subgroups. Based on one-year transition matrices, 24 (35) percent of the Canadian (American) college graduates who were observed in poverty in year t rose above poverty line the next year. The comparable figures for people with high school or less education were about 14 and 18 for Canada and the U.S. respectively (see Figure 2.3).
2. Canada's redistributive system significantly increased income stability. Using both pre-transfer and post-transfer income measures, Canada's redistributive system significantly reduced the variations of bad or good years for an individual and greatly increased the probability of staying in the middle-income groups.

From any given year ($t-1$ to t), the chance of staying both years in either of the two extremes of income distribution was reduced from 43.5 to 23 percent when post-transfer measures were used, while the chance of staying in the same middle income group increased correspondingly (from 21%–39%). The redistributive system in the U.S. also contributes to income stability, but the effect was relatively smaller.

3. The Canadian transfer system also exhibited great impacts on income stability among subgroups. The rates of persistent poverty among less-educated people dropped from 22.4 percent to 4.7 or 6.3 percent and from 18 percent to 2.7 or 4.2 percent for immigrants who did not speak one of the two official languages (see Figure 2.2).
4. There is considerable immobility in both countries. About 65 percent (70%) of Canadians (Americans) who were in poverty at the beginning of the survey year were still in poverty after 6 years. Rates of upward mobility out of poverty were lower for less-educated (high school or less) people and for visible minorities: About 75 percent of less-educated people in both countries and 82 percent of non-whites in the U.S. who were in poverty in the first year of the survey were still in poverty 6 years later (see Figure 2.3).

5. There is little evidence that Canadian immigrants are more likely to experience higher risks of poverty persistence if they spoke non-official languages as a first language. The empirical hazard model suggests that these immigrants tended to stay slightly longer in poverty, but they were less likely to fall back once they reached higher levels of income. The parametric estimates from the econometric model show that these immigrants and native-born Canadians have the same probability of poverty leaving or reentry, given that other things were equal.
6. Household events are more relevant to the spell beginnings or endings in Canada, while income transitions in the U.S. were mostly associated with events concurrent with changes in earnings. About 43 percent of low-income spell endings among single-parent households in Canada were related to partnership or household merges, the comparable figure is about 28 percent in the U.S.

This present study complements Canadian studies that were based on tax data. Basically, evidence from both tax and survey data suggest that although many individuals experienced poverty in any given year, poverty is a temporary state.³² Given the advantages of the data, this study uncovered income dynamics across finer demographic groups, which was not possible in previous studies. This new information provides implications for developing different types of policy initiatives.

Furthermore, using comparable longitudinal data from the U.S., it was found that Canada does not appear to be an outlier in terms of income mobility in general. There are common aspects as well as differences in income dynamics between Canada and the U.S. Market source income mobility displays similar patterns across both countries, suggesting a more integrated economy between Canada and the United States. The differences, on the other hand, are likely to reflect the heterogeneity of the population as well as differences in welfare programs.

³²Finnie (2000) shows that more than one-quarter of the population experienced poverty between 1992 and 1996, but only 6 percent were poor in every year. The present study found that about 39 percent of the population experienced poverty between 1993 and 1998, while persistent poverty was about 3 percent. This study's estimates are relatively smaller. However, the use of equivalent income rather than family income and the inclusion of longer period (6 instead of 5 years) in this study are likely to result in a smaller estimate in poverty persistence.

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Table 2.1
Summary Statistics for the Household Equivalent Incomes in the 1990s*

(CPI and PPP adjusted. Currencies are expressed in 1997 U.S. dollar equivalent)

Year**	Median	Mean	Gini.	90-10 Ratio	90-50 Ratio	10-50 Ratio	% ¹ Low income	% ¹ High income	Unwgt. sample size
Pre-transfer Income									
Canada									
1993	20.591	23.286	0.42	20.4	2.18	0.11	25.6	27.1	38.811
1994	20.918	23.493	0.42	23.3	2.15	0.09	26.2	27.3	38.549
1995	21.001	23.784	0.42	23.7	2.17	0.09	25.6	27.7	37.856
1996	20.751	23.744	0.43	22.0	2.20	0.10	27.0	27.2	79.208
1997	21.114	24.331	0.43	21.9	2.21	0.10	26.2	28.1	79.218
1998	22.695	26.067	0.44	22.5	2.20	0.10	25.0	30.2	79.636
1999	22.928	26.364	0.43	18.3	2.19	0.12	24.1	31.2	78.891
United States									
1990	25.068	31.358	0.45	15.6	2.46	0.16	24.7	27.8	15.199
1991	24.149	30.175	0.45	15.2	2.45	0.16	25.3	26.9	15.173
1992	24.017	30.398	0.46	16.9	2.48	0.15	25.6	27.1	15.289
1993	24.359	30.990	0.46	18.6	2.54	0.14	25.4	29.0	14.924
1994	23.600	31.055	0.49	21.6	2.52	0.12	27.1	27.3	14.977
1995	23.653	30.876	0.47	19.4	2.56	0.13	26.8	26.5	15.548
1996	24.121	31.501	0.47	17.3	2.59	0.15	26.1	28.0	15.087
1997	23.606	30.743	0.50	62.9	2.69	0.04	29.1	28.3	11.675
Post-transfer Income									
Canada									
1993	19.436	21.616	0.29	3.86	1.84	0.48	11.3	20.2	38.811
1994	19.533	21.695	0.30	4.01	1.83	0.46	12.3	20.1	38.549
1995	19.703	21.748	0.29	3.95	1.83	0.46	12.0	20.2	37.856
1996	19.801	21.890	0.30	4.07	1.83	0.45	12.9	20.3	79.208
1997	20.012	22.288	0.30	4.17	1.88	0.45	12.4	21.3	79.218
1998	21.122	23.637	0.31	4.13	1.88	0.45	11.6	23.2	79.636
1999	21.417	23.926	0.30	4.11	1.87	0.46	10.7	24.8	78.891
United States									
1990	22.116	26.394	0.37	5.83	2.12	0.36	17.9	24.3	15.199
1991	21.479	25.442	0.36	5.60	2.07	0.37	18.5	23.0	15.173
1992	21.617	25.654	0.37	5.84	2.10	0.36	18.2	23.1	15.289
1993	21.900	25.957	0.37	5.98	2.11	0.35	18.2	24.8	14.924
1994	20.904	25.413	0.40	6.74	2.15	0.32	20.4	22.1	14.977
1995	21.045	25.504	0.38	6.09	2.16	0.35	19.7	22.3	15.548
1996	21.445	26.140	0.38	5.96	2.21	0.37	18.6	23.3	15.087
1997	21.825	26.057	0.42	10.64	2.23	0.21	22.0	25.5	11.779

*Data source: CNEF. Incomes are total household equivalent incomes, standardized through an equivalence scale to adjust household demographic components. In this context, equivalence scale is defined as the "square root of household size."

**Year in Canada refers to reference year, while year in the U.S. refers to survey year.

¹Individuals are defined as being in low income if their equivalent incomes fall below half of the national median in the first year of the analysis. Similarly, individuals are classified as being in high income if their equivalent incomes are above 1.5 times the national median in the first year of the analysis.

Table 2.2
Incidence of Low and High income, by characteristic *

	Poverty at least once (%)	Poverty in all years (%)	Poverty in all years by average income ¹ (%)	High income at least once (%)	High income in all years (%)	High income in all years by average income ¹ (%)	Unwgt. Number of obs. (n)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Pre-transfer Income</i>							
Canada	39.1	13.2	21.1	55.8	14.4	28.1	29,772
High school or less	52.0	22.4	32.7	30.4	7.3	16.4	13,876
College or more	29.4	6.7	12.8	56.8	19.5	36.8	14,768
Non-White	43.0	19.3	27.4	43.1	10.6	24.3	1,062
Native-born Canadians Anglophone	35.5	10.5	17.6	50.2	16.6	31.2	18,141
Native-born Canadians Francophone	43.6	16.5	25.8	35.7	10.5	21.0	6,459
Immigrants— Official languages	34.6	11.6	18.0	58.2	23.8	36.4	1,131
Immigrants— Nonofficial languages	44.4	18.2	26.8	41.2	11.0	25.6	1,782
United States	40.3	10.7	20.5	47.7	16.3	30.1	12,150
High school or less	54.7	17.5	31.2	30.5	5.81	14.3	6,819
College or more	22.4	2.53	7.14	67.7	29.5	49.6	4,709
Non-White	65.9	26.9	46.0	22.2	6.07	11.4	4,558
<i>Post-transfer Income</i>							
Canada	24.1	2.88	8.2	37.5	9.40	20.7	29,772
High school or less	28.1	4.75	11.3	24.3	4.62	12.1	13,876
College or more	20.6	1.46	5.92	47.1	12.8	27.0	14,768
Non-White	34.3	4.92	15.0	37.0	10.5	19.5	1,062
Native-born Canadians Anglophone	22.7	1.94	6.6	41.6	11.4	23.6	18,141
Native-born Canadians Francophone	25.7	5.10	10.6	24.6	4.5	12.7	6,459
Immigrants— Official languages	20.2	1.96	5.31	48.4	15.9	29.6	1,311
Immigrants— Nonofficial languages	24.6	2.74	10.8	38.6	9.40	19.3	1,782

Table 2.2 (Cont'd)

	Poverty at least once (%)	Poverty in all years (%)	Poverty in all years by average income ¹ (%)	High income at least once (%)	High income in all years (%)	High income in all years by average income ¹ (%)	Unwgt. Number of obs. (n)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
United States	32.8	5.73	13.6	43.1	13.6	25.3	12,150
High school or less	43.6	9.37	20.7	27.8	4.31	11.8	6,819
College or more	17.8	1.17	4.25	61.5	22.5	42.1	4,709
Non-White	60.9	18.8	36.6	19.1	4.39	8.49	4,558
<i>Post-transfer Income</i> <i>(using the same cutoffs as pre-transfer income)</i>							
Canada	26.44	3.78	9.75	32.57	7.44	17.15	29,772
High school or less	31.06	6.33	13.36	19.83	3.13	9.82	13,876
College or more	22.31	1.88	7.07	41.84	10.39	22.54	14,768
Non-White	35.62	6.88	18.76	31.74	8.80	16.25	1,062
Native-born Canadians Anglophone	24.86	2.92	7.71	36.66	8.77	19.91	18,141
Native-born Canadians Francophone	28.23	5.61	12.30	20.54	3.39	10.11	6,459
Immigrants— Official languages	22.37	2.97	6.50	43.06	15.14	24.47	1,131
Immigrants— Nonofficial languages	25.97	4.19	13.66	33.74	7.35	16.26	1,782
United States	38.09	7.89	17.54	34.90	8.24	18.64	12,150
High school or less	50.03	12.60	26.15	20.13	2.14	8.13	6,819
College or more	21.75	2.07	6.31	52.69	15.93	31.83	4,709
Non-White	66.22	23.81	43.36	14.60	2.68	6.25	4,558

*CNEF subsample for individuals presented in all 6 years period (1993–1998 for Canada, and 1991–1996 for U.S.). The last year of longitudinal weights are used to take into account the problem of panel attrition. Subgroups are divided by characteristics of household head.

¹Based on average incomes, people are considered always in poverty (wealth) if their sum of equivalent incomes across all years is less (greater) than the sum of the low (high) income threshold across all years.

Table 2.3.1**Distribution of Income among Longitudinal Sample (Annual Average)***

Distribution of income among Longitudinal Sample (Annual Average)							
	% in each income category relative to fixed median cutoff						
	< 0.5	0.5 ~ 0.75	0.75 ~ 1.0	1.0 ~ 1.25	1.25 ~ 1.5	> 1.5	Total
Canada							
Pre-transfer income	24.42	11.42	12.65	12.65	10.63	28.24	100
Post-transfer income	12.85	19.93	20.73	17.43	11.85	17.20	100
USA							
Pre-transfer income	23.93	11.91	13.11	11.35	9.30	30.38	100
Post-transfer income	20.73	17.96	17.72	14.08	10.07	19.44	100

One-Year Transition Rates (Annual Average)*

Outflow rates (%) from year $t-1$ to year t							
	< 0.5	0.5 ~ 0.75	0.75 ~ 1.0	1.0 ~ 1.25	1.25 ~ 1.5	> 1.5	
Pre-transfer Income							
Canada							
< 0.5	82.0	10.7	3.6	1.7	1.0	1.1	
0.5 ~ 0.75	19.7	46.6	21.8	7.3	2.3	2.3	
0.75 ~ 1.00	6.9	14.8	45.9	21.6	6.2	4.7	
1.00 ~ 1.25	3.8	4.8	15.3	45.0	22.0	9.1	
1.25 ~ 1.50	2.6	3.3	6.0	16.9	41.0	30.2	
> 1.50	1.4	1.4	2.2	3.8	7.6	83.5	
USA							
< 0.5	77.5	12.7	4.8	1.9	1.0	2.1	
0.5 ~ 0.75	24.6	42.3	21.0	6.1	2.8	3.1	
0.75 ~ 1.00	9.5	16.1	42.7	19.6	6.1	5.9	
1.00 ~ 1.25	5.7	7.5	19.6	38.0	18.3	11.0	
1.25 ~ 1.50	3.9	3.4	6.3	19.3	36.7	30.5	
> 1.50	2.3	1.5	2.8	4.2	8.0	81.4	
Post-transfer Income							
(using the same cutoffs as pre-transfer income)							
Canada							
< 0.5	69.55	20.57	5.42	2.21	1.18	1.07	
0.5 ~ 0.75	12.00	63.28	18.87	3.79	1.12	0.94	
0.75 ~ 1.00	3.88	14.62	56.02	20.09	3.59	1.80	
1.00 ~ 1.25	1.95	3.99	17.08	52.77	19.24	4.97	
1.25 ~ 1.50	1.30	2.90	5.49	19.11	46.37	24.84	
> 1.50	1.34	1.32	2.54	4.46	11.50	78.83	
USA							
< 0.5	73.49	17.59	5.17	1.76	0.85	1.14	
0.5 ~ 0.75	19.39	52.45	20.37	4.54	1.84	1.41	
0.75 ~ 1.00	6.73	19.02	47.89	18.16	4.56	3.64	
1.00 ~ 1.25	3.51	6.46	19.95	45.04	16.90	8.14	
1.25 ~ 1.50	2.59	3.15	8.73	19.91	38.48	27.14	
> 1.50	1.66	1.50	3.45	5.86	12.53	74.99	

*Data source: CNEF subsample for individuals presented in all 6 years period (1993–1998 for Canada and 1991–1996 for USA). There are 29,772 longitudinal samples from SLID and 12,150 from PSID. People are classified into income groups according to the size of their income relative to fixed real income cut-offs equal to 0.5, 0.75, 1.0, 1.25, and 1.5 times median year 1 income.

Table 2.3.2
Income Mobility by Characteristics* (Annual Average)

	From year $t-1$ to year t , percent (%) of individuals				
	Spent both years in poverty or high income	Stayed in the same income group (not the two ends)	moved into neighboring income group	moved over 2 + income groups	Total
<i>Pre-transfer Income</i>					
Canada	43.49	21.26	23.82	11.42	100
HS or less	44.75	21.69	23.41	10.13	100
College or more	42.74	21.06	24.04	12.16	100
Non-White	45.68	19.88	22.76	11.68	100
Native-born Canadians					
Anglophone	43.33	21.25	23.56	11.85	100
Francophone	41.53	23.81	24.33	10.34	100
Immigrants—OL ¹	50.02	20.21	19.77	10.00	100
—NOL	45.83	17.72	25.48	10.97	100
United States	42.92	18.70	24.50	13.89	100
HS or less	39.16	20.78	26.26	13.81	100
College or more	47.56	16.86	22.56	13.02	100
Non-White	50.07	16.50	22.20	11.25	100
<i>Post-transfer Income</i>					
<i>(using the same cutoffs as pre-transfer income)</i>					
Canada	22.79	38.69	29.44	9.08	100
HS or less	19.92	43.94	28.43	7.72	100
College or more	24.78	35.21	30.19	9.82	100
Non-White	30.49	30.86	30.07	8.59	100
Native-born Canadians					
Anglophone	23.40	37.36	29.38	9.87	100
Francophone	18.68	45.21	28.82	7.30	100
Immigrants—OL ¹	28.39	37.54	25.45	8.63	100
—NOL	25.09	35.10	31.88	7.95	100
United States	26.67	28.20	29.80	12.33	100
HS or less	28.24	29.55	30.34	11.88	100
College or more	31.17	27.33	29.17	12.32	100
Non-White	42.08	21.73	26.58	9.59	100

Data source: CNEF subsample for individuals presented in all 6 years period (1993–1998 for Canada and 1991–1996 for USA). There are 29,772 longitudinal samples from SLID and 12,150 from PSID. People are classified into income groups according to the size of their income relative to fixed real income cut-offs equal to 0.5, 0.75, 1.0, 1.25, and 1.5 times median year 1 income.

*Characteristics of household head (defined as major income earner).

¹OL: Speak official languages as mother tongue; NOL: Speak nonofficial languages as mother tongue.

Table 2.4
Probability of Moving Out of the Low- and High-Income Group^{*}, by
Characteristics^{}**

	1-year mobility		3-year mobility		6-year mobility	
	Moving up from poverty	Moving down from high income	Moving up from poverty	Moving down from high income	Moving up from poverty	Moving down from high income
<i>Pre-transfer Income</i>						
Canada	18.0	16.5	27.6	26.0	35.8	29.8
HS or less	14.0	20.0	20.0	31.6	24.4	35.9
College or more	24.0	15.1	37.6	23.8	48.3	27.6
Non-White	14.2	19.4	22.7	33.9	32.6	38.6
Native-born Canadians						
Anglophone	20.5	16.1	31.6	25.0	39.8	28.3
Francophone	15.5	16.8	24.0	27.1	26.8	33.0
Immigrants—OL ¹	21.8	13.2	30.8	21.1	34.9	24.2
—NOL	14.8	16.5	22.4	26.2	29.6	33.6
United States	22.5	18.6	27.7	26.3	29.7	27.3
HS or less	18.2	29.0	22.2	41.5	24.5	44.2
College or more	35.2	14.3	44.6	19.8	44.5	20.7
Non-White	13.8	23.0	16.3	33.6	17.9	36.0

Data source: CNEF subsample for individuals presented in all 6 years period (1993–1998 for Canada and 1991–1996 for USA). There are 29,772 longitudinal samples from SLID and 12,150 from PSID.

*An individual is classified in the low- (high-) income group if his or her equivalent income was less (greater) than 0.5 (1.5) of the median.

**Characteristics of household head (defined as major income earner).

¹OL: Speak official languages as mother tongue; NOL: Speak non-official languages as mother tongue.

Table 2.5
Five-year Earnings Mobility for Wage/Salary Workers, Cross-National Comparison

(Sample: Wage/Salary workers in both survey years)

	Transitions among quintiles				
	Year	Average quintile move	Stayed in the same quintile (%)	Move one quintile (%)	Move 2 or more quintiles (%)
	(1)	(2)	(3)	(4)	(5)
<i>OECD (1996)</i>¹					
Denmark	1986-1991	0.812	46.2	34.8	19.0
Finland	1985-1990	0.891	44.1	34.4	21.5
France	1986-1991	0.683	53.0	32.4	14.6
Germany	1986-1991	0.647	52.3	35.3	12.4
Italy	1986-1991	0.685	50.3	35.4	8.5
Sweden	1986-1991	0.684	50.5	36.1	13.4
United Kingdom	1986-1991	0.660	51.4	35.4	13.2
United States	1986-1991	0.758	47.2	36.4	16.4
<i>Burkhauser et al. (1997)</i>²					
United States	1982-1988	-	55.2	43.3	21.9
Germany	1983-1988	-	56.1	42.2	22.1
<i>Results in this study</i>					
United States	1991-1995	0.626	55.4	31.8	12.8
United States	1992-1996	0.645	54.2	32.3	13.5
Canada	1993-1994	0.637	54.4	32.5	13.1
Canada	1994-1998	0.650	53.8	32.9	13.3

¹Source: Table 3.6 (OECD, 1996)

²Source: Table 2 (Burkhauser, Holtz-Eakin, and Rhody, 1997). Notice that columns (3) to (5) do not sum to 100 (see their text for explanation).

Table 2.6
Kaplan-Meier Estimates of Low Income Transitions

Exiting from Low Income¹

Number of years since start of low- income spell	Cumulative percentage remaining in low income (%) (Annual exit rate from low income)							
	Canada							
	<i>All</i>	High school or less	College or more	Non- Whites	Native-born Canadians		Immigrants	
					Anglo phone	Franco phone	Official lang.	Non- official lang.
1	100	100	100	100	100	100	100	100
2	66.5 (.335)	70.9 (.291)	61.3 (.387)	75.4 (.246)	65.5 (.345)	67.1 (.328)	61.4 (.386)	71.4 (.286)
3	50.7 (.237)	58.0 (.182)	42.3 (.310)	46.2 (.387)	49.9 (.238)	51.2 (.237)	44.8 (.270)	51.5 (.279)
4	40.3 (.206)	49.1 (.153)	29.8 (.296)	33.4 (.277)	39.1 (.217)	42.3 (.175)	31.7 (.293)	40.1 (.222)
5	34.5 (.141)	41.7 (.152)	26.1 (.123)	31.7 (.050)	33.2 (.150)	36.9 (.128)	21.1 (.333)	36.2 (.095)
Spells	19,943	10,887	8,095	777	11,799	4,121	724	1,315
Unweighted individuals	9,069	4,831	3,770	343	5,323	1,852	323	590

Number of years since start of low- income spell	Cumulative percentage remaining in low income (%) (Annual exit rate from low income)			
	United States			
	<i>All</i>	High school or less	College or more	Non- Whites
1	100	100	100	100
2	65.4 (.345)	70.2 (.298)	55.9 (.441)	72.2 (.278)
3	50.3 (.232)	56.1 (.201)	40.2 (.282)	57.8 (.200)
4	40.3 (.199)	45.9 (.182)	29.7 (.260)	48.4 (.162)
5	35.4 (.145)	40.8 (.110)	25.5 (.143)	42.6 (.121)
6	30.3 (.120)	34.0 (.167)	22.3 (.100)	38.5 (.095)
Spells	9,993	6,815	2,532	4,893
Unweighted individuals	3,769	2,508	1,015	1,766

¹ Kaplan-Meier estimates are based on all non-left censored low-income spells. All people starting a low-income spell are assumed to last at least 1 year. Post-transition earnings that rose to not more than 10% above low-income line are not considered an exit.

Table 2.6 (Cont'd)

Reentering into Low Income¹

Number of years since start of non-low-income spell	Cumulative percentage remaining in non-low income (%) (Annual reentry rate to low income)							
	Canada							
	<i>All</i>	High school or less	College or more	Non-Whites	Native-born Canadians		Immigrants	
					Anglo phone	Franco phone	Official lang.	Non-official lang.
1	100	100	100	100	100	100	100	100
2	81.5 (.185)	77.6 (.224)	85.0 (.150)	92.6 (.074)	81.6 (.184)	80.3 (.197)	84.2 (.158)	86.1 (.139)
3	72.0 (.117)	66.4 (.144)	77.2 (.092)	80.1 (.127)	72.7 (.108)	70.5 (.121)	71.5 (.150)	76.7 (.110)
4	63.5 (.118)	56.6 (.148)	70.2 (.091)	70.8 (.125)	64.4 (.114)	62.2 (.118)	60.2 (.158)	71.5 (.068)
5	59.7 (.060)	52.0 (.081)	67.5 (.039)	- -	60.1 (.068)	59.0 (.053)	- -	- -
Spells	22,623	11,295	10,019	1,062	13,620	4,812	801	1,479
Unweighted individuals	10,090	4,958	4,437	518	6,012	2,091	356	686

Number of years since start of non-low-income spell	Cumulative percentage remaining in non-low income (%) (Annual reentry rate to low income)			
	United States			
	<i>All</i>	High school or less	College or more	Non-Whites
1	100	100	100	100
2	70.7 (.293)	67.1 (.329)	79.1 (.209)	63.8 (.367)
3	57.4 (.188)	52.8 (.216)	67.2 (.150)	47.3 (.259)
4	47.9 (.166)	43.9 (.169)	55.5 (.174)	38.0 (.196)
5	41.0 (.143)	38.0 (.134)	46.0 (.171)	31.5 (.172)
6	37.2 (.094)	34.3 (.098)	42.6 (.073)	27.0 (.143)
Spells	9,183	5,700	2,738	4,193
Unweighted individuals	3,494	2,173	963	1,653

¹Kaplan-Meier estimates are based on all non-left censored low-income spells. All people starting a non-low-income spell are assumed to last at least 1 year. Post-transition earnings that fell to not more than 10% below low-income line are not considered a reentry.

Table 2.7
Kaplan-Meier Estimates of High-Income Transitions

Exiting from High-Income¹

Number of years since start of high- income spell	Cumulative percentage remaining in high income (%) (Annual exit rate from high income)							
	Canada							
	<i>All</i>	High school or less	College or more	Non- Whites	Native-born Canadians		Immigrants	
					Anglo phone	Franco phone	Official lang.	Non- official lang.
1	100	100	100	100	100	100	100	100
2	77.1 (.229)	73.2 (.268)	79.4 (.206)	85.6 (.144)	77.1 (.229)	80.0 (.203)	81.8 (.182)	80.9 (.191)
3	63.7 (.175)	57.4 (.216)	66.6 (.161)	62.8 (.266)	63.4 (.177)	66.5 (.166)	69.6 (.149)	65.0 (.197)
4	55.6 (.127)	47.0 (.180)	60.1 (.091)	60.1 (.031)	55.5 (.124)	58.5 (.119)	67.5 (.029)	60.3 (.071)
5	48.6 (.125)	37.5 (.204)	54.9 (.094)	50.7 (.167)	50.0 (.100)	50.1 (.133)	60.0 (.111)	34.5 (.429)
Spells	16,420	5,317	9,975	683	10,600	2,692	664	1,020
Unweighted individuals	7,868	2,528	4,726	330	4,946	1,308	351	507

Number of years since start of high- income spell	Cumulative percentage remaining in high income (%) (Annual exit rate from high income)			
	United States			
	<i>All</i>	High school or less	College or more	Non- Whites
1	100	100	100	100
2	65.2 (.349)	51.8 (.482)	74.6 (.254)	57.5 (.425)
3	53.4 (.180)	36.4 (.297)	65.3 (.125)	47.0 (.183)
4	45.8 (.143)	27.8 (.237)	58.0 (.112)	38.8 (.174)
5	39.7 (.133)	22.0 (.208)	51.9 (.105)	35.1 (.096)
6	34.6 (.128)	18.7 (.150)	45.9 (.115)	33.1 (.056)
Spells	6,017	2,073	3,653	1,128
Unweighted individuals	2,310	866	1,287	473

¹Kaplan-Meier estimates are based on all non-left censored high-income spells. All people starting a high-income spell are assumed to last at least 1 year. Post-transition earnings that fell to not more than 10% below high-income line are not considered an exit.

Table 2.7 (Cont'd)

Reentering into High-Income¹

Number of years since start of non high-income spell	Cumulative percentage remaining in non-high income (%) (Annual reentry rate to high income)							
	Canada							
	<i>All</i>	High school or less	College or more	Non-Whites	Native-born Canadians		Immigrants	
					Anglo phone	Franco phone	Official lang.	Non-official lang.
1	100	100	100	100	100	100	100	100
2	85.0 (.185)	88.0 (.120)	83.8 (.162)	83.7 (.163)	85.2 (.148)	86.8 (.162)	75.0 (.250)	84.2 (.158)
3	74.9 (.117)	77.7 (.117)	73.8 (.120)	78.2 (.066)	74.8 (.122)	78.5 (.162)	62.4 (.168)	76.1 (.096)
4	69.1 (.118)	72.6 (.066)	68.1 (.077)	74.6 (.045)	69.2 (.075)	74.6 (.162)	-	67.5 (.116)
5	62.9 (.06)	67.4 (.071)	61.0 (.105)	59.4 (.204)	62.5 (.097)	70.8 (.162)	56.5 (.094)	55.9 (.171)
Spells	16,298	5,679	9,975	690	10,596	2,466	641	1,072
Unweighted individuals	6,984	2,467	4,726	268	4,466	1,088	288	438

Number of years since start of non high-income spell	Cumulative percentage remaining in non-high income (%) (Annual reentry rate to high income)			
	United States			
	<i>All</i>	High school or less	College or more	Non-Whites
1	100	100	100	100
2	82.8 (.172)	87.8 (.122)	78.5 (.215)	89.7 (.103)
3	70.9 (.144)	78.3 (.108)	64.9 (.174)	81.1 (.096)
4	63.1 (.110)	70.0 (.106)	57.8 (.109)	71.0 (.124)
5	55.0 (.129)	64.3 (.081)	48.1 (.168)	62.8 (.115)
6	53.2 (.032)	63.1 (.019)	45.4 (.057)	61.9 (.014)
Spells	6,682	3,086	3,300	1,549
Unweighted individuals	2,316	1,042	1,170	498

¹Kaplan-Meier estimates are based on all non-left censored high-income spells. All people starting a non-high income spell are assumed to last at least 1 year. Post-transition earnings that rose to not more than 10% above high-income line are not considered a reentry.

Table 2.8

Low Income Spell Ending Types, by Person's Household Type in the Last Year of Low-Income Spell, Canada (1993-1999) and United States (1990-1996)

Main event associated with spell ending	Canada						United States					
	Age 60			Age < 60			Age 60			Age < 60		
	All people	Single	Couple no kids	Couple w/kids	Single parent	All people	Single	Couple no kids	Couple w/kids	Single parent	Single parent	Single parent
<i>Rise of income from:</i>	(73.1)					(79.1)						
Head's labour income	38.9	27.4	49.4	55.0	30.5	44.1	50.6	55.4	52.0	40.1		
Partner's labour income	9.2	3.2	16.8	15.9	2.1*	15.2	10.9	26.9	24.4	4.9		
Other labour income	5.3	7.0	1.1*	4.5	5.7	3.8	1.6*	-	1.9	6.2		
Asset income	2.3	2.0	0.8*	2.0	1.0*	3.2	2.2*	1.9*	2.2	1.7*		
Private transfers ¹	4.0	4.8	3.9*	2.0	3.6	6.7	4.6	6.3*	3.5	7.2		
Public transfers ²	6.8	5.0	10.3	7.0	7.9	1.9	1.2*	2.2*	2.3	1.5*		
Social security pension ³	5.8	3.3	3.3*	0.9	0.9*	4.0	3.6	3.2*	1.2*	2.8		
Taxes fall	0.8	0.1*	1.9*	0.8	0.2*	0.1*	0.3*	-	0.1*	-		
<i>Demographic event:</i>	(26.9)					(20.9)						
Newly established family ⁴	2.2	4.6	-	1.0	2.1	2.5	6.3	-	0.7*	3.6		
Separation/divorce	0.3*	-	0.8*	0.5*	0.2*	0.6	-	0.6*	1.0*	0.2*		
Partnership/marriage	6.9	7.3	-	-	28.5	5.7	7.3	-	-	17.7		
Household merge ⁵	12.8	26.3	6.1	7.1	14.2	6.5	3.6	1.0*	5.0	10.6		
Addition to family (child)	1.0	-	3.6*	1.5	-	1.0	-	1.3*	2.0	-		
(non-child)	2.3	8.0	0.8*	-	1.8	1.7	5.7	0.6*	-	2.0		
Needs fall ⁶	1.5	0.9*	1.0*	1.9	1.3	2.9	2.0*	0.6*	3.6	1.5*		
Others	0.02*	-	0.1*	-	-	0.02*	-	-	0.04*	-		
Number of spell endings	9,495	1,106	2,085	3,818	1,748	5,809	860	316	2,435	1,518		

*Estimates based on less than 30 observations; - No observation. Note: Analysis based on all people with low-income spell ending observed in CNEF regardless of left censoring. Post-transition earnings that rise to not more than 10% above low-income line are not considered an ending.

¹Private transfers include non-government pensions, alimony, child support, and income from non-household members.

²Public transfers in SLID include child tax benefit, UI, WC, SA, OAS, GIS, and tax credits. In PSID, public transfers contain AFDC payment, SSI, UI, WC, other welfare income, and the face value of food stamps (see also footnote 4).

³Social security pensions in SLID are CPP and QPP. In PSID, they are old age security, disability allowance, and widowed mother's allowance.

⁴Examples are child became head/spouse or split-off household.

⁵Examples include adult head/spouse return to parent home, or non-head/spouse individuals move to other household.

⁶It is due to a reduction in household size.

Table 2.9

Low Income Spell Beginning Types, by Person's Household Type in the First Year of Low-Income Spell, Canada (1993–1999) and United States (1990–1996)

Main event associated with spell beginning	United States									
	Canada					Age < 60				
	All people	Age 60 +	Single	Couple no kids	Couple w/kids	All people	Age 60 +	Single	Couple no kids	Couple w/kids
<i>Fall of income from:</i>	(62.9)					(73.5)				
Head's labour income	29.6	22.6	15.9	35.4	49.5	39.9	14.2	47.9	45.0	55.6
Partner's labour income	6.7	7.2	3.6	14.4	9.3	9.0	4.4	0.7*	24.2	16.6
Other labour income	2.7	4.0	4.1	1.8*	2.1	7.4	18.3	4.4	4.7*	3.4
Asset income	2.2	7.6	0.9*	1.9*	2.4	4.4	13.2	2.7*	2.3*	3.7
Private transfers ¹	4.2	8.0	3.9	5.7	3.5	4.8	12.9	4.9	6.4*	2.1
Public transfers ²	12.6	11.1	10.6	11.3	14.0	3.5	4.8	4.2	3.7*	3.5
Social security pension ³	3.6	16.2	4.4	1.4*	0.5*	4.3	15.5	2.7*	1.7*	1.5*
Taxes rise	1.3	3.8	0.4*	1.6*	1.8	0.1*	0.1*	0.5*	-	-
										0.1*
<i>Demographic event:</i>	(37.1)					(26.5)				
Newly established family ⁴	14.8	7.2	37.7	15.5	2.8	4.2	0.5*	14.8	3.7*	2.1
Separation/divorce	8.6	0.5*	4.6	-	-	8.9	0.5*	4.6	-	-
Partnership/marriage	0.3*	0.3*	-	0.3*	0.4*	0.5	0.2*	-	2.4*	0.8*
Household merge ⁵	7.4	6.4	8.0	0.7*	6.9	6.8	6.0	4.6	2.0*	5.4
Subtraction to family	4.4	4.0	5.9	9.5	3.1	2.9	6.6	5.0	2.4*	1.3*
Needs rise ⁶	1.7	1.3*	0.04*	0.5*	3.9	3.2	2.9*	3.0*	1.7*	4.2
Others	0.01*	-	-	0.1*	-	-	-	-	-	-
Number of spell beginnings	8,283	881	2,378	737	2,811	5,538	957	856	298	1,991
										1,436

*Estimates based on less than 30 observations: - No observation. Note: Analysis based on all persons with low-income spell beginning observed in CNEF regardless of left censoring. Post-transition earnings that fall to not more than 10% below low-income line are not considered a beginning.

¹Private transfers include non-government pensions, alimony, child support and income from non-household members.

²Public transfers in SLID include Child tax benefit, UI, W/C, SA, OAS, GIS and tax credits; In PSID public transfers contain AFDC payment, SSI, UI, W/C, other welfare income, and the face value of food stamps (see also footnote 4).

³Social security pensions in SLID are CPP and QPP. In PSID, they are old age security, disability allowance, and widowed mother's allowance.

⁴Examples are child became head/spouse or split-off household.

⁵Examples include adult head/spouse return to parent home, or non-head/spouse individuals move to other household.

⁶It is due to an addition in household size.

Table 2.10

High Income Spell Ending Types, by Person's Household Type in the Last Year of High-Income Spell, Canada (1993-1999) and United States (1990-1996)

Main event associated with spell ending	Canada										United States				
	All					Age < 60					Age < 60				
	people	Age 60 +	Single	Couple no kids	Couple w/kids	Single parent	Single parent	All people	Age 60 +	Single no kids	Couple no kids	Couple w/kids	Single parent	Single parent	Single parent
<i>Fall of income from:</i>	(63.0)							(82.8)							
Head's labour income	27.4	31.3	22.9	35.3	25.2	14.2*	41.3	23.6	53.3	48.1	46.1	17.5*	-	-	-
Partner's labour income	12.6	9.2	-	19.9	14.9	-	11.8	6.8	-	19.2	14.0	-	-	-	-
Other labour income	5.5	6.6	14.1	1.9*	3.7	17.5	8.0	15.9	13.8*	0.4*	5.3	25.4*	-	-	-
Asset income	3.6	9.2	1.5*	3.2	2.8	4.4*	10.0	22.5	7.1*	4.3*	7.6	6.1*	-	-	-
Private transfers ¹	10.0	20.5	3.6	10.9	8.5	10.9*	8.9	19.1	7.1*	6.4*	5.7	13.2*	-	-	-
Public transfers ²	1.8	3.4*	1.5*	2.2*	1.2	2.7*	0.9*	1.2*	1.4*	0.8*	0.5*	4.4*	-	-	-
Social security pension ³	-	0.1*	-	-	-	-	1.4	3.6*	0.9*	1.3*	0.7*	1.8*	-	-	-
Taxes rise	2.0	4.2	1.5*	1.4*	2.0	-	0.4*	-	1.9*	0.4*	0.4*	-	-	-	-
<i>Demographic event:</i>	(37.0)							(17.2)							
Newly established family ⁴	13.5	3.3	25.5	1.8*	17.1	22.4	3.9	1.7*	1.9*	0.8*	5.3	13.2*	-	-	-
Separation/divorce	3.5	1.1*	-	4.7	4.6	1.6*	1.7	0.2*	-	3.0*	2.1	0.9*	-	-	-
Partnership/marriage	0.1*	-	0.9*	-	-	0.6*	0.1*	-	0.5*	-	-	0.9*	-	-	-
Household merge ⁵	8.7	3.3	17.0	1.5*	10.2	18.6	3.6	1.0*	1.4*	0.2*	5.6	7.9*	-	-	-
Subtraction to family	5.4	6.9	6.8	2.8	5.6	6.1*	3.1	3.1*	1.4*	3.0*	3.2	6.1*	-	-	-
Needs rise ⁶	5.7	1.0*	4.7	14.2	4.2	1.1*	4.8	1.4*	9.1*	12.1	3.5	2.6*	-	-	-
Others	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of spell endings	6,280	841	866	1,246	3,144	183	2,953	586	210	470	1,573	114	-	-	-

*Estimates based on less than 30 observations; - No observation. Note: Analysis based on all people with high-income spell ending observed in CNEF regardless of left censoring. Post-transition earnings that fall to not more than 10% below high-income line are not considered an ending.

¹Private transfers include non-government pensions, alimony, child support and income from non-household members.

²Public transfers in SLID include Child tax benefit, UI, WC, SA, OAS, GIS and tax credits; In PSID public transfers contain AFDC payment, SSI, UI, WC, other welfare income, and the face value of food stamps (see also footnote 4).

³Social security pensions in SLID are CPP and QPP. In PSID, they are old age security, disability allowance, and widowed mother's allowance.

⁴Examples are child became head/spouse or split-off household.

⁵Examples include adult head/spouse return to parent home, or non-head/spouse individuals move to other household.

⁶It is due to an addition in household size.

Table 2.11

High Income Spell Beginning Types, by Person's Household Type in the First Year of High-Income Spell, Canada (1993-1999) and United States (1990-1996)

Main event associated with spell beginning	Canada						United States					
	All people			Age < 60			Age 60 +			Age < 60		
	people	Age 60 +	Single	Couple no kids	Couple w/kids	Single parent	people	Age 60 +	Single	Couple no kids	Couple w/kids	Single parent
<i>Rise of income from:</i>	(78.3)						(87.3)					
Head's labour income	32.8	18.1	27.8	37.7	35.7	20.3	45.1	21.4	57.7	35.5	53.2	36.0
Partner's labour income	15.0	6.5	-	26.6	17.7	-	15.2	5.2*	-	31.5	14.9	-
Other labour income	12.5	9.7	14.1	1.1*	15.7	22.0	3.2	5.9*	3.5*	0.5*	2.8	12.8*
Asset income	4.5	17.4	1.7*	3.3	3.5	5.3*	9.6	22.7	5.7*	5.9	8.4	9.6*
Private transfers ¹	9.1	29.9	4.7	5.6	8.0	12.3*	11.9	26.6	11.9*	7.1	9.1	24.8
Public transfers ²	1.6	3.6*	1.2*	0.7*	1.7	1.3*	0.7*	0.2*	2.6*	0.7*	0.2*	4.0*
Social security pension ³	0.3*	2.0*	0.3*	0.3*	-	-	1.4	8.4	-	1.1*	-	2.4*
Taxes fall	2.5	2.9*	2.1*	1.1*	3.0	1.8*	0.2*	1.0*	0.4*	-	-	-
<i>Demographic event:</i>	(21.7)						(12.7)					
Newly established family ⁴	1.6	0.4*	5.5	2.0*	0.6*	1.8*	1.2	0.3*	1.8*	3.1*	0.7*	1.6*
Separation/divorce	0.1*	-	0.1*	0.1*	-	1.8*	0.1*	0.7*	0.4*	-	-	-
Partnership/marriage	2.1	-	-	6.2	1.9	-	2.8	1.2*	-	5.3	2.7	1.6*
Household merge ⁵	10.4	2.6*	30.9	2.5	7.6	25.1	2.9	1.7*	2.6*	0.3*	3.9	4.8*
Addition to family (Child)	1.3	1.2*	-	-	2.2	-	0.4*	-	-	-	0.8*	-
(Non-child)	2.2	0.9*	4.7	6.0	0.2*	5.3*	1.0	0.7*	3.1*	2.1*	0.5*	-
Needs fall ⁶	4.0	4.8	7.0	6.7	2.2	3.1*	4.3	3.9*	10.1*	6.9	2.7	2.4*
Others	0.1*	-	-	0.2*	0.1*	-	-	-	-	-	-	-
Number of spell beginnings	7,515	664	1,162	1,321	4,141	227	3,475	480	269	704	1,964	130

*Estimates based on less than 30 observations; - No observation. Note: Analysis based on all people with high-income spell beginning observed in CNEF regardless of left censoring. Post-transition earnings that rise to not more than 10% above high-income line are not considered a beginning.

¹Private transfers include non-government pensions, alimony, child support and income from non-household members.

²Public transfers in SLID include Child tax benefit, UI, WC, SA, OAS, GIS and tax credits; In PSID public transfers contain AFDC payment, SSI, UI, WC, other welfare income, and the face value of food stamps (see also footnote 4).

³Social security pensions in SLID are CPP and QPP. In PSID, they are old age security, disability allowance, and widowed mother's allowance.

⁴Examples are child became head/spouse or split-off household.

⁵Examples include adult head/spouse return to parent home, or non-head/spouse individuals move to other household.

⁶It is due to a reduction in household size.

Table 2.12
Coefficients of Hazard Model, Canada (1993–1998)

	Probability of low income		Probability of high income	
	Leaving (1)	Reentry (2)	Leaving (3)	Reentry (4)
Duration (year=1)				
2	-.151*	-.316*	.021	-.092*
3	-.388*	-.370*	-.080	-.185*
4	-.482*	-.383*	-.116	-.033
Year (base=1997)				
Age group (18-34)				
< 6	-.041	.202*	.161*	.119
6-17	-.061	.188*	.037	.003
35-64	-.134*	.114*	-.001	.050
65 +	-.576*	.401*	.312*	-.154*
Family Structure (Couple w/kids)				
Single	-.286*	.150*	.264*	-.393*
Single-parent	-.544*	.309*	.622*	-.562*
Couple w/o kids	-.110*	.084**	.127*	-.251*
Regions (Ontario)				
Atlantic	-.133*	.142*	.444*	-.063
Quebec	-.116**	-.009	.096	.041
Prairie	.088*	.096*	.068**	.052
B.C.	.030	.076	.043	.135*
Female-head	-.280*	.231*	.450*	-.357*
Non-white-head	-.272*	-.245*	-.332*	-.108
Mother tongue (English)				
French	.092	.141*	-.078	-.017
Others	-.020	.249*	.011	.017
Ethnic Origin-head (Native)				
Immigrant-official languages	.261*	-.065	-.221*	.281*
Immigrant-non-official lang.	.066	-.112	.080	-.060
Education-head (High School)				
Less than HS	-.208*	.250*	.037	.004
More than HS	.109*	-.159*	-.196*	.119*
<i>Binary Event variables</i>				
Newly established family	.070	.985*	1.53*	.020
Separation/Divorce	.033	1.07*	1.61*	-.178
Partnership/Marriage	.838*	-.445	-.633	.670*
Household merge	1.17*	.124	.769*	.955*
Addition to family (Child)	-.920*	.420*	.408*	-.1.11*
(Non-child)	.464*	-.009	.550*	.318*
Subtraction to family	.255*	.188*	.156*	.364*
Constant	-.164*	-1.343*	-1.439*	-.847*
Log Likelihood	-5204.51	-4454.14	-4167.66	-3697.79
Predicted transition rate for Reference person	0.435	0.090	0.075	0.198

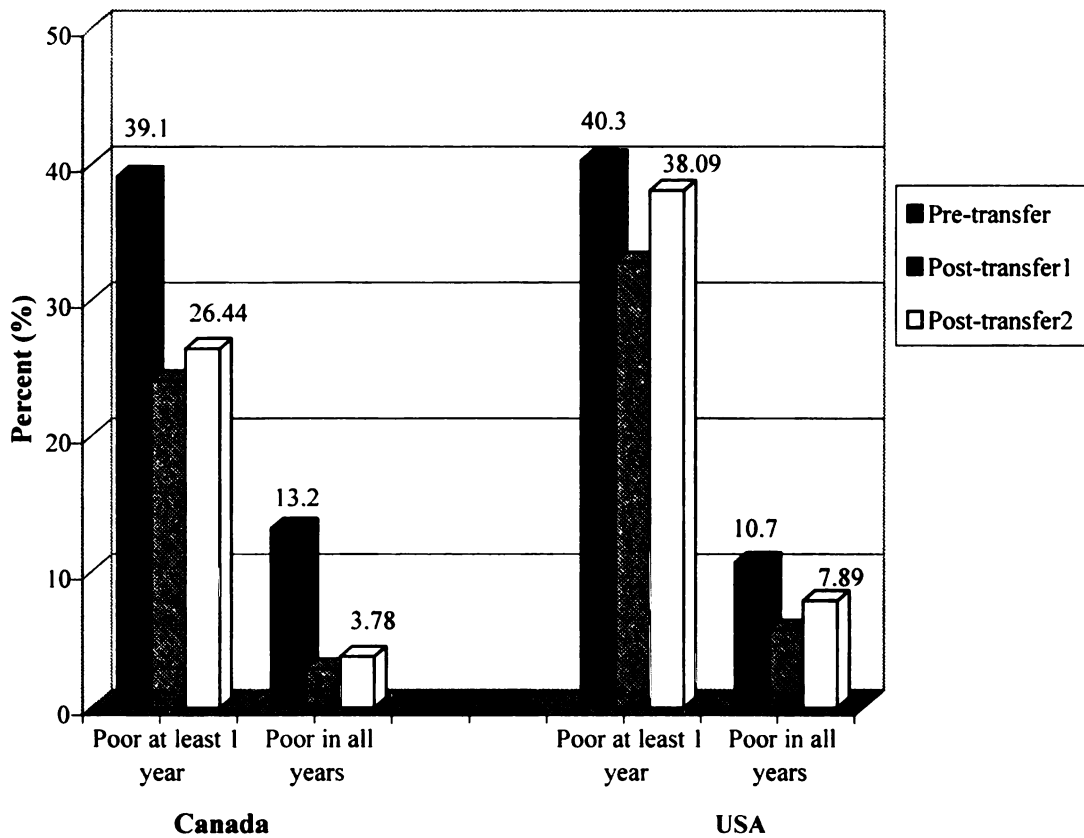
* Indicates significance at the 5 percent level, ** at the 10 percent level.

Table 2.13
Coefficients of Hazard Model, USA (1990–1996)

	Probability of low income		Probability of high income	
	Leaving	Reentry	Leaving	Reentry
	(1)	(2)	(3)	(4)
Duration (year=1)				
2	-.312*	-.283*	-.494*	-.184*
3	-.415*	-.335*	-.709*	-.275*
4	-.548*	-.394*	-.726*	-.263*
5	-.815*	-.513*	-.667*	-.588*
Year (base=1996)				
Age group (18-34)				
< 6	-.210*	.130**	-.180**	.085
6-17	.036	-.013	-.228*	.223*
35-64	-.080**	.084**	-.069	.103**
65 +	-.507*	.752*	.777*	-.400*
Family Structure (Couple w/kids)				
Single	-.184*	.084	-.049	-.101
Single-parent	-.456*	.335*	.193**	-.786*
Couple w/o kids	-.032	-.162*	-.165*	.297*
Regions (Northeast)				
Midwest	-.008	.062	.335*	-.011
South	-.023	-.012	.140*	-.048
West	-.021	.054	.159*	.008
Female-head	-.162*	.219*	.302*	-.197*
Non-white-head	-.199*	.302*	.107**	-.306*
Education-head (High School)				
Less than HS	-.302*	.278*	.259*	-.123
More than HS	.239*	-.249*	-.426*	.243*
<i>Binary Event variables</i>				
Newly established family	.351*	.621*	1.93*	-.365
Separation/Divorce	-.383**	.865*	.831*	.145
Partnership/Marriage	.727*	-.151	-.178	.986*
Household merge	.652**	.426	1.30*	.632*
Addition to family (Child)	.207	-.200	-0.99	-.197
(Non-child)	-.399*	.395*	.541*	-.188
Subtraction to family	.181*	-.070	.038	.385*
Constant	.200*	-.968*	-.262	-.833*
Log Likelihood	-3593.86	-3078.77	-2051.30	-1933.80
Predicted transition rate for Reference person	0.579	0.167	0.397	0.202

* Indicates significance at the 5 percent level, ** at the 10 percent level.

Figure 2.1
Incidence of Low Income

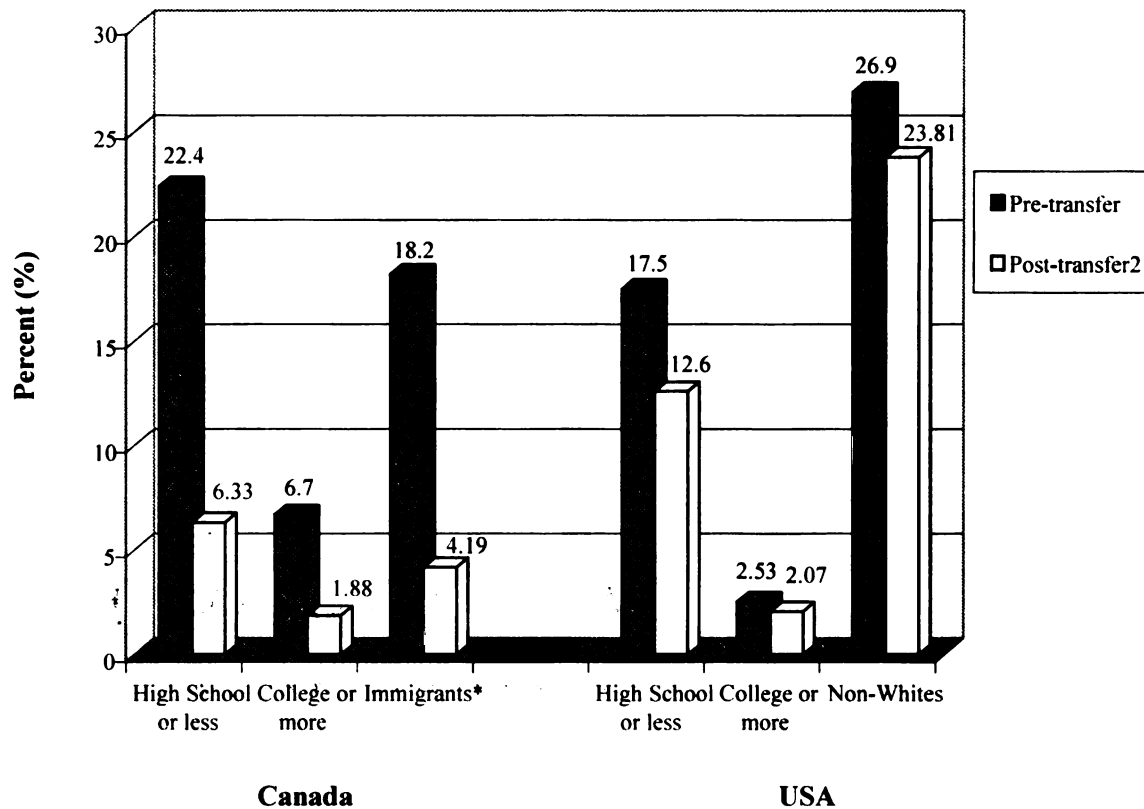


Data Source: Subsample for individuals present in all 6 years periods (1993–1998 for Canada and 1991–1996 for U.S.).

Post-Transfer1: Poverty cutoffs are calculated based on post-transfer income.

Post-Transfer2: Poverty cutoffs are calculated based on pre-transfer income.

Figure 2.2
Persistence of Low Income by Demographic Groups

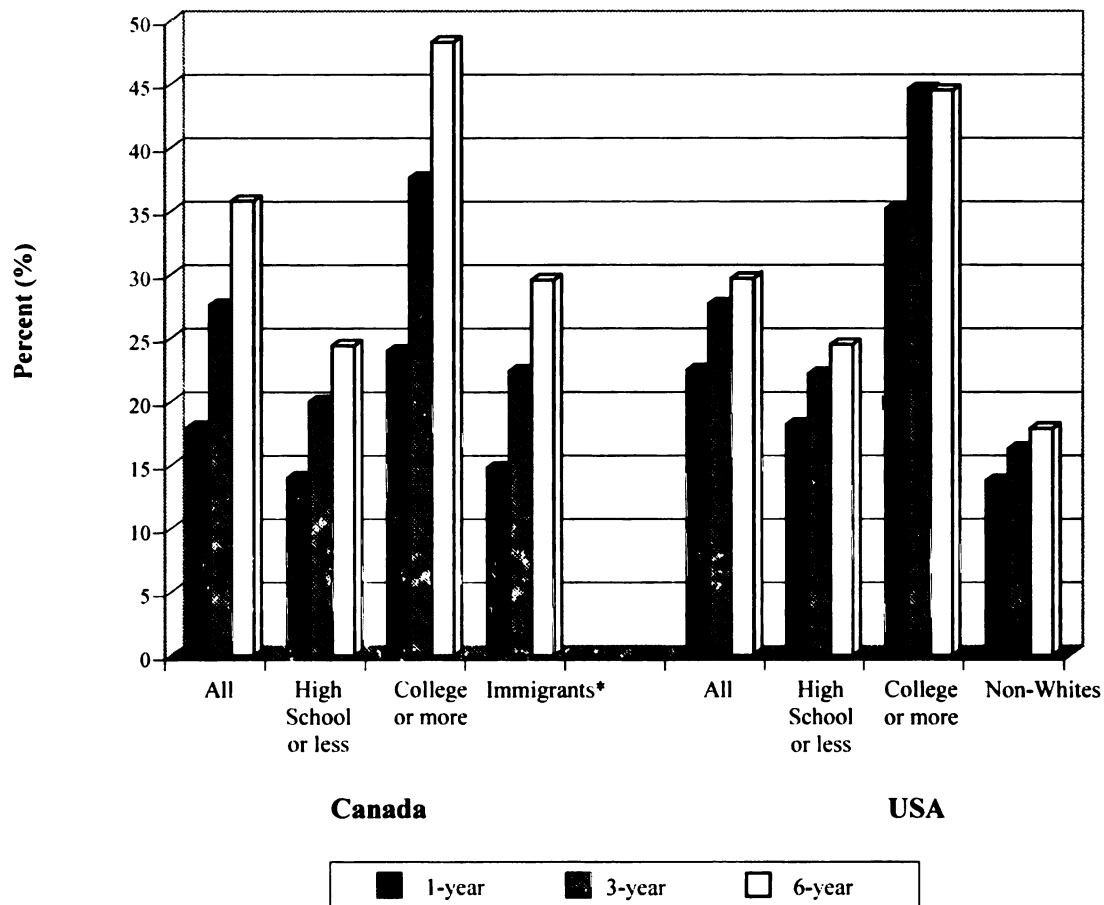


Data Source: Subsample for individuals present in all 6 years periods (1993–1998 for Canada and 1991–1996 for U.S.).

Post-Transfer2: Poverty cutoffs are calculated based on pre-transfer income.

*Immigrants who speak nonofficial languages as mother tongue

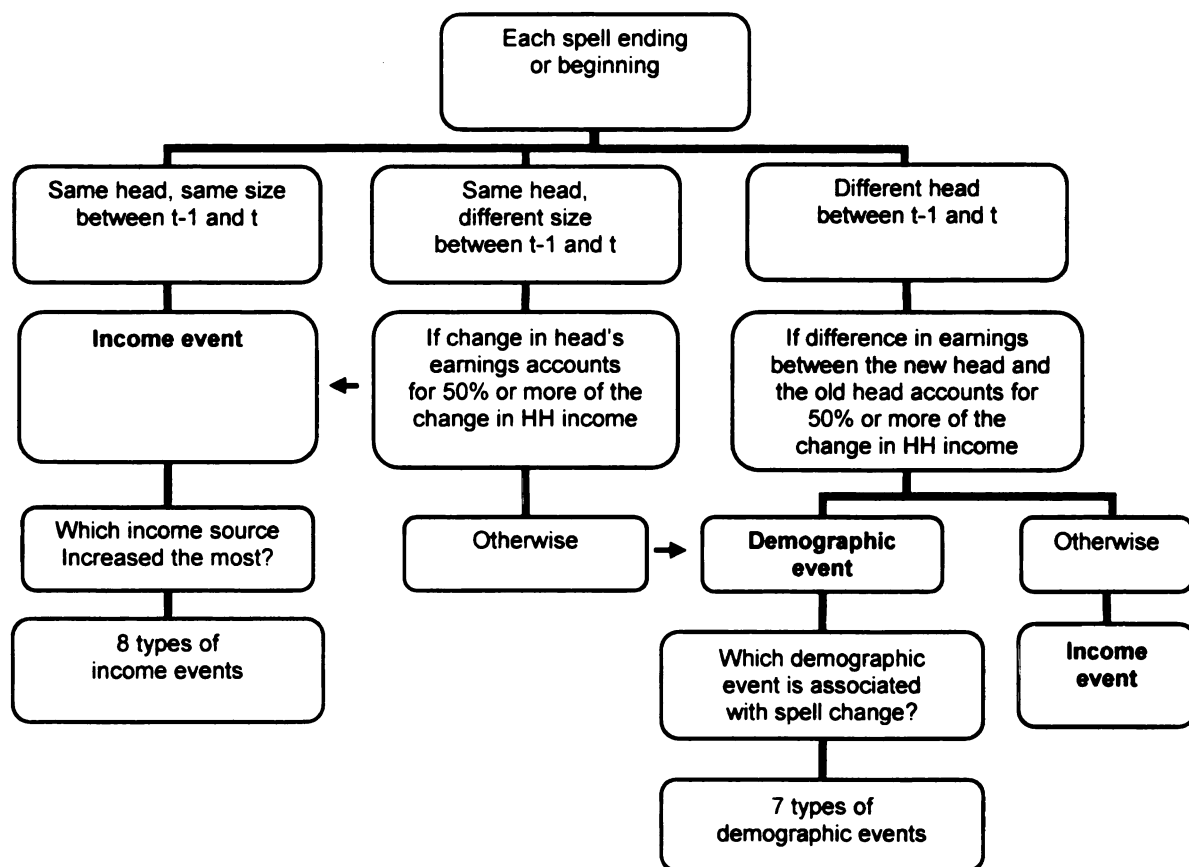
Figure 2.3
Probability of Moving out of Low Income by Length of Income Tracked and
Characteristics (pre-transfer income)



Data Source: Subsample for individuals present in all 6 years periods (1993–1998 for Canada and 1991–1996 for U.S.).

*Immigrants who speak nonofficial languages as mother tongue.

Figure 2.4
Classification of Income and Demographic Events Associated with a Spell Transition Between Year $t-1$ and t



Chapter 3

Evolution in the Structure of Family Income in Canada, 1980 to 1997: The Effects of Changing Family Structure and Changing Characteristics of Immigrants

3.1 Introduction

Previous Canadian studies have shown that pre-transfer income and earnings inequality have increased since the mid-1970s, particularly during the two recessions—early 1980s and early 1990s, respectively.³³ The widening gap in family income was observed between and within virtually all age groups and family types (see, for example, Zyblock, 1996b). Studies that examine the underlying causes of increasing inequality have received much attention over the past decade. Issues such as technological change or changing trade structures are often discussed as important forces contributing to increasing earnings disparities. While growing earnings disparities have undoubtedly contributed to the trend in family income inequality, previous research shows that demographic shifts also influence changes in income distribution. The study discussed in this chapter employs a relatively new decomposition technique to assess the importance of demographic shifts on the evolution of family income in Canada. Of particular interest are the effects of changing family structures and the characteristics of immigrants.

Changes in family composition and immigrant characteristics and their relationship to income distribution are of interest because both factors have undergone substantial changes in the past few decades, and economic outcomes vary greatly by

³³See Morissette (1995), Morissette, Myles, and Picot (1995), and Zyblock (1996a) for discussions about the changes in earnings inequality. See also Wolfson (1986), Zyblock (1996b), Beach and Slotsve (1996), and Frenette, Green, and Picot (2003) for discussions about changes in family income inequality.

family structure and by cohorts of immigrants. In 2000, about 7.7 percent of two-parents families and 35.8 percent of single-mother families were in the low-income bracket, and about 18.5 percent of all immigrants and 34 percent of recent immigrants (living in Canada 10 years or less) fell below the low-income line in 2000.³⁴ As a result, information about this relationship is essential for implementing policies, such as anti-poverty measures, or initiating active labour-market programs. Such issues are especially relevant because government transfers have been declining since the 1990s. If an increase in non-traditional families and new immigrants is associated with low income, then it may be imperative to find ways to reduce the hardship suffered by single parents and help newly-arrived immigrants use their foreign skills. In addition, the impact of immigrants on overall income inequality has not received much attention. The number of immigrants increased significantly over the past decade, and immigrant characteristics changed dramatically. Country of origin, for instance, changed greatly: from Western European countries in the 1970s and 1980s to Asia and developing countries in the 1990s. The extent to which changes in immigrant characteristics affected earnings or overall income distributions is discussed in this chapter.

The decomposition approach (DiNardo, Fortin, and Lemieux, 1996) used in this study has two advantages compared to the often-used standard regression-based decomposition (Daly and Valletta, 2000). First, it enables estimation of the entire density of income rather than just the mean or quintiles uncovered by the standard regression model. Second, it provides more behavioral content because the counterfactual

³⁴ Source: Statistics Canada (2003) and Picot and Hou (2002).

distributions constructed by this approach allow a conditional relationship between explanatory factors and a set of other attributes.

The results of this decomposition show that the increase in non-traditional families had a substantial impact on family income inequality, explaining one-fifth of the increase in the Gini coefficient and one-third of the growth in the low-income rate between 1980 and 1997. Changing characteristics of immigrants also affected income distributions, particularly in the lower half of the income distribution. It explained about one-third of the increase in the 50-10 and 90-10 ratios, and it was responsible for \$462 of the decline in median income during this period. Nevertheless, a substantial proportion of changes in income distribution remained unexplained, indicating the important influence of other factors (e.g., technological change, trade structure etc.) on income inequality.

3.2 Literature Review

The growth in income or earnings inequality has been investigated extensively over the past decade. In the United States, the increasing polarization of family-income distribution often is associated with a dramatic increase in male earning disparities that are driven by changes in the demand for skilled workers. These changes in the labour market have been caused by technological changes (Bound and Johnson, 1992), fluctuations in the demand rate for skilled workers (Katz and Murphy, 1992),³⁵ shifts in industrial composition that are largely associated with trade or economic integration (Murphy and Welch, 1991), and changes in institutional settings (DiNardo, Fortin, and Lemieux, 1996; Katz and Murphy, 1992; Podgursky, 1983). Other studies have found that demographic changes have as much impact as earning disparities on the growing

family income inequality. For instance, Karoly and Burtless (1995), Burtless (1999), and Daly and Valletta (2000) show that the increase in single-head families is responsible for a larger proportion of the spread in overall income inequality in the United States. There is also literature that discusses the increasing role of wives' earnings in family income growth. Shorrocks (1983), Lerman and Yitzhaki (1985), and Karoly and Butless (1995) decompose the change in inequality indices (e.g., Gini) by family income components and find that wives' earnings magnify family income inequality. In contrast, Cancian, Danziger and Gottschalk (1993) show that wives' earnings equalize the distribution of family income. Although such mixed results are due in large part to differences in sample, time period considered, or definition of income and inequality indices, Cancian and Reed (1998) argue that the impact of wives' earnings on inequality can be assessed meaningfully only by comparing the observed distribution of income with a reference distribution.

Increasing income inequality has also been well documented in Canada. Gera, Gu, and Lin (2001) show that, at the aggregate level, the demand for skilled workers did not increase significantly from 1981 to 1994—a period of rapid technological change. Although they also show that the variations are very substantial across industrial sectors, skill upgrading at the national level is less evident. Their results implicitly suggest a smaller role for technological change in increasing income inequality. With respect to earning disparities, Morissette (1995) shows that the increase in earnings inequality in the 1980s not only occurred with changes in income, but also in conjunction with changes in the distribution of hours worked.

³⁵Technological change and rising wage inequality is discussed in Card and DiNardo (2002).

Picot (1998) reviewed the earnings inequality trends in the 1990s and found that real-wage rates had declined among young Canadians, while overall income inequality changed little from 1980 to the mid-1990s. An early study by Henderson and Rowley (1977) suggests that the decline in family size is one of the major reasons for the increase in income inequality because income variation is much stronger in smaller families. Wolfson (1986) examines the impact of changing family structure on income inequality. His results suggest that the increasing incidence of single-parent families, reflected by lower fertility rates or rising separation rates, enhanced income inequality from 1965 to 1983.

Studies by Beach (1988) and McWatters and Beach (1990) discuss changes in family income distribution in relation to the “vanishing” middle class from the 1960s to 1980s. They examine many possible factors from both sides of supply and demand and conclude that the declining middle class is largely associated with a drop in the labour market participation rate of males and a rise in the labour market participation rate of females. Effects from other possible factors, such as business cycles or industrial shifts, are relatively small.

Zyblock (1996b) analyzes the effect of both demographic and non-demographic factors on the change in family incomes from 1981 to 1993. His results show that, in either age group or family type, the within-group contribution dominates the between-group contribution to overall family income inequality. He also points out that the shift toward one-parent families accounted for nearly 40 percent of the increase in inequality over this period.

A recent study by Picot and Hou (2002) discusses the impact of immigrants on family income distribution. They show that aggregate low-income rates in Canada increased 2.3 percent between 1989 and 1999, and two-thirds of this increase was the result of low-income rates among immigrants. The effect was even stronger in regions with high immigrant populations, such as Toronto and Vancouver.

3.3 Data and Historical Trends

The study discussed in this chapter used data from the Survey of Consumer Finance (SCF) for 1980 to 1997. The sample includes individuals aged 15 years and older in families (unattached individuals also included), but it excludes families whose major income recipients are aged 65 years and older because market-based (pre-transfer) incomes usually account for a small proportion of household income among elderly families. In this study, family is defined as the “census family,” which consists of a married couple or common-law couple with or without unmarried children or a single parent with an unmarried child or children. Compared to economic family, definition of census family is much narrower because it excludes relatives living in the same unit.³⁶ However, it is also more plausible when equivalent income (see below) is discussed because the pooling of family income resources is more likely to occur among members of a census family.

Family income is the sum of earnings, investment, and private transfers from all family members. Sources of income are measured in annual terms rather than at the time of an interview, which avoids temporary income fluctuation and is more likely to reflect

³⁶Economic family people refer to household members who are related to each other by blood, marriage, common-law, or adoption.

the true well being of a family. To properly measure the well being of an individual, the total family income is standardized through an equivalence scale in order to adjust for demographic components. In this context, the equivalence scale is defined as the square root of family size. The use of an equivalence scale reduces part of the inequality caused by big-sized families. In this setting, individuals rather than families are considered the basic unit of analysis.

The definition of low income is quite controversial in Canada.³⁷ In this study, an individual is considered in low-income if his or her equivalent income falls below one-half of the median equivalent income. For the decomposition section, data from two peak years, 1980 and 1989, and one near peak year, 1997, are used. These three particular years are used to reduce any variations that may result from business cycle effects.³⁸ All income measures are expressed in 2000 constant Canadian dollars.

Figure 3.1 illustrates trends of income inequality (as indicated by the 75-25 percentile ratio) as well as the low-income rate. The cyclical effects were very obvious as shown by the two spiked areas that represent the 1983–1984 and 1992–1993 recessions, respectively. Income inequality increased during the peak or near-peak years of 1980, 1989, and 1997, while the low-income rate increased only during the 1990s. While both indices increased substantially during the early 1990s, the economic trends failed to return to the previous levels, despite an upswing in economic growth in the late 1990s.

Figure 3.2 shows that increasing income inequality was mainly associated with a poor economic performance by people from the bottom end of the income distribution.

³⁷Three low-income cutoffs are commonly used and discussed in the Canadian literature: low income cutoff (LICO), low income measure (LIM), and the recently developed market basket measure (MEM). See, for example, Statistics Canada (2003) for detailed definitions.

For example, the real income for people at the 25th percentile in 1997 was about 15 percent lower compared to the level in 1980. The situation was even worse for those who were extremely poor: Between 1980 and 1997, real income dropped by as much as 40 percent for people at the 10th percentile. Yet people at the top of the distribution scale experienced very little change in terms of real income during this period. The increase in real income between 1980 and 1997 for persons at the 75th and 90th percentile were only 4 and 7 percent, respectively. These patterns are very different from those found in U.S., where polarization was obvious (see, for example, Daly and Valletta, 2000).

In order to display changes in the entire income distribution scenario, estimates of kernel density for the equivalent income are shown in Figures 3.3a, 3.3b, and 3.3c.³⁹ Between 1980 and 1997, the distribution widened, with a hollowing of the middle and a density shift at both ends of the scale. However, the shift of density was more concentrated to the left of the income distribution, suggesting the deterioration of well being among individuals located at the lower half of the scale. The evaluation was significantly influenced when the two periods were individually assessed. Change in income distribution in the 1980s was mostly concentrated in the movement from the middle portion to the upper portion, and it showed very little change in the lower portion. Also, much of the density mass shifted to the left in the 1990s, while changes in the upper tail were relatively small.

Figure 3.4 displays inequality measures for male earnings between 1980 and 1997. The sample, which includes people with zero earnings, shows that earning disparity

³⁸In terms of business cycles, 1999 or 2000 rather than 1997 should be considered a peak year. Unfortunately, SCF was terminated in 1997 and replaced by the Survey of Labour and Income Dynamics (SLID). For consistency, SCF is used throughout the analysis, and 1997 is the last available year from SCF.

was relatively stable in the 1980s, but it increased notably in the 1990s. Moreover, the increasing earning disparity was likely a result of declining earnings among individuals in the lower portion of the distribution (as indicated by a declining median) and was less likely to represent individuals' increased earnings in the upper portion. This pattern contrasts with findings from the U.S., where earnings polarization was apparent and where technological changes and trade were thought to have a substantial impact on earning disparity.

Figure 3.5 depicts the correlation between husband's earnings and wife's labour market participation. It shows that, in general, female participation rates had increased over time. However, women whose husband had relatively high earnings showed the highest participation rates. For example, among husbands whose earnings were right on the top quartile of the distribution scale, the proportion of working wives increased significantly, from .55 in 1980 to nearly .8 in 1997. On the other hand, the proportion of working wives remained relatively stable over time among husbands whose earnings were on the bottom quartile of the distribution. The increasing correlation between a husband's earnings and a wife's labour market participation is likely to be an important source of increasing inequality in family income.

Figure 3.6 illustrates a historical trend of family composition. Generally, family structure in Canada has been changing. Traditional "husband-wife-children" families have declined (62% in 1980 versus 55% in 1997), while the three other family types have increased. Single-adult families (single unattached and single parents) increased about 5.1 percent from 1980 to 1997. The movement toward single-adult families is believed to

³⁹The kernel density is estimated using the Gaussian functional form and optimal bandwidth (see Silverman, 1986 for more details).

increase the proportion of low-income families and, therefore, result in increasing income inequality.

Immigrants could possibly affect overall income inequality. During the past 2 decades, the number of recent immigrants increased substantially, and immigrant characteristics also changed.⁴⁰ According to SCF, recent immigrants accounted for about 25 percent of the total immigrants throughout the 1980s, but the share increased to 33 percent in 1997. Figure 3.7 illustrates that new immigrants who arrived in the 1990s were more likely to experience economic difficulties compared to their counterparts in the 1980s. In the 1983 recession, for example, median equivalent income for immigrants was about \$4,000 lower than the national average; the gap increased to \$15,000 in the 1993 recession. Part of the decline can be attributed to the weaker labour market performance among immigrants during the recession, particularly full-time employment probabilities. A historical trend of full-time employment is provided in Figure 3.8. It shows that full-time employment rates did not differ significantly between recent immigrants and the national average during the 1980s, but these rates plunged quickly in the 1990s and never returned to original levels.⁴¹

Recession in the early 1990s obviously had a negative impact on immigrants. As pointed out by many studies (for example, McDonald and Worswick, 1998), the rate of earnings assimilation by immigrants was quite sensitive to macroeconomic conditions. However, Figure 3.8 suggests a cohort effect because recent immigrants from the 1990s

⁴⁰In this chapter, an immigrant family is defined as a family headed by an immigrant. The person with the highest earnings is identified as the household head. In case of a tie in earnings, the oldest male is considered the head. Recent immigrants are defined as those who have been living in Canada 10 years or less.

⁴¹Frenette and Morissette (2003) show that real earnings of immigrants have dropped over the past 2 decades, even among those employed full year full time. They suggest that changes in the wage structure are likely to play a significant role in explaining the decline in recent immigrants' median income.

experienced more difficulty finding full-time jobs during recessions compared to the earlier cohorts from the 1980s. It would be interesting to see how skill distribution changed among immigrants. Figure 3.9 shows the share of immigrants who speak either of Canada's two official languages as their mother tongue. Ability to speak official languages is considered one of the most important skills for immigrants in host countries. Immigrants who are proficient in either of Canada's official languages were more attractive to Canadian employers and able to transfer their foreign skill effectively. Surprisingly, Figure 3.9 shows that about 45 percent of immigrants or recent immigrants spoke either English or French as mother tongue in 1981, while in 1997, the figures declined to 28 percent and 16 percent among immigrants and recent immigrants, respectively. The changes in immigrant characteristics shown in Figures 3.8 and 3.9 suggest a potential impact on the change in family income inequality.

3.4 Methodology

The technique used to decompose changes in the density of equivalent income is based on the “conditional re-weighting procedure” developed by DiNardo, Fortin, and Lemieux (1996)—hereafter called DFL. This technique has been used in many recent studies (see Daly and Valletta, 2000; Chiquiar and Hanson, 2002). Basically, it is similar to the commonly used “Oaxaca-Blinder decomposition” (Oaxaca, 1973). The main advantage of this procedure is that it allows the entire conditional distribution to be projected, while the Oaxaca-Blinder decomposition only focuses on the means of distribution. The estimated conditional weights can be combined with sampling survey weights to produce a counterfactual distribution.

Notice that a standard Oaxaca-Blinder decomposition follows from an income equation:

$$\bar{y}_{97} - \bar{y}_{80} = \hat{\beta}_{97} * (\bar{X}_{97} - \bar{X}_{80}) + \bar{X}_{80} * (\hat{\beta}_{97} - \hat{\beta}_{80}). \quad (1)$$

The left-hand side is the change in average equivalent income ($\bar{y}$) between 1980 and 1997. It is equal to the sum of two components: one, which is due to differences in the mean characteristics ($\bar{X}$), and two, which is due to differences in the returns to these characteristics ($\hat{\beta}$). The first term on the right-hand side (1) represents a counterfactual “what would the average equivalent income have been in year 1997 for individuals with the mean characteristics of the 1980 levels.” As mentioned, this decomposition only estimates the means of distribution and ignores changes, for example, at the tails.

Distribution changes other than changes in means (such as quintiles or deciles) cannot be investigated. Fortunately, DFL proposed an approach that allows analysts to construct counterfactual densities that work with the entire density of incomes through kernel density estimation:

$$\hat{f}(y) = \frac{1}{n} \sum_{i=1}^n \frac{\theta_i}{h} K\left(\frac{y - Y_i}{h}\right) \quad (2)$$

Equation (2) is an estimate of kernel density based on a random sample ($Y_1, \dots, Y_n$), with sampling weights ($\theta_1, \dots, \theta_n$), h , which is the smoothing function referred to as the bandwidth, and K , the kernel function.⁴² The choice of h and K may be sensitive to the distribution and has been subject to many discussions in the literature. In this context, the “optimal bandwidth” (Silverman, 1986) and Gaussian kernel function are used.

⁴²See Silverman (1986) for a detailed discussion about kernel density estimation.

To provide an exposition of this technique, consider a simple binary variable—mother tongue—that equals 1 if an immigrant communicates in either of the official languages as a mother tongue and zero if neither language is spoken as a mother tongue. Without controlling other characteristics, the proportion of immigrants who speak either of the official languages as a mother tongue has declined significantly over time (see Figure 3.9). Therefore, the simplest way to impose the earlier distribution of languages on current income distribution is to “up-weight” immigrants who communicate in official languages as a mother tongue by a number that is equal to the percentage decrease in the share of this group over time. Similarly, immigrants who do not speak either English or French as a mother tongue will be “down-weighted” because the possibility of being part of this group has increased over time. Every immigrant is, therefore, assigned a new weight ($\psi_{\text{mother tongue}}$), with adjusted mother-tongue distribution.

In the real world, the decline in English- or French-speaking immigrants may be more concentrated in certain groups—the young age group, for example. Therefore, it is more plausible to construct a counterfactual distribution that held constant mother-tongue distribution at an earlier year’s level and also was conditional on age ($\psi_{\text{mother tongue} | \text{Age}}$). In other words, each immigrant would be re-weighted according to the proportional change in mother-tongue distribution within each age group. Daly and Valletta (2000) refer to this technique as “greater behavioral content” because the counterfactual distributions constructed in this way allow conditional relationships between explanatory factors and a set of other variables.

To begin with, consider the distribution of equivalent income, Y , in 1997, which consists of four explanatory factors: (1) a binary variable, I , that equals 1 if an immigrant

is employed full time and 0 if not employed full time; (2) a discrete variable, L , that indicates the four combinations of mother tongue and duration of residency characteristics for an immigrant;⁴³ (3) a discrete variable, S , that indicates the four types of family structure;⁴⁴ and (4) a vector X of other attributes, including age, sex, education, province dummies, size of area dummies, and 16 census metropolitan area dummies. The distribution of income can be shown as the product of joint densities I , L , S , and X :

$$\begin{aligned} f_t(Y) &= f(Y | t_Y = 97, t_{I|L,S,X} = 97, t_{L,S,X} = 97, t_{S,X} = 97, t_X = 97) \\ &= \int \int \int \int f(Y | I, L, S, X, t_Y = 97) dF(I | L, S, X, t_{I|L,S,X} = 97) dF(L | S, X, t_{L,S,X} = 97) \\ &\quad \cdot dF(S | X, t_{S,X} = 97) dF(X | t_X = 97) \end{aligned} \quad (3)$$

The challenge here is to construct counterfactual densities that satisfy the following:

“What would the density of equivalent income have been in 1997 if immigration factors, family structure, and other attributes—but nothing else—had remained the same as the 1980 levels?”

$$\begin{aligned} f_t(Y) &= f(Y | t_Y = 97, t_{I|L,S,X} = 80, t_{L,S,X} = 80, t_{S,X} = 80, t_X = 80) \\ &= \int \int \int \int f(Y | I, S, X, t_Y = 97) dF(I | L, S, X, t_{I|L,S,X} = 80) dF(L | S, X, t_{L,S,X} = 80) \\ &\quad \cdot dF(S | X, t_{S,X} = 80) \cdot dF(X | t_X = 80) \end{aligned} \quad (4)$$

With proper arrangement, the counterfactual density in (4) can be expressed as

$$\begin{aligned} f_t(Y) &= f(Y | t_Y = 97, t_{I|L,S,X} = 80, t_{L,S,X} = 80, t_{S,X} = 80, t_X = 80) \\ &= \int \int \int \int f(Y | I, L, S, X, t_Y = 97) dF(I | L, S, X, t_{I|L,S,X} = 97) \frac{dF(I | L, S, X, t_{I|L,S,X} = 80)}{dF(I | L, S, X, t_{I|L,S,X} = 97)} \end{aligned}$$

⁴³The four combinations are (1) official languages speaking, non-recent immigrant, (2) official languages speaking, recent immigrant, (3) non-official languages speaking, non-recent immigrant, and (4) non-official languages speaking, recent immigrant.

⁴⁴The four family types refer to (1) single unattached, (2) couple without children, (3) couple with children, and (4) single-parent family.

$$\begin{aligned}
& \cdot dF(L | S, X, t_{L,S,X} = 97) \frac{dF(L | S, X, t_{L,S,X} = 80)}{dF(L | S, X, t_{L,S,X} = 97)} \\
& \cdot dF(S | X, t_{S,X} = 97) \frac{dF(S | X, t_{S,X} = 80)}{dF(S | X, t_{S,X} = 97)} \cdot dF(X | t_X = 97) \frac{dF(X | t_X = 80)}{dF(X | t_X = 97)} \\
& = \iiint f(Y | I, L, S, X, t_Y = 97) dF(I | L, S, X, t_{I,L,S,X} = 97) dF(L | S, X, t_{L,S,X} = 97) \\
& \quad \cdot dF(S | X, t_{S,X} = 97) dF(X | t_X = 97) \\
& \quad \cdot \lambda_{I,L,S,X}(I, L, S, X) \cdot \lambda_{L,S,X}(L, S, X) \cdot \lambda_{S,X}(S, X) \cdot \lambda_X(X)
\end{aligned} \tag{5}$$

which is equal to the exact density of equivalent income in 1997 times four re-weighting functions: $\lambda_{I,L,S,X}(I, L, S, X)$, $\lambda_{L,S,X}(L, S, X)$, $\lambda_{S,X}(S, X)$, and $\lambda_X(X)$. The new weights (λ) can then be incorporated into the estimation of the kernel density:

$$\hat{f}(y) = \frac{1}{n} \sum_{i=1}^n \frac{\theta_i \cdot \lambda}{h} K\left(\frac{y - Y_i}{h}\right) \tag{6}$$

3.4.1 Estimation of Conditionally Re-weighting Functions

As seen in the previous section, labour market performance among immigrants has been deteriorating since 1990. To investigate impacts of immigrants on the change in overall income distribution, the following question was asked: “What would the family income distribution look like if the labour market performance (in terms of full-time employment) of immigrants, conditional on other observable characteristics (e.g., age, education, family structure, geography, mother tongue, and duration of residency), had remained at their 1980 levels?”

In terms of notation, let I be a binary variable with value 1 if an immigrant is employed full time and zero if not employed full time:

$$\lambda_{I|L,S,X}(I, L, S, X) = \frac{dF(I | L, S, X, t_{I|L,S,X} = 80)}{dF(I | L, S, X, t_{I|L,S,X} = 97)}$$

$$= I \frac{\Pr(I = 1 | L, S, X, t_{I|L,S,X} = 80)}{\Pr(I = 1 | L, S, X, t_{I|L,S,X} = 97)} + (1 - I) \frac{\Pr(I = 0 | L, S, X, t_{I|L,S,X} = 80)}{\Pr(I = 0 | L, S, X, t_{I|L,S,X} = 97)} \quad (7)$$

$\lambda_{I|L,S,X}(I, L, S, X)$ in (7) represents changes in the probability that immigrants would work full time between 1980 and 1997, conditional on the characteristics (L , S , and X). Every immigrant in the distribution will be either up-weighted (if $\lambda_{I|L,S,X} > 1$) or down-weighted (if $\lambda_{I|L,S,X} < 1$) in order to adjust full-time employment status to its 1980 level. An estimate of the conditionally re-weighting function $\lambda_{I|L,S,X}(I, L, S, X)$ can be derived by assessing the conditional probabilities in (7) through a probit model. For non-immigrants, the original sample weights are used without implementing an adjustment. In other words, the re-weighting function for non-immigrants is set to 1.

In addition to the change in full-time employment probabilities, the characteristics of immigrants—in terms of mother tongue and duration of residency—also changed significantly. Thus, the second decomposition sequence is to hold constant the interaction effect of mother tongue and duration of residency to 1980 levels. In a simple framework, the population of immigrants can be divided into four mutually exclusive groups in a given year according to mother tongue (= 1 if speaks official languages, = 0 if speaks another language) and duration of residency (= 1 if in Canada more than 10 years, = 0 if in Canada less than 10 years). The re-weighting function for this factor is then expressed as

$$\lambda_{L|S,X}(L, S, X) = \frac{dF(L | S, X, t_{L|S,X} = 80)}{dF(L | S, X, t_{L|S,X} = 97)}$$

$$\begin{aligned}
&= L_1 \frac{\Pr(L = 1 | S, X, t_{L,S,X} = 80)}{\Pr(L = 1 | S, X, t_{L,S,X} = 97)} + L_2 \frac{\Pr(L = 2 | S, X, t_{L,S,X} = 80)}{\Pr(L = 2 | S, X, t_{L,S,X} = 97)} \\
&+ L_3 \frac{\Pr(L = 3 | S, X, t_{L,S,X} = 80)}{\Pr(L = 3 | S, X, t_{L,S,X} = 97)} + L_4 \frac{\Pr(L = 4 | S, X, t_{L,S,X} = 80)}{\Pr(L = 4 | S, X, t_{L,S,X} = 97)} \\
&= \sum_{c=1}^4 L_c \frac{\Pr(L = c | S, X, t_{L,S,X} = 80)}{\Pr(L = c | S, X, t_{L,S,X} = 97)}. \tag{8}
\end{aligned}$$

Since the dependent variable in equation (8) is now a categorical variable rather than a binary variable, the estimate of (8) can be obtained through a “multi-nominal logit” model. Again, the re-weighting function is set to 1 for all non-immigrants.

Similarly, an estimate of the conditional re-weighting function for the family structure $\lambda_{S|X}(S, X)$ can be derived in a same fashion as equation (9):

$$\lambda_{S|X}(S, X) = \frac{dF(S | X, t_{S,X} = 80)}{dF(S | X, t_{S,X} = 97)} = \sum_{c=1}^4 S_c \frac{\Pr(S = c | X, t_{S,X} = 80)}{\Pr(S = c | X, t_{S,X} = 97)} \tag{9}$$

Finally, applying Bayes’ rule, the conditional re-weighting function for “other attributes”

$\lambda_X(X)$ is written as

$$\lambda_X(X) = \frac{dF(X | t_X = 80)}{dF(X | t_X = 97)} = \frac{\Pr(t_X = 80 | X)}{\Pr(t_X = 97 | X)} \cdot \frac{\Pr(t_X = 97)}{\Pr(t_X = 80)}. \tag{10}$$

It is equal to the relative probability of observing an individual with the characteristics X in the 1980 sample versus the 1997 sample times the unconditional probabilities of being in either sample. The conditional probabilities are obtained through a probit model, while the unconditional probabilities are the population ratio.

Changes in the density of equivalent income between 1980 and 1997 are, therefore, model-based on the following decomposition:

$$f_{97}(Y) - f_{80}(Y) = f_{97}(Y; t_{I|L,S,X} = 97, t_{L|S,X} = 97, t_{S|X} = 97, t_X = 97) - f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 97, t_{S|X} = 97, t_X = 97) \quad (i)$$

$$+ f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 97, t_{S|X} = 97, t_X = 97) - f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 97, t_X = 97) \quad (ii)$$

$$+ f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 97, t_X = 97) - f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 80, t_X = 97) \quad (iii)$$

$$+ f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 80, t_X = 97) - f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 80, t_X = 80) \quad (iv)$$

$$+ f_{97}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 80, t_X = 80) - f_{80}(Y; t_{I|L,S,X} = 80, t_{L|S,X} = 80, t_{S|X} = 80, t_X = 80) \quad (v)$$

The five components in the above equation represent the effects of the changing full-time employment rate of immigrants, changing characteristics of language/duration of residency among immigrants, changing family structure, changing other attributes, and residual factors, respectively.⁴⁵

Criticism of this approach is often related to its inability to distinguish overlapping effects between factors. The possibility of a general equilibrium or an endogenous relationship between factors would confound the true contribution of each factor. A simple alternative is to perform the same decomposition but in different order sequences and see whether the results are as sensitive under an alternative arrangement. In this study, reverse-order decomposition was also employed.

3.5 Results

In this section, the impact of factors from the decomposition procedure is discussed, and Table 3.1 shows the weights used in the density decomposition. In the primary-order decomposition (panel A), immigration factors are placed in the first two sequences, followed by family structure, other attributes, and residuals. Variables in the “other attributes, X” include age, sex, education,⁴⁶ dummies for provinces, size of areas, and census metropolitan areas. Thus, effects such as an aging population, a shift in educational attainment, or geographic location are captured in this category. Finally, some important but unexplained factors, such as “skill-biased technological shocks,” “international trade,” and “correlation between husband and wife earnings,” were placed into the last category.

Figures 3.10 to 3.13 display changes in the density of equivalent income between 1980 and 1997 in primary-order decomposition sequences. Each graph adjusts an additional modeled factor to its 1980 level. The solid line in Figure 3.10 represents the original density of equivalent income for 1997, while the dash line represents the counterfactual density that has been adjusted for the full-time employment rate of immigrants. It shows that the lower portion of the income distribution would have been slightly narrower if a full-time employment rate among immigrants held constant at 1980 levels. While the adjusted distribution moved density from the left tail to the middle, it made virtually no impact on the right tail. Figure 3.11 further adjusts distribution by holding constant the mother tongue/duration of residency characteristics of immigrants at the 1980 level. Changing these two immigrant characteristics reduced the density in the

⁴⁵Notice that changes in the wage structure that affect the earnings of recent immigrants employed full year full time are considered as effect in residual factors.

upper middle, with a corresponding increase of mass in the lower middle of the distribution. The visual effect became more significant when the effect of changing the family structure was estimated. Figure 3.12 shows that changes in family structure between 1980 and 1997 resulted in a uniform shift of income distribution to the left, but the effects were more concentrated in the lower tail of the distribution. As for the impact of changing other attributes, Figure 3.13 shows an opposite movement. The whole density shifted toward the left when other attributes were held constant to 1980 levels, suggesting some changes in this factor—likely education or age structure—contributed a notable gain in median income between 1980 and 1997. Finally, residual effect is illustrated in Figure 3.14. Compared with the original densities in Figure 3.3, it shows that the counterfactual distribution explained some changes in the lower portion of the income distribution, while most of the change in the upper half of the distribution remained unexplained.

The quantitative contributions of graphic analysis are shown in Table 3.2. Statistics include changes in a series of distribution measures, low-income rates, and median income between 1980 and 1997. Generally, inequality indices and the low-income rate—based on equivalent income—increased during this period. Overall inequality, as measured by Gini coefficients, increased about 4.2 percent. However, the increasing inequality was principally concentrated in the lower half of the income distribution. Despite a declining median income, changes in the 90-50 ratio were less noticeable, but increases in the 50-10 ratio were quite substantial, suggesting that people in the lower end suffered major income losses during this period.

⁴⁶It includes 3 educational categories: less than high school, high school graduated, and college or more.

Turning to the contribution of each factor, column 1 shows the effects of a changing full-time employment rate among immigrants. Overall, it explained 24 and 26 percent of the increase in the 90-10 and 50-10 ratio, respectively, 12 percent of the increase in the Gini coefficient, and about 17 percent (or 0.7 percentage points) of the increase in the low-income rate during this period. The stronger effects on the 90-10 and 50-10 ratios indicate that a proportionate increase of non-full-time jobs was likely associated with low incomes.

Column (2) displays the effects that were attributed to the changes in mother tongue and duration of residency among immigrants. By holding these two characteristics at 1980 levels, column (2) indicates that these factors contributed to an increase of about 7 percent in the Gini coefficient, a 0.5 percentage point growth in the low-income rate, and about \$228 of the decline in median income. The magnitudes were not large in terms of overall changes. When the effects from (1) and (2) are combined, changes in immigration factors accounted for a total of 19 percent of the increase in the Gini coefficient, 33 percent of the increase in the 50-10 ratio, a 1.2 percentage point growth in the low-income rate, and \$462 of the decline in median.

Among explanatory factors, the change in family structure had the most influence on income distribution (column 3). It accounted for about 20 percent of the increase in the Gini coefficient and 32 percent (equivalent to 1.4 percentage points) of the growth in the low-income rate. The impacts were more apparent in the lower half of the income distribution, explaining 33 and 36 percent, respectively, of the increase in the 90-10 and 50-10 ratios. However, it contributed relatively little to the change in the upper half of the income distribution, explaining only 13 percent of the increase in the 90-50 ratio. The

counterfactual suggests that the growing number of single-adult families (single unattached or single parents) was more likely associated with low income. It is also noteworthy that changes in the family structure resulted in a decline of median income by about \$755 during this period.

As for the contributions of other attributes, column (4) shows that such effects were fairly small across different measures, except for movement in median income. Actually, factors in this category contributed to inequality in an opposite way: The low-income rate dropped by 0.7 percentage points, and the median income grew by \$803 between 1980 and 1997. Embedded factors, such as increasing proportion of prime-age population, growing educational attainment, as well as urbanization, seem to increase the national median and had some equalizing effects on inequality.

Finally, the contributions of residual factors were fairly large (see column 5). More than half of the increase in the Gini coefficient and low-income rate remained unexplained. The residual effects were even stronger in the upper half of the income distribution. For instance, more than 70 percent of the increase in the 90-50 and 75-50 ratios cannot be explained by any of the four explanatory factors. The relatively large residuals raise concerns about the creditability of the estimated effects of factor. Are large residuals really a result of changes from unknown or unexplained factors? Could they also come from a poor estimation during the decomposition process? In the latter case, the previous estimates on factor effects will not have much creditability. To validate these effects, an alternative decomposition based on a different reference (base) year was employed (see Table 3.3). That is, 1980 was used as a reference year rather than 1997

and factors were held constant to 1997 levels. If factors were estimated consistently in both years, similar results would be expected, regardless of reference year.

Basically, with few exception, results from these two alternative counterfactuals exhibited similar patterns. Most of the changes in the inequality measures remained unexplained even if the counterfactual was evaluated at a different reference year. This suggests that most of the residuals can be attributed to factors that were not included in the model, which requires further investigation in future studies. It is also noteworthy that compared to the data in Table 3.2 the change in family structure had a relatively strong impact on income distributions. One of the reasons is that single-adult households were not very common 20 years ago, and the labour market participation rate among this type of family (e.g., single mother) was relatively low at that time. As a result, using 1980 as the reference year and holding constant family structure to the 1997 level would introduce more low-income families than it would have with reference year values at 1997 levels.

3.5.1 Reverse-Order Decomposition

As mentioned, the effect of a factor might change with respect to its order in the decomposition if there are overlapping effects between factors. To examine the extent of sensitivity, a reverse-order decomposition was conducted (see Table 3.4). The weights used in the reverse-order are shown in panel B, Table 3.1, and the derivation of re-weighting functions for reverse-order is described in Appendix D. Generally, all measures display similar patterns as those shown in the primary-order decomposition in Table 3.2. The contributions of other attributes with respect to income disparities remained insignificant (except for distribution in the lower tail), even if they were

considered first in the decomposition process. Interestingly, the contribution of the 50-10 ratio associated with “other attributes” increased noticeably, at the expense of immigration factors. One possibility is that immigrants, particularly low-skilled immigrants, were likely to be younger and were more concentrated in the metropolitan areas. Therefore, part of the immigration effect is captured by the “other attributes” when the decomposition sequence is reversed.

The effects of changes in the family structure increased slightly in the reverse-order decomposition, notably in the upper half of the distribution. For instance, changes in the family structure accounted for 20 percent of the increase in the 90-50 ratio in the reverse-order decomposition, while the share was only 13 percent in the primary-order decomposition in which the immigration factors were conditioned. It is likely that this effect overlapped with some immigrant effects because changes in family structure, especially the growth in single-unattached households, are linked to the increase in young professional immigrants under the skill-based “independent” visa category. Finally, effects due to changes in immigrant-related factors were slightly lower when they were considered last in the decomposition. Nevertheless, immigration factors were still responsible for 0.8 percentage points of the increase in the low-income rate, with a notable \$376 reduction in median income during this period.

3.5.2 Decomposition Breakdown during Two Periods: 1980–1989 and 1989–1997

Tables 3.5 and 3.6 broke down the previous analysis into two periods, namely 1989–1989 and 1989–1997, representing a peak-to-peak (or near peak) year in the 1980s and 1990s, respectively. Peak-to-peak years were selected to avoid possible variations

due to business cycles. Generally, the results displayed very distinct patterns between these two periods. Levels of inequality remained unchanged, and the median income increased substantially (\$1,441), suggesting an overall improvement in the economy between 1980 and 1989. Nevertheless, the significant increase in median income in this period was largely associated with residual factors, and part of the growth was actually offset by immigration factors and family structure.

On the other hand, the increase in overall inequality was principally concentrated in the second period. More than two-thirds of the increase in inequality and nearly 100 percent of the increase in the low-income rate between 1980 and 1997 took place in the 1990s. Changes in the family structure continued to influence income distribution, particularly in the lower half of the income dispersions, explaining 25 percent of the increase in the 50-10 ratio and about a 0.6 percentage point increase in the low-income rate during this period. Also, in the 1990s, immigration factors became noticeable in the decomposition. Immigrant factors (columns 1 and 2 of Table 3.6) accounted for about 20 percent of the increase in the Gini coefficient and about a 1 percentage point increase in the low-income rate. Again, residuals or unexplained factors dominated other aspects in explaining changes in inequality, accounting for more than three-quarters of the increase in most of the measures during this period. The residual factors alone reduced the median income by about \$1,604 and accounted for 74 percent (or 3.1 percentage points) of the increase in the low-income rate between 1989 and 1997. This raises concerns about the years of selection. Perhaps the 1997 economy was not good enough to compare to the 1989 or 1980 economy.

3.6 Conclusion

Income inequality, based on pre-transfer family income, in Canada increased between 1980 and 1997, mainly in the 1990s. A number of previous studies have shown the importance of demand-side factors (e.g., technological change or changing trade structures) as well as supply-side factors (e.g., shifts in demographic compositions) on increasing family income inequality. In this study, a relatively new re-weighting technique—developed by DiNardo, Fortin, and Lemieux (1996)—was used to examine the underlying causes of increasing inequality, with special attention paid to the demographic shifts. Of particular interest were the effects of changing family structures and the characteristics of immigrants.

The results from this chapter echo Zyblock's (1996b) finding that changing family structure contributes to rising family income inequality. Despite differences in time period considered and methodology, this present study confirms Zyblock's finding that the shift toward more single-parent families accounted for a considerable proportion of rising inequality, and the effects were more concentrated in the lower half of the distribution.⁴⁷ With respect to immigrant effects, Picot and Hou (2002) use a regression-based decomposition approach and suggest that two-thirds (1.5 percentage points) of the increase in the low-income rate between 1989 and 1999 was the result of increasing low-income rates among immigrants. The decomposition results in the present study suggest that the low-income rate would have been reduced by 28 percent (or 1.2 percentage points) between 1980 and 1997 if the full-time employment rate and the

language/duration of residency characteristics of immigrants had remained at their 1980 levels.

The impact of changing family structure on family income distribution is similar in the U.S. and Canada. Daly and Vallettea (2000) use the same DFL technique with 1969 and 1989 data from the U.S. Current Population Survey (CPS) and conclude that changes in family structure substantially increased inequality over this period. They found that its effects were concentrated in the lower half of the distribution of family income, and changes in family structure explained about 50 percent of the increase in the 50-10 ratio and about 9 percent of the increase in the 90-50 ratio (compared to 36% and 13%, respectively, in this study). Cancian and Reed (2001) use the CPS from 1969 and 1998 to investigate the impact of changes in family structure on the poverty rate and construct a counterfactual level of poverty using the 1998 shares of persons by family type and 1969 poverty rates. They found that the total change resulting from family structure and female employment would have produced an increase of 1.6 percentage points in the poverty rate if all else had remained as it was in 1969. By comparison, this present study shows that changes in family structure (conditional on the distribution of other attributes) led to a 1.4 percentage points increase in the Canadian poverty rate between 1980 and 1997.

The major findings of this study can be summarized as follows. First, a growth toward more non-traditional families contributed the largest share in rising income disparities among the four explained factors. Conditional on other attributes, changes in

⁴⁷Zyblock's finding, which was based on the decomposition of population subgroups, shows that the shift toward single-parent families accounted for nearly 40 percent of the increase in the mean log deviation. To compare, the same inequality measure (mean log deviation) is applied to the counterfactual distributions. This reveal that, conditional on other attributes, changing family structure accounted for about 30 percent

the family structure were responsible for 20 percent of the increase in the Gini coefficient and a 1.4 percentage point increase in the low-income rate between 1980 and 1997. The impact was especially salient on the lower-half income distribution, suggesting that the increase in single-adult families was more likely associated with low income.

Second, changes in immigrant characteristics influenced growing income disparities. Holding constant full-time employment rates of immigrants at an earlier year level would have reduced the increase in the 50-10 ratio by 26 percent and reduced the low-income rate by 0.7 percentage points. When the share of recent immigrants and mother-tongue characteristics were held constant at the 1980 level, it further explained the nearly 0.5 percentage point growth in the low-income rate and about 7 percent of the increase in the Gini coefficient. The above-mentioned immigration factors account for about 17 percent (or 1.2 percentage points) of the increase in the low-income rate and a \$462 decline in median between 1980 and 1997. When separate decompositions were conducted for two different periods (1980 to 1989 and 1989 to 1997), it was found that nearly all the immigration effects took place in the 1990s—the period with the highest intake of immigrants and the largest proportion of non-European-born immigrants since the beginning of the century.⁴⁸

Third, the effects of other attributes (e.g., age, education) were relatively small and actually showed an equalizing effect on the distribution of equivalent income. Its counterfactual effect reduced the low-income rate by 0.7 percentage points and pushed

of the increase in the mean log deviation between 1980 and 1997 (i.e., from 0.881 to 0.903 out of 0.074, where 0.074 is the total increase in the mean log deviation over this period).

⁴⁸Statistics Canada (2003) reports that between 1991 and 2000, 2.2 million immigrants were admitted to Canada, the highest number for any decade in the past century. Among immigrants who arrived during the 1990s, 58% were born in the Asian countries, and 19% were born in Africa, the Caribbean, Central or South America. These figures were up from 12.1% and 11% respectively of those who came during the 1960s, and were from these regions.

the median to more than \$800. The growing prime-age population, urbanization, as well as the growing educational attainments of Canadian workers during this period all worked together to lift the median income. These aspects might explain the equalizing effect in this category.

Finally, a substantial proportion of the increase in inequality and the low-income rate remained unexplained during this period. The residual effects were even stronger in the upper half of the income distribution and accounted for more than 70 percent of the increase in both the 90-50 and 75-50 ratios. The residual effects remained substantial, even if the counterfactual was evaluated at a different reference year. It is possible that large residuals may be the result of unexplained factors such as technological change, changing trade structures, or a correlation between husband-and-wife earnings. Future studies are needed to properly distinguish the influence of these factors.

Table 3.1
Weights Used in Density Decomposition

A. Primary-Order Decomposition

Order	Counterfactual distribution of family equivalent income in 1997 held constant factors to 1980 in the following order	Equivalent family income	Re-weighting
	Original Distribution	Y_{97}	W_{97}
I	Full-time employment rate of immigrants	Y_{97}	$W_{97} * R_{I L,S,X}$
L	Mother tongue/duration of residency characteristics of immigrants	Y_{97}	$W_{97} * R_{I L,S,X} * R_{L S,X}$
S	Family structure	Y_{97}	$W_{97} * R_{I L,S,X} * R_{L S,X} * R_{S X}$
X	Other attributes (age, sex, education, province, size of area, CMA)	Y_{97}	$W_{97} * R_{I L,S,X} * R_{L S,X} * R_{S X} * R_X$

B. Reverse-Order Decomposition

Order	Counterfactual distribution of family equivalent income in 1997 held constant factors to 1980 in the following order	Equivalent family income	Re-weighting
	Original Distribution	Y_{97}	W_{97}
X	Other attributes (age, sex, education, province, size of area, CMA)	Y_{97}	$W_{97} * R_{X S,L,I}$
S	Family structure	Y_{97}	$W_{97} * R_{X S,L,I} * R_{S L,I}$
L	Mother tongue/duration of residency characteristics of immigrants	Y_{97}	$W_{97} * R_{X S,L,I} * R_{S L,I} * R_{L I}$
I	Full-time employment rate of immigrants	Y_{97}	$W_{97} * R_{X S,L,I} * R_{S L,I} * R_{L I} * R_I$

Note: Y_{97} refers to equivalent family income in 1997, W_{97} is survey sampling weight, and Rs are estimated conditioning weightings. The subscripts for the adjusted variables—I, L, S, and X—refer to full-time employment rate among immigrants, mother tongue/duration of residency characteristics of immigrants, family structure, and other attributes, respectively.

Table 3.2
Primary-Order Decomposition of Changes in the Distribution of Family Equivalent
Income, 1980–1997 (1997 as Reference Distribution)

Statistics	Total change	Effect of				
		Immigrant	Immigrants	Family	Other	Residual
		FT rate ¹	MT/DR ²	structure	attributes ³	factors
		(1)	(2)	(3)	(4)	(5)
Gini	0.042	0.005	0.003	0.008	0.001	0.024
		(0.12)	(0.07)	(0.20)	(0.03)	(0.57)
C.V.	0.095	0.009	0.006	0.008	0.020	0.052
		(0.09)	(0.07)	(0.09)	(0.21)	(0.55)
90-10	5.384	1.278	0.379	1.789	-0.153	2.091
		(0.24)	(0.07)	(0.33)	(-0.03)	(0.39)
90-50	0.169	0.009	0.011	0.022	0.009	0.118
		(0.06)	(0.06)	(0.13)	(0.05)	(0.70)
75-25	0.526	0.079	0.027	0.104	-0.034	0.350
		(0.15)	(0.05)	(0.20)	(-0.07)	(0.67)
75-50	0.088	0.010	0.005	0.014	-0.008	0.068
		(0.11)	(0.06)	(0.15)	(-0.09)	(0.77)
50-25	0.252	0.040	0.012	0.053	-0.014	0.161
		(0.16)	(0.05)	(0.21)	(-0.05)	(0.64)
50-10	2.263	0.586	0.154	0.814	-0.095	0.804
		(0.26)	(0.07)	(0.36)	(-0.04)	(0.36)
Low-income	0.043	0.007	0.005	0.014	-0.007	0.024
rate		(0.17)	(0.11)	(0.32)	(-0.15)	(0.55)
Median	-457.17	-233.65	-228.13	-754.97	802.71	-43.13
		(0.51)	(0.50)	(1.65)	(-1.76)	(0.09)

Note: Percent of total variation explained in parenthesis.

¹Effect of immigrants held proportion of full-time working immigrants constant at earlier year levels.

²Effect of immigrants held mother tongue (MT) and duration of residency (DR) constant at earlier year levels.

³Other attributes are age, sex, education, province indicators, CMA, and sizes of area.

Table 3.3
Primary-Order Decomposition of Changes in the Distribution of Family Equivalent Income, 1980–1997 (1980 as Reference Distribution)

Statistics	Total change	Effect of				
		Immigrant FT rate ¹	Immigrants MT/DR ²	Family structure	Other attributes ³	Residual factors
		(1)	(2)	(3)	(4)	(5)
Gini	-0.042	-0.006 (0.14)	-0.002 (0.06)	-0.011 (0.27)	-0.001 (0.03)	-0.021 (0.50)
C.V.	-0.095	-0.010 (0.11)	-0.001 (0.01)	-0.019 (0.20)	-0.009 (0.10)	-0.056 (0.59)
90-10	-5.384	-0.565 (0.11)	-0.391 (0.07)	-2.574 (0.48)	-0.131 (0.02)	-1.722 (0.32)
90-50	-0.169	-0.016 (0.09)	-0.011 (0.06)	-0.022 (0.13)	-0.004 (0.02)	-0.117 (0.69)
75-25	-0.526	-0.051 (0.10)	-0.020 (0.04)	-0.161 (0.31)	0.046 (-0.09)	-0.340 (0.65)
75-50	-0.088	-0.009 (0.10)	-0.007 (0.08)	-0.013 (0.14)	0.000 (0.00)	-0.060 (0.68)
50-25	-0.252	-0.025 (0.10)	-0.005 (0.02)	-0.096 (0.38)	0.031 (-0.12)	-0.157 (0.62)
50-10	-2.263	-0.260 (0.12)	-0.179 (0.08)	-1.256 (0.56)	-0.056 (0.02)	-0.512 (0.23)
Low-income rate	-0.043	-0.009 (0.21)	-0.005 (0.11)	-0.018 (0.44)	0.006 (-0.16)	-0.017 (0.40)
Median	457.17	353.66 (0.77)	319.97 (0.70)	677.79 (1.48)	-790.43 (-1.73)	-103.83 (-0.23)

Note: Percent of total variation explained in parenthesis.

¹Effect of immigrants held proportion of full-time working immigrants constant at earlier year levels.

²Effect of immigrants held mother tongue (MT) and duration of residency (DR) constant at earlier year levels.

³Other attributes are age, sex, education, province indicators, CMA, and sizes of area.

Table 3.4
Reverse-Order Decomposition of Changes in the Distribution of Family Equivalent
Income, 1980–1997

Statistics	Total change	Effect of				
		Other attributes ¹ (1)	Family structure (2)	Immigrants MT/DR ² (3)	Immigrants FT rate ³ (4)	Residual factors (5)
Gini	0.042	0.003 (0.07)	0.010 (0.24)	0.003 (0.07)	0.002 (0.05)	0.024 (0.57)
C.V.	0.095	0.017 (0.18)	0.016 (0.17)	0.005 (0.05)	0.004 (0.04)	0.052 (0.55)
90-10	5.384	0.710 (0.13)	1.961 (0.36)	0.433 (0.08)	0.189 (0.04)	2.091 (0.39)
90-50	0.169	-0.001 (0.00)	0.034 (0.20)	0.010 (0.06)	0.007 (0.04)	0.118 (0.70)
75-25	0.526	0.011 (0.02)	0.118 (0.23)	0.034 (0.06)	0.012 (0.02)	0.350 (0.67)
75-50	0.088	-0.006 (-0.06)	0.019 (0.22)	0.003 (0.03)	0.004 (0.05)	0.068 (0.77)
50-25	0.252	0.014 (0.06)	0.055 (0.22)	0.019 (0.08)	0.003 (0.01)	0.161 (0.64)
50-10	2.263	0.341 (0.15)	0.857 (0.38)	0.186 (0.08)	0.076 (0.03)	0.804 (0.36)
Low-income rate	0.043	-0.002 (-0.06)	0.014 (0.32)	0.004 (0.10)	0.004 (0.08)	0.024 (0.55)
Median	-457.17	441.45 (-0.97)	-479.56 (1.05)	-153.34 (0.34)	-222.59 (0.49)	-43.13 (0.09)

Note: Percent of total variation explained in parenthesis.

¹Other attributes are age, sex, education, province indicators, CMA, and sizes of area.

²Effect of immigrants held mother tongue (MT) and duration of residency (DR) constant at earlier year levels.

³Effect of immigrants held proportion of full-time working immigrants constant at earlier year levels.

Table 3.5
Primary-Order Decomposition of Changes in the Distribution of Family Equivalent Income, 1980–1989

Statistics	Total change	Effect of				
		Immigrant FT rate ¹ (1)	Immigrants MT/DR ² (2)	Family structure (3)	Other attributes ³ (4)	Residual factors (5)
Gini	0.013	0.001 (0.06)	0.001 (0.06)	0.004 (0.35)	0.001 (0.09)	0.006 (0.45)
C.V.	0.050	0.000 (0.00)	0.001 (0.03)	0.010 (0.20)	-0.002 (-0.04)	0.041 (0.81)
90-10	0.820	0.047 (0.06)	0.102 (0.12)	0.525 (0.64)	0.021 (0.03)	0.125 (0.15)
90-50	0.048	0.001 (0.02)	0.003 (0.06)	0.003 (0.05)	0.002 (0.04)	0.040 (0.83)
75-25	0.145	0.007 (0.05)	0.010 (0.07)	0.038 (0.26)	0.013 (0.09)	0.077 (0.53)
75-50	0.018	0.001 (0.05)	0.000 (0.01)	0.002 (0.13)	0.002 (0.10)	0.013 (0.72)
50-25	0.080	0.004 (0.05)	0.007 (0.09)	0.024 (0.29)	0.007 (0.09)	0.039 (0.48)
50-10	0.323	0.022 (0.07)	0.046 (0.14)	0.262 (0.81)	0.007 (0.02)	-0.013 (-0.04)
Low-income rate	0.002	0.001 (0.77)	0.003 (1.70)	0.008 (5.10)	-0.003 (-1.64)	-0.008 (-4.94)
Median	1440.59	-44.81 (-0.03)	-84.30 (-0.06)	-333.82 (-0.23)	417.78 (0.29)	1485.74 (1.03)

Note: Percent of total variation explained in parenthesis.

¹Effect of immigrants held proportion of full-time working immigrants constant at earlier year levels.

²Effect of immigrants held mother tongue (MT) and duration of residency (DR) constant at earlier year levels.

³Other attributes are age, sex, education, province indicators, CMA, and sizes of area.

Table 3.6
Primary-Order Decomposition of Changes in the Distribution of Family Equivalent Income, 1989–1997

Statistics	Total change	Effect of				
		Immigrant FT rate ¹ (1)	Immigrants MT/DR ² (2)	Family structure (3)	Other attributes ³ (4)	Residual factors (5)
Gini	0.029	0.004 (0.14)	0.002 (0.06)	0.004 (0.14)	0.000 (0.01)	0.019 (0.65)
C.V.	0.044	0.007 (0.16)	0.004 (0.08)	0.004 (0.08)	0.010 (0.23)	0.020 (0.44)
90-10	4.564	1.014 (0.22)	0.192 (0.04)	1.023 (0.22)	-0.094 (-0.02)	2.429 (0.53)
90-50	0.121	0.006 (0.05)	0.016 (0.13)	0.007 (0.06)	0.004 (0.03)	0.089 (0.74)
75-25	0.381	0.062 (0.16)	0.032 (0.08)	0.033 (0.09)	-0.021 (-0.06)	0.276 (0.72)
75-50	0.071	0.006 (0.09)	0.010 (0.15)	0.002 (0.03)	-0.005 (-0.07)	0.057 (0.80)
50-25	0.172	0.033 (0.19)	0.008 (0.05)	0.019 (0.11)	-0.008 (-0.05)	0.120 (0.70)
50-10	1.940	0.469 (0.24)	0.050 (0.03)	0.477 (0.25)	-0.055 (-0.03)	0.999 (0.52)
Low-income rate	0.042	0.006 (0.14)	0.003 (0.07)	0.006 (0.15)	-0.005 (-0.11)	0.031 (0.74)
Median	-1897.76	-163.49 (0.09)	-243.60 (0.13)	-255.18 (0.13)	368.45 (-0.11)	-1603.95 (0.85)

Note: Percent of total variation explained in parenthesis.

¹Effect of immigrants held proportion of full-time working immigrants constant at earlier year levels.

²Effect of immigrants held mother tongue (MT) and duration of residency (DR) constant at earlier year levels.

³Other attributes are age, sex, education, province indicators, CMA, and sizes of area.

Figure 3.1
Trends of Inequality and Low-income, Equivalent Income

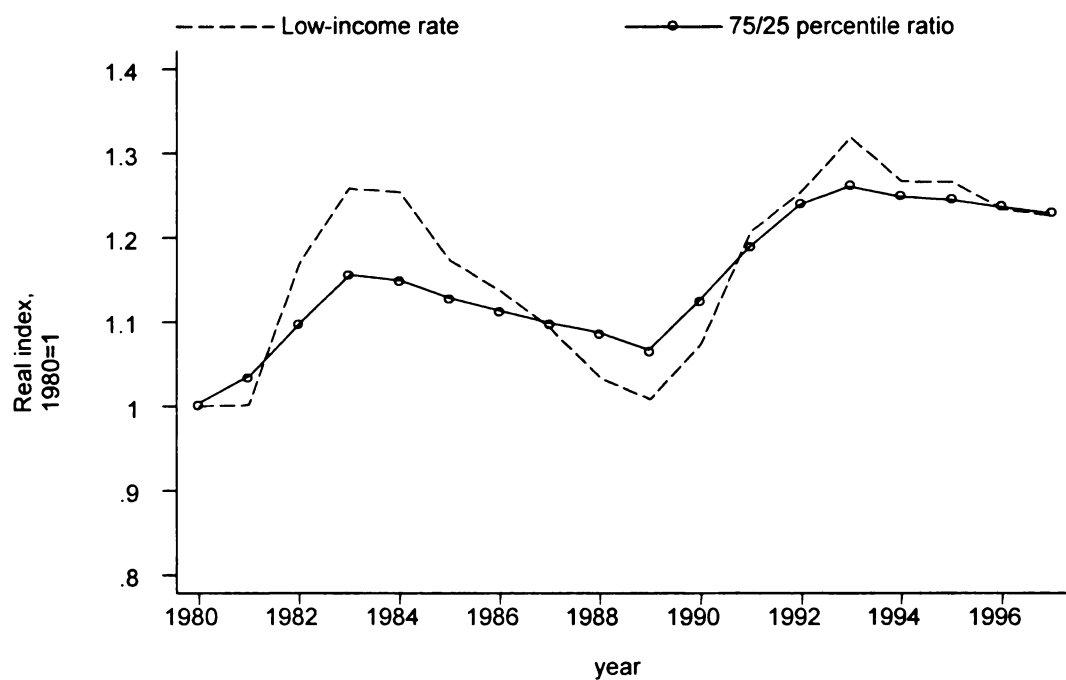


Figure 3.2
Indexed Equivalent Income by Percentile, 1980–1997

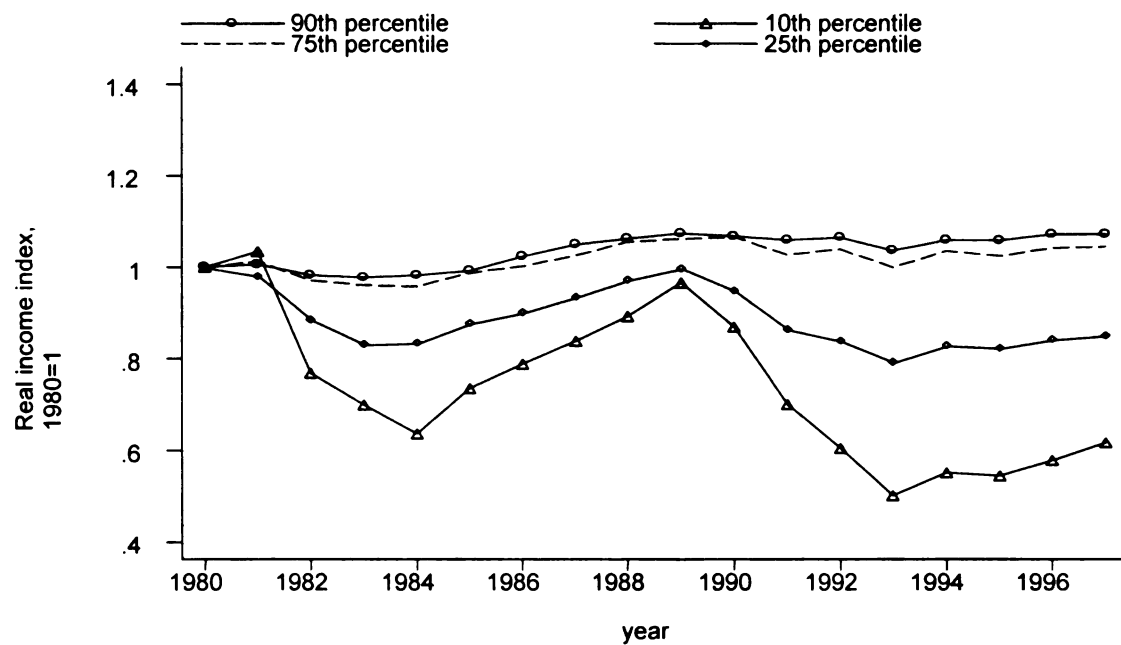


Figure 3.3a
Kernel Density for Equivalent Income, 1980 and 1997

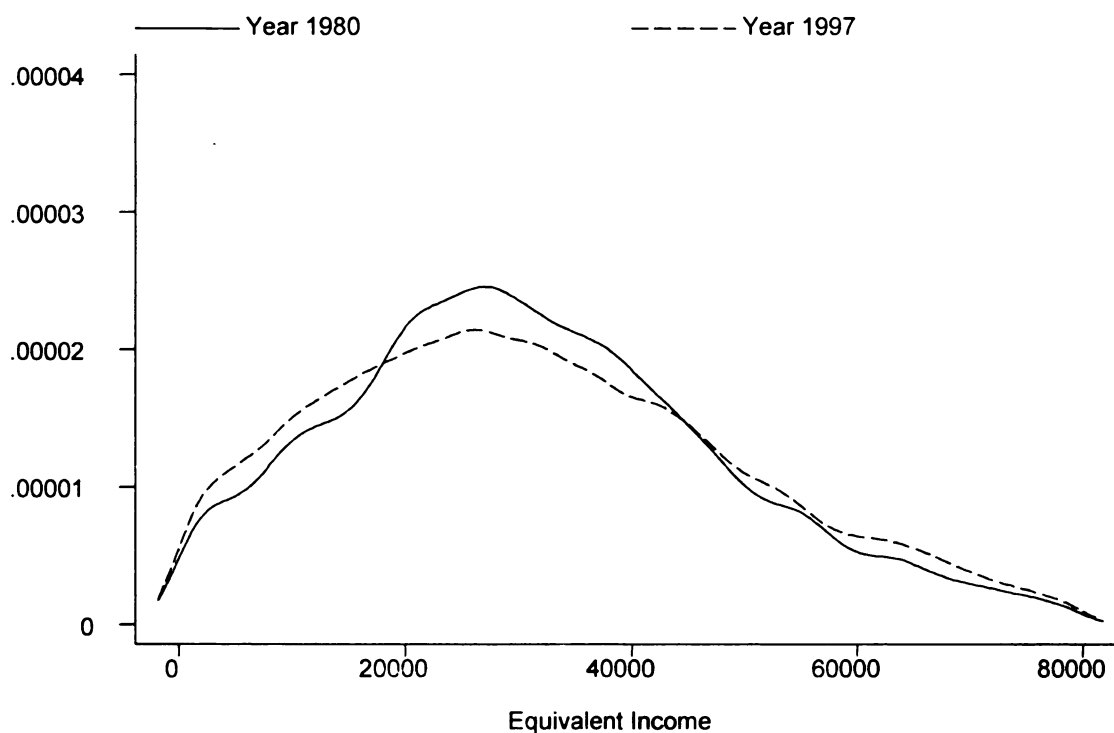


Figure 3.3b
Kernel Density for Equivalent Income, 1980 and 1989

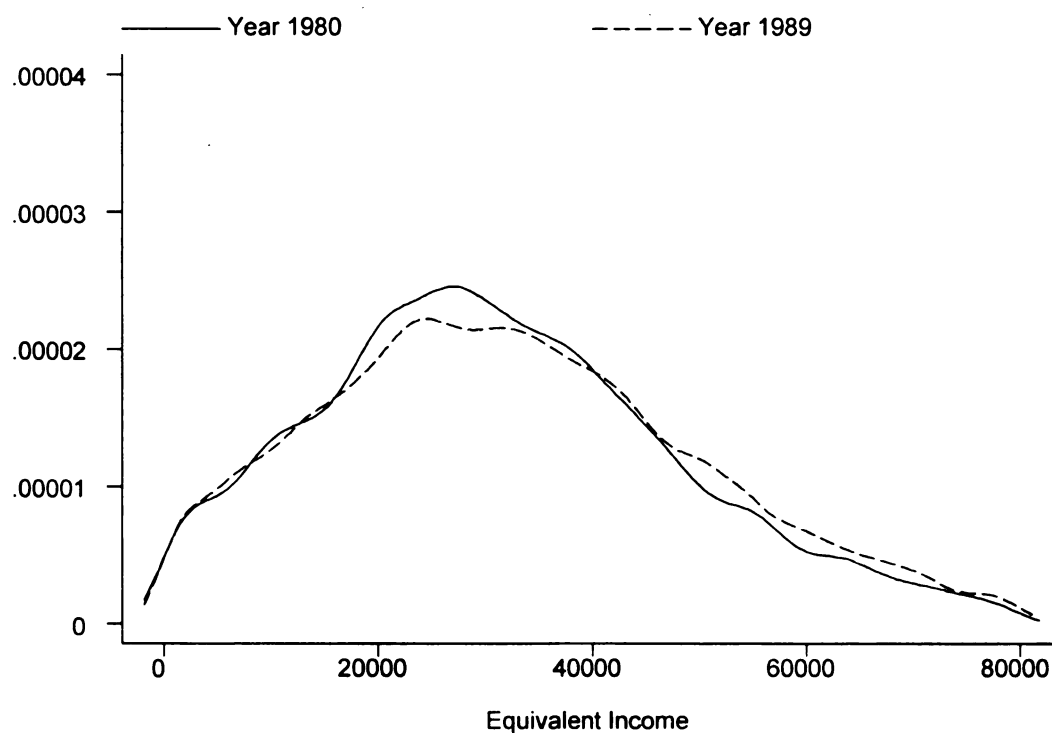


Figure 3.3c
Kernel Density for Equivalent Income, 1989 and 1997

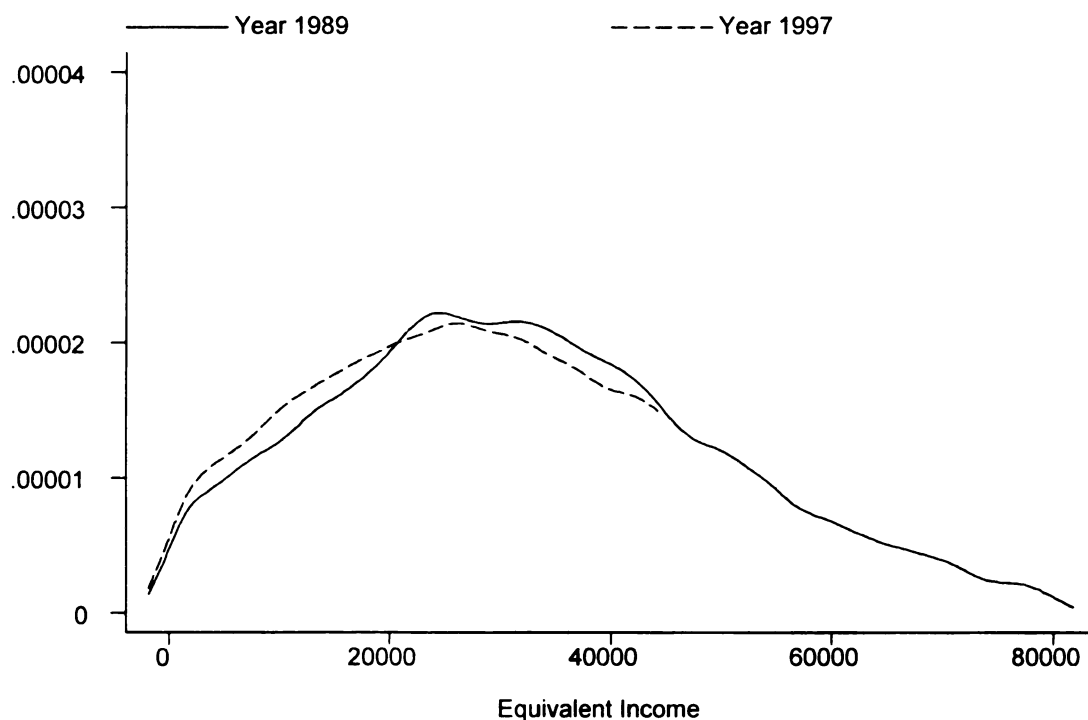


Figure 3.4
Inequality Measures for Male Earnings (age 15–64)

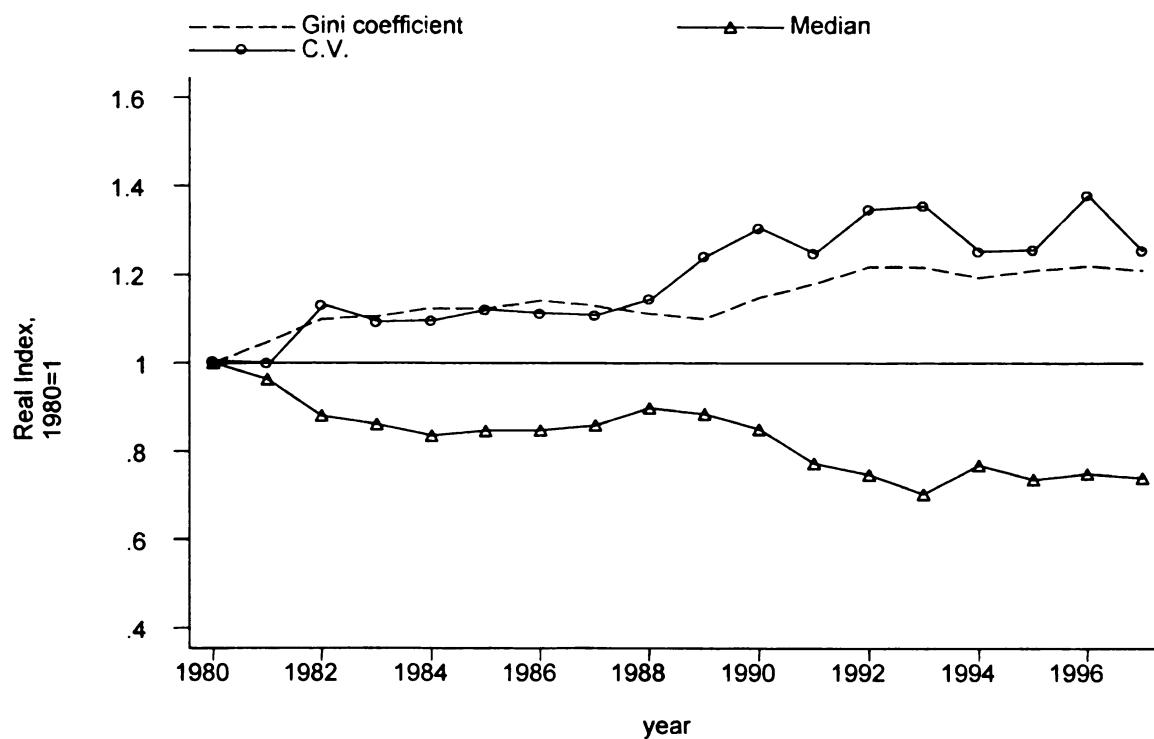


Figure 3.5
Proportion of Working Wives by Husband's Quartile Earnings Distribution, Couple Families

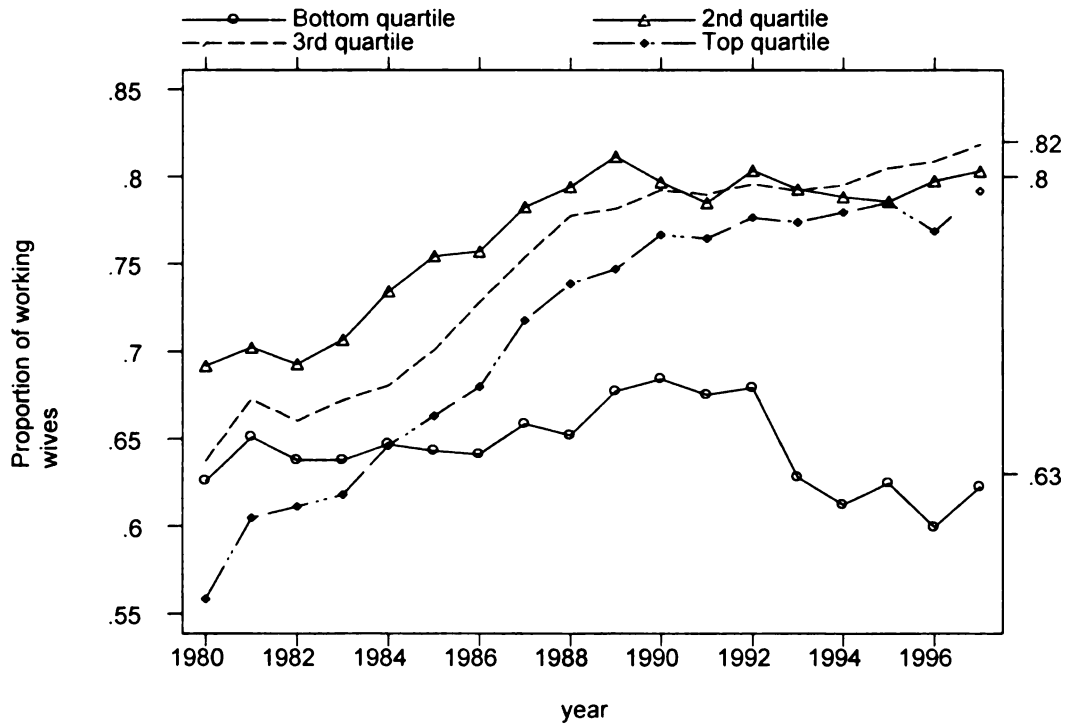


Figure 3.6
Family Composition

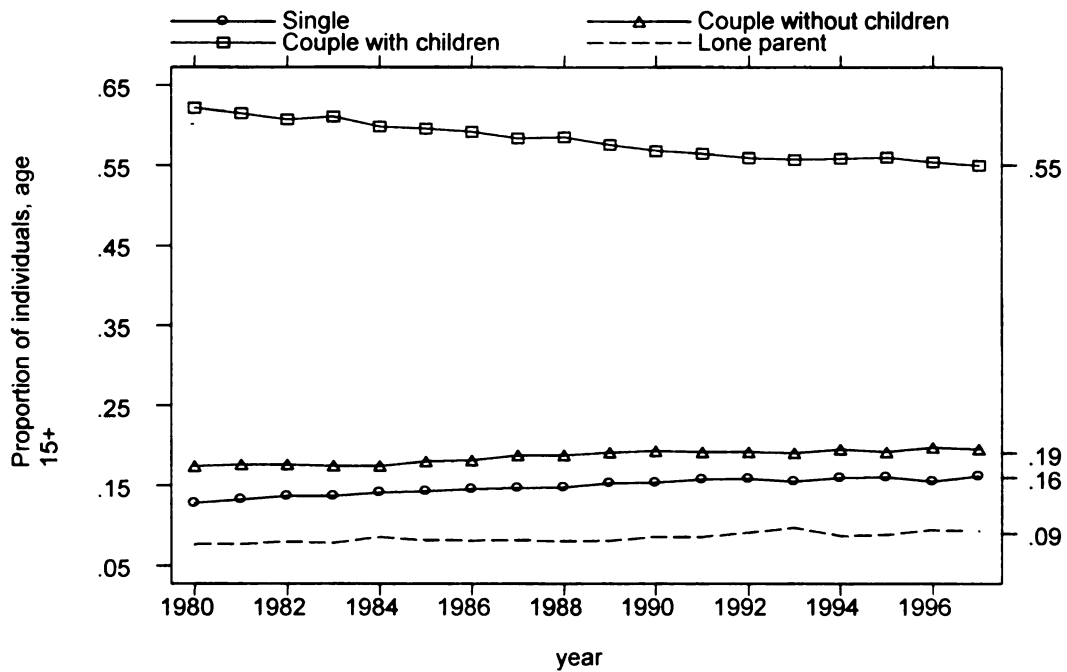


Figure 3.7
Median Equivalent Market Income (age 15-64)

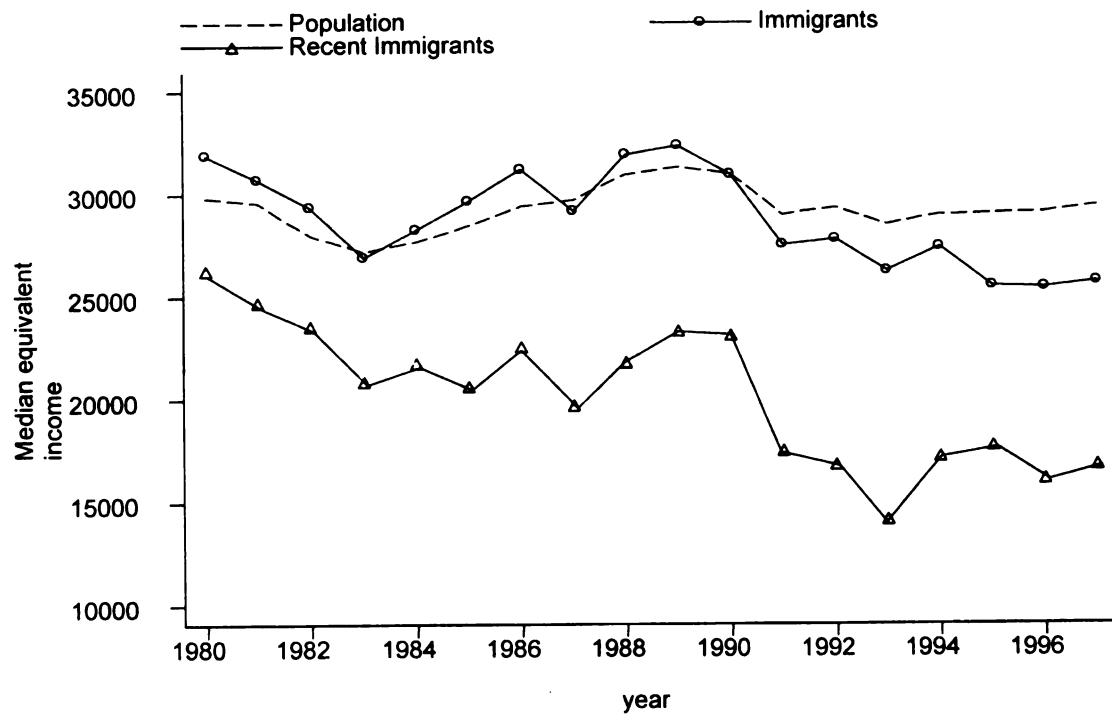


Figure 3.8
Full-time Employment Rate (age 15-64)

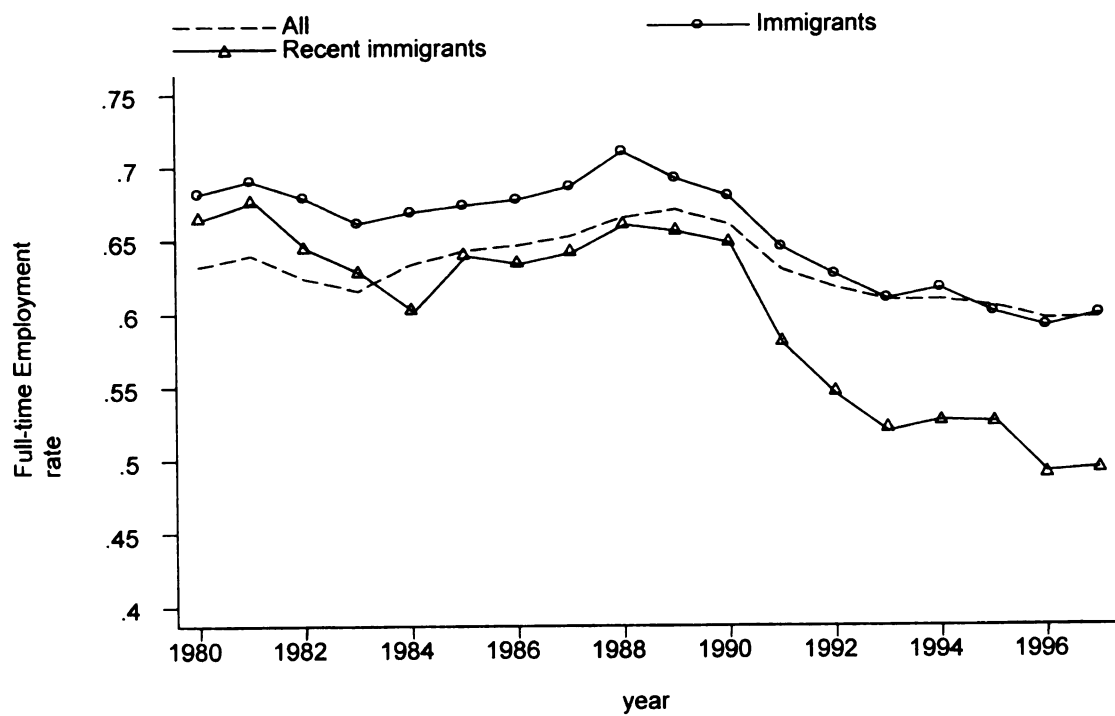


Figure 3.9
Proportion of Immigrants Whose Mother Tongue is English or French

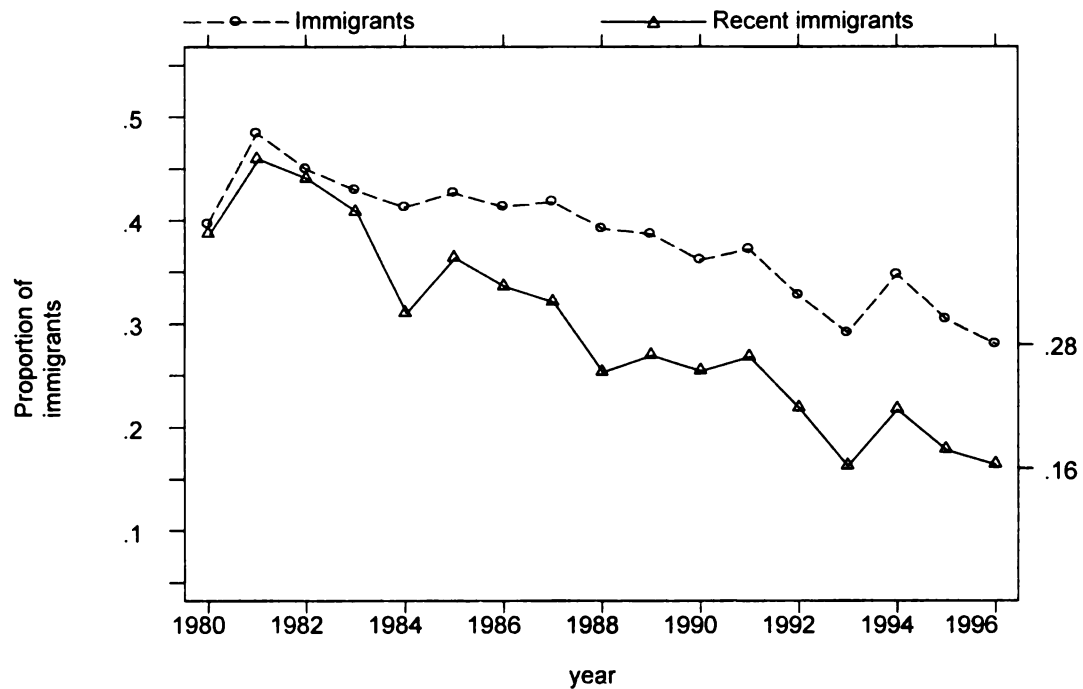


Figure 3.10
1997 Equivalent Incomes with 1980 Immigrants' Full-time Employment

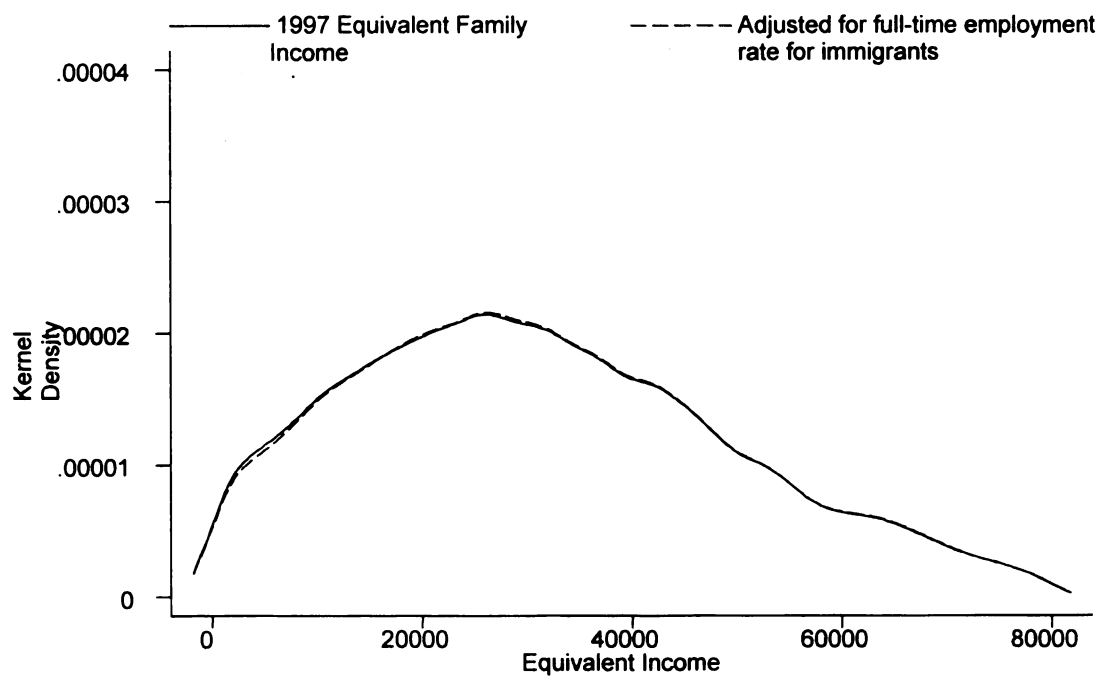


Figure 3.11
1997 Equivalent Incomes with 1980 Immigrants' Full-time Employment, Mother Tongue, and Duration of Residency Characteristics

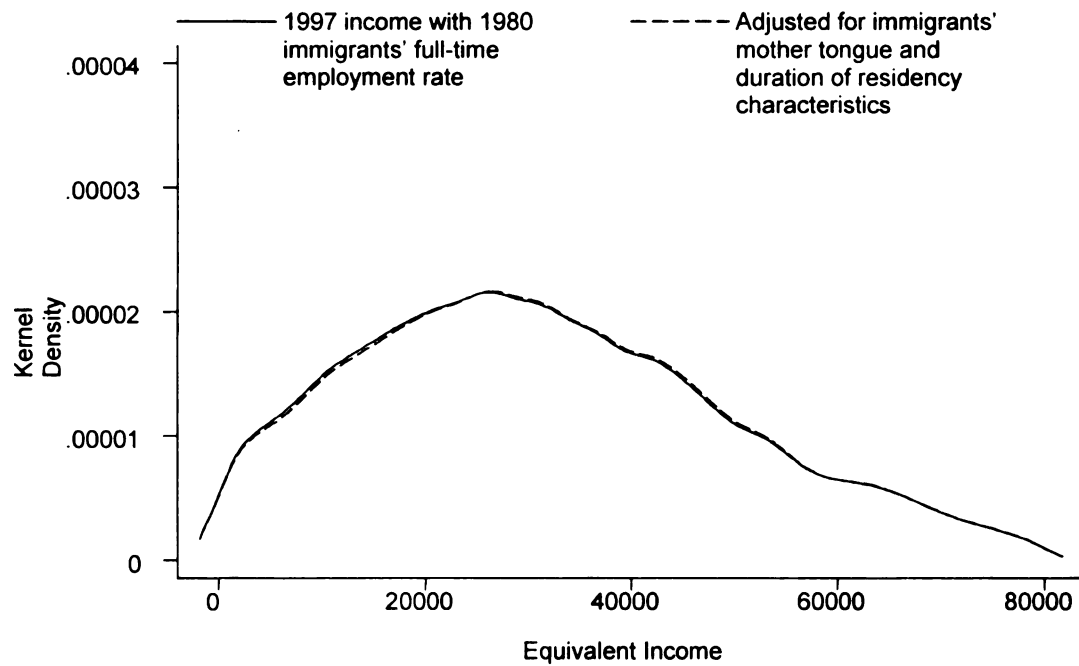


Figure 3.12
1997 Equivalent Incomes with 1980 Immigration Factors and Family Structure

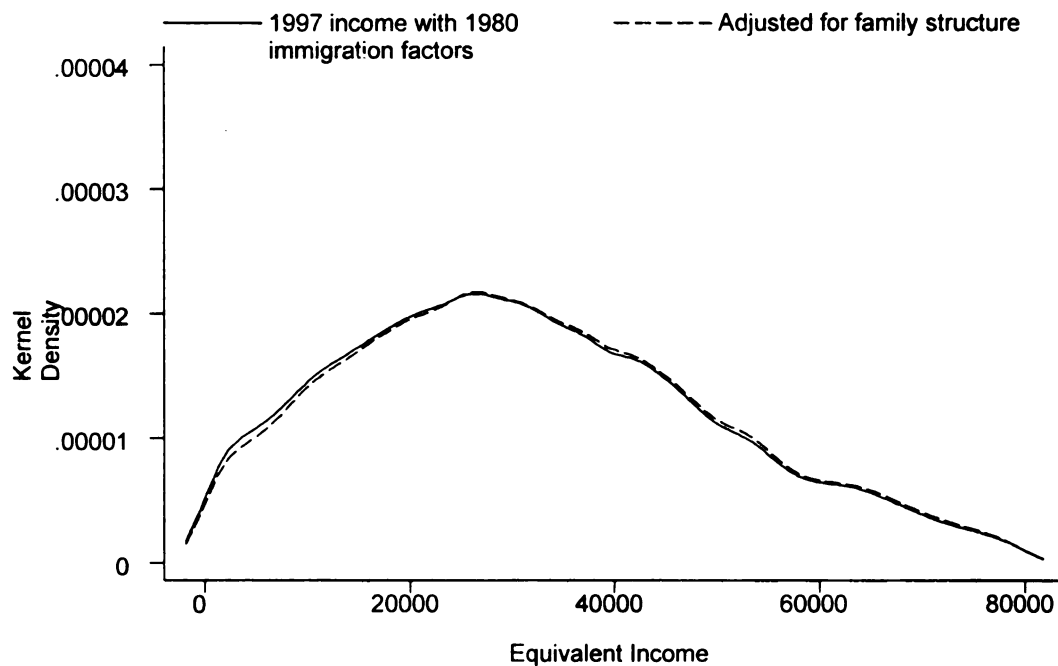


Figure 3.13
1997 Equivalent Incomes with 1980 Immigration Factors, Family Structure, and Other Attributes

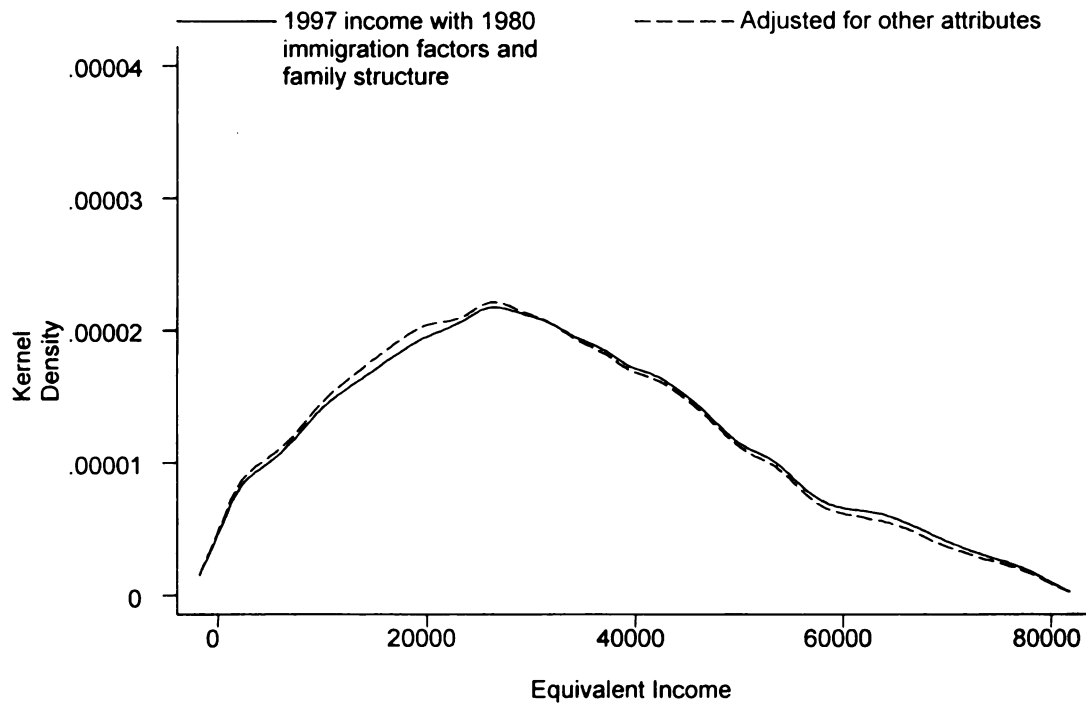
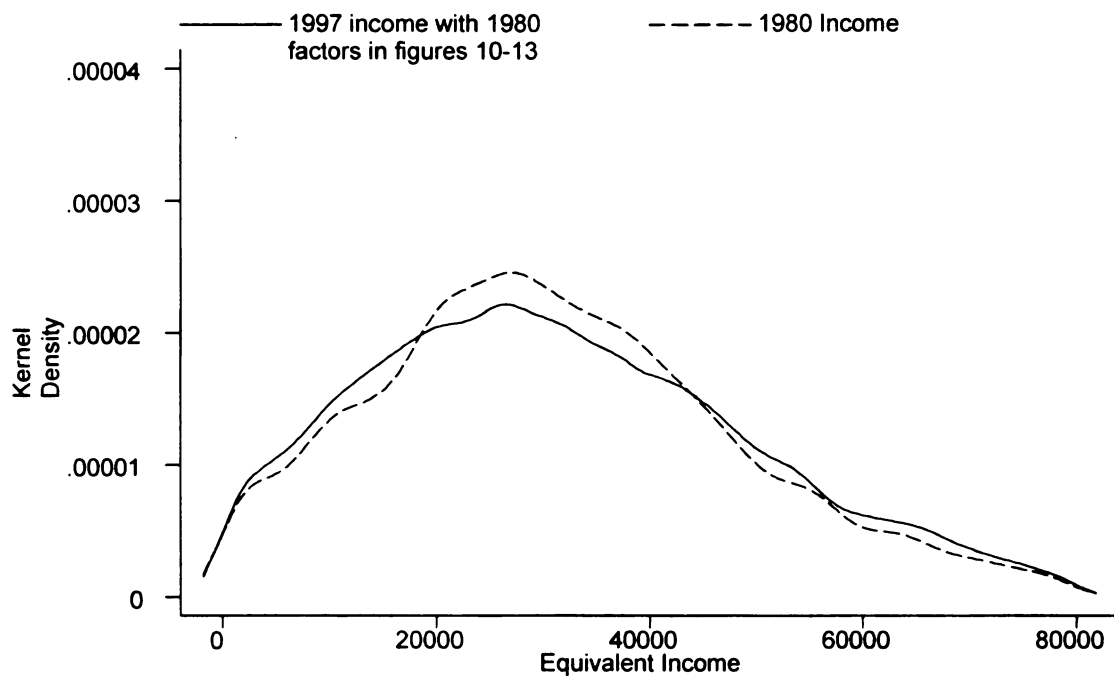


Figure 3.14
Residual



CONCLUSION

The chapters in this dissertation cover empirical research into three specific areas: (1) employment insurance, (2) income mobility, and (3) family income distribution. The conclusions are summarized as follows.

Chapter 1

The new EI repayment provision has reduced the probabilities of filing a claim

The switch to the EI system led to a substantial reduction in the EI participation rate among high-income workers. Applying propensity score matching and regression methods with data from two different data sources—the Survey of Changes in Employment (CIE) and the Survey of Labour and Income Dynamics (SLID)—this study shows that the new repayment policy has reduced the probabilities of filing a claim among high-income individuals by about 4.2 to 6.2 percentage points for the CIE sample and about 9.7 to 12.7 percentage points for the SLID sample. Based on the estimate of a 6.2 percentage point decline in claim rate, this study suggests that the new rules could have reduced the average monthly number of regular beneficiaries in the post-policy period by about 31,482 and reduced the total annual regular benefits by about \$629 million.

However, it should be noted that both matching and regression estimates relied on observables, thus the existence of unobserved heterogeneity could seriously bias the parameter estimates. In addition, the decline in claim rates could be due to employment effects. With the effective reduction in benefits imposed by the repayment policy, many frequent claimants will leave for stable industries. The claim rates for the remaining at-

risk population are, therefore, smaller. Future research on repayment should take employment effects into account.

Chapter 2

There is substantial income mobility in Canada and the United States

Using the longitudinal survey data from Canada (the Survey of Labour and Income Dynamics, SLID) and the United States (Panel Study of Income Dynamics, PSID), this chapter shows that there is significant household income mobility in both the U.S. and Canada. For most individuals, poverty is a temporary experience. For example, although 40 percent of the population in both countries experienced poverty at least once during the survey years, only 10 to 13 percent of them were in poverty every year. It was also found that mobility rates vary across subgroups. Based on 1-year transition matrices, 24 (35) percent of the Canadian (American) college graduates who were observed in poverty in year t rose above the poverty line the next year. The comparable figures for people with high school or less education were about 14 percent and 18 percent for Canada and the U.S., respectively.

Canada's redistributive system contributes to income stability

Applying both pre-transfer and post-transfer income measures, this study discovered that Canada's redistributive system significantly reduced the variations of bad or good years for an individual and greatly increased stability. From any given year ($t-1$ to t), the chance of staying both years in either of the two extremes of income distribution was reduced from 43.5 to 23 percent when post-transfer measures were used, while the

chance of staying in the same middle income group increased correspondingly (from 21% to 39%). The effect of the transfer system on income stability was also evident among subgroups. The rates of persistent poverty among less-educated people dropped from 22.4 percent to 4.7 or 6.3 percent and from 18 percent to 2.7 or 4.2 percent for immigrants whose mother tongue was neither English nor French. The redistributive system in the U.S. also contributed to income stability, but the effect was relatively smaller.

Household events are more relevant to spell beginnings or endings in Canada

Using the Bane-Ellwood hierarchical classification, it was found that the beginning or ending of an income spell was more likely to be associated with changes in household income sources (mostly earnings) in both the U.S. and Canada. However, household events were more relevant to the spell beginnings or endings in Canada, especially among single-adult households. About 43 percent of low-income spell endings among single-parent households in Canada were related to partnership or household merges. The comparable figure is about 28 percent in the United States. Similarly, as many as 38 percent of low-income spell beginnings among single unattached households in Canada were associated with newly established family, compared to 15 percent in the United States.

Chapter 3

Changing family structure and the characteristics of immigrants contribute to an increase in income inequality and the poverty rate

What would be the inequality or poverty rates if family structure and the characteristics of immigrants had remained as they were 20 years ago? This study addressed this question by constructing counterfactual distributions through a newly developed re-weighting procedure. This study shows that, conditional on other attributes, changes in family structure were responsible for 20 percent of the increase in the Gini coefficient and a 1.4 percentage point increase in the low-income rate between 1980 and 1997. The impact was especially salient on the lower half of the income distribution, suggesting that the increase in single-adult families was more likely associated with low income. Similarly, in this study, a counterfactual distribution was constructed by holding constant three immigrants' characteristics—full-time employment rate, duration of residency, and mother tongue—to 20 years ago. The changes in these three characteristics accounted for about 33 percent of the increase in the 50-10 ratio, 17 percent (or 1.2 percentage points) of the increase in the low-income rates, and a \$462 decline in median income over this period.

A large proportion of the changes in inequality remain unexplained

The results of this study show substantial residual effects, particularly in the upper half of the income distribution. These residual effects accounted for more than 70 percent of the increase in both the 90-50 and 75-50 ratios. The residual effects remained significant, even if the counterfactual was evaluated for a different reference year. The large residuals may be due to the fact that many important changes (e.g., changes in

earnings disparities or changes in the correlation of wives' earnings with other income sources) were not factored into the decompositions. Future studies are needed to properly distinguish the influence of other factors.

APPENDICES

APPENDIX A Additional Tables for Chapter 1

Table A1
Major Changes of Legislation from UI to EI

Program parameter	Unemployment Insurance (UI)	Employment Insurance (EI)	Remark
Entrance requirements	12–20 insurable weeks	420–700 hours	Change from weeks-based to hours-based system
Entrance requirements for new or re-entrants	Minimum 20 weeks	Minimum 26 weeks (or 910 hours)	Re-entrants refer to those absent from work for 2 years
Minimum hours for insurability	15 hours/week	No	All hours are counted for eligibility; part-time workers are covered
Entitlement schedule	Maximum 50 weeks	Maximum 45 weeks	
Maximum insurable earnings (MIE)	\$845/week	\$750/week	
Replacement rate (the divisor rule)	55% (No)	55% (Yes)	The average weekly benefits are calculated by summing earnings over the last 26 weeks by the greater of (1) the number of weeks worked or (2) the minimum divisor number (see Divisor Table below)
Replacement rate for claimants with dependents (Family income supplement)	60%	65%–80%	
Maximum benefit amount	\$465/week	\$413/week	
Intensity Rule	No	Replacement rate will drop 1–5%, depending on claim history	Replacement rate is reduced by 1 percent (up to 5%) for every 20 weeks of regular benefits claimed in the past 5 years
Repayment (Clawback)	Repay 30% of benefit received if net income > 1.5 times the annual MIE	Repay 30–100% of benefit received if net income > 1.25 times the annual MIE, depending on claim history	See Table A2 in Appendix A for detailed schedule for repayment

Divisor Table

Regional Unemployment rate	Minimum divisor	Regional Unemployment rate	Minimum divisor
0% to 6%	22	10.1% to 11%	17
6.1% to 7%	21	11.1% to 12%	16
7.1% to 8%	20	12.1% to 13%	15
8.1% to 9%	19	13.1% and over	14
9.1% to 10%	18		

Table A2
EI Repayment: Repayment of Benefits at Income Tax Time

Number of EI benefits paid since June 30, 1996 (over a 5-year claim history)	Qualifying for repayment	Percentage repayment
0–20 weeks	Net income > 1.25* Maximum Insurable Earnings (\$48,750)	30%
21–40 weeks		50%
41–60 weeks	Net income > Maximum Insurable Earnings (\$39,000)	60%
61–80 weeks		70%
81–100 weeks		80%
100–120 weeks		90%
Over 120 weeks		100%

*Source: Human Resources Development Canada

Table A3
Data Collection Period for CIE data

Cohort	Job loss date	Reference period	Interview date	Obs. Full sample
<i>Pre-policy sample</i>				
2	1995 Q4	04/95–09/96	09/96	4,016
3	1996 Q1	07/95–11/96	11/96	4,578
4	1996 Q2	10/95–02/97	02/97	4,909
<i>Post-policy sample</i>				
5	1996 Q3	01/96–05/97	05/97	5,128
6	1996 Q4	04/96–09/97	09/97	4,043
7	1997 Q1	07/96–11/97	11/97	3,664
8	1997 Q2	10/96–02/98	02/98	4,049
9	1997 Q3	01/97–05/98	05/98	4,433
10	1997 Q4	04/97–09/98	09/98	4,486
13	1998 Q3	01/98–05/99	05/99	3,731
17	1999 Q3	01/99–05/00	05/00	4,927
Total				47,964

APPENDIX B

Sample Construction for CIE and SLID data

B.1 Identifying UI or EI Eligibility Condition in CIE and SLID

In Canada, the eligibility conditions for UI or EI benefits are based on two criteria: (1) work history and (2) region of residency. To be eligible, an individual must work at least 12 to 20 weeks under UI (or 420–700 hours under EI), depending on the regional unemployment rate at the time of being unemployed. For new entrants and re-entrants, 20 weeks (or 910 hours under EI) of work is required, regardless of the unemployment rate. It should be noted that neither survey provides all the information needed to calculate a person's eligibility. As a result, certain assumptions are required for each survey, and any comparison of results from these two datasets should be interpreted carefully.

For the CIE data, work history can be obtained directly, while information about residency is only available at provincial levels and not regional levels. Work history (pre-displacement tenure) is taken from a variable labeled “e1djrdr,” which records the duration of employment (in weeks) within the reference period. Using unemployment rates at the provincial level might be misleading because variations could be very large between regions within the same province. It would include some people who are not supposed to qualify for benefits in the sample and vice versa. An alternative way is to include everybody who had at least 12 weeks of pre-displacement tenure in the sample. As expected, some of the ineligible people were also included, and the UI or EI participation rate was understated. Fortunately, this bias can be reduced by using another variable in the survey, “p1qd1b.” This variable is determined by asking the respondent who had been unemployed for at least 4 weeks why they have not applied for benefits.

Those who answered “not eligible/did not work long enough” were excluded from the sample.

For the SLID data, work history is not identified directly, while information about region of residency is available. To select an unemployed sample, two variables in SLID were used. First, unemployed people were identified with the variable “enddat1” if they were permanently displaced or with the variable “strdat8” if they were absent from work (e.g., temporary layoffs). Second, pre-displacement tenure for each unemployed person was calculated from the weekly labour force vector “wylfst28” if eligibility was based on “weeks,” or it was calculated from usual hours per month “hwjmv1” if eligibility was based on “hours.” With region of residency noted with the variable “eir25,” the regional unemployment rate at the month of job separation for each individual can be calculated by combining unemployment rates from the monthly labour force survey. Each individual’s eligibility can then be obtained from the derived variables.

B.2 Identifying UI or EI Participation Rate (take-up) in CIE and SLID

In CIE, survey variable “plqd1” is used to identify an individual’s UI or EI participation rate. This variable is determined by asking respondents a yes/no question about whether he or she received any EI income since the ROE date. Those who answered “Don’t know” (only about 0.4%) were not included.

Identifying UI or EI participation in SLID is not straightforward. SLID does ask respondents whether they received UI or EI benefits during the reference year; however, it might be misleading because individuals who made no UI or EI claim for the observed job interruption could have received benefits in the early months of the year. Similarly,

individuals who lost their jobs at the end of the year might actually claim their benefits in the next calendar year. To make sure benefits have been received after the observed interruption, the longitudinal monthly compensation vector “mthrcv14” and the compensation type variable “comptype” were used. An individual was defined as receiving benefits if UI or EI activities were observed following his or her job interruption.

B.3 Calculation of Potential Annual Income for CIE

Computing potential individual annual income from the CIE data requires information from various variables in the survey and some assumptions. First, CIE asks respondents about total personal income (p1qf18) and household income (p1qf17) in the past 4 weeks at the time of the survey, whether household income has changed compared to the month before the ROE date (p1qf17a), and by how much per month (p1qf17b). If an individual is the only income source in the household ($p1qf18 = p1qf17$), his or her pre-displacement income can be derived using the above variables. However, if there are other members who contributed to the household income, it is not possible to separate an individual’s earnings from household income using the above variables. As a result, calculations of potential income for this type of person (accounts for 61% of final CIE sample) are based on the yearly wage/salary variable (e1dgppy). The drawback to using this measure is that it likely overestimated the true income because these people did not actually work throughout the year due to job interruption. Therefore, it might underestimate the policy effect.

APPENDIX C

Stata Output for Propensity Score Matching

CIE Sample

```
*****
Algorithm to estimate the propensity score
*****
```

The treatment is treat_48

treat_48	Freq.	Percent	Cum.
0	920	30.82	30.82
1	2,065	69.18	100.00
Total	2,985	100.00	

Estimation of the propensity score

```
(sum of wgt is 7.8222e+05)
Iteration 0: log pseudo-likelihood = -1790.0313
Iteration 1: log pseudo-likelihood = -1605.2942
Iteration 2: log pseudo-likelihood = -1603.56
Iteration 3: log pseudo-likelihood = -1603.5585
```

Probit estimates	Number of obs	=	2985
	Wald chi2(24)	=	154.15
	Prob > chi2	=	0.0000
Log pseudo-likelihood = -1603.5585	Pseudo R2	=	0.1042

treat_48	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
age	.0074447	.0056042	1.33	0.184	-.0035393 .0184287
sex	-.1462884	.2152577	-0.68	0.497	-.5681858 .275609
edu2	.0104486	.1212429	0.09	0.931	-.2271831 .2480803
edu3	.1431281	.1089022	1.31	0.189	-.0703162 .3565725
edu4	.1429511	.208648	0.69	0.493	-.2659914 .5518936
hhcomp2	-.1391189	.1255095	-1.11	0.268	-.385113 .1068751
hhcomp3	-.1125886	.1142304	-0.99	0.324	-.336476 .1112988
hhcomp4	.0380538	.2870789	0.13	0.895	-.5246105 .6007181
_Iprov_2	.0294675	.1417924	0.21	0.835	-.2484404 .3073754
_Iprov_3	-.0725862	.2021522	-0.36	0.720	-.4687971 .3236248
_Iprov_4	-.2596783	.2110278	-1.23	0.218	-.6732851 .1539285
_Iprov_5	-.1037929	.1692809	-0.61	0.540	-.4355773 .2279915
_ur_jend	-.0304951	.0228681	-1.33	0.182	-.0753157 .0143254
qtroe2	1.271901	.1197398	10.62	0.000	1.037215 1.506587
qtroe3	.6959259	.1080812	6.44	0.000	.4840907 .9077612
blue_wk	.1702511	.1458186	1.17	0.243	-.1155481 .4560503
fmsize2	-.0296974	.116347	-0.26	0.799	-.2577333 .1983385
fmsize3	.010592	.1178537	0.09	0.928	-.220397 .2415811
fmsize4	-.1513779	.1440676	-1.05	0.293	-.4337451 .1309894
anotice	-.0437274	.0961549	-0.45	0.649	-.2321876 .1447328
peremp	-.0498306	.096191	-0.52	0.604	-.2383615 .1387002
can	-.1310617	.1294141	-1.01	0.311	-.3847086 .1225852
season	.0459809	.0962916	0.48	0.633	-.1427472 .234709
recall	-.0593268	.1058514	-0.56	0.575	-.2667918 .1481381
_cons	.1518435	.4626813	0.33	0.743	-.7549952 1.058682

Note: the common support option has been selected
The region of common support is [.28642705, .9536743]

Description of the estimated propensity score
in region of common support

Estimated propensity score				

	Percentiles	Smallest		
1%	.3304967	.2864271		
5%	.3887933	.2875965		
10%	.4307575	.2910511	Obs	2984
25%	.5825589	.2915601	Sum of Wgt.	2984
50%	.7257523		Mean	.6985926
		Largest	Std. Dev.	.1694598
75%	.8533551	.9468658		
90%	.8905292	.9485399	Variance	.0287166
95%	.9056701	.9515638	Skewness	-.5865272
99%	.9267302	.9536743	Kurtosis	2.187079

Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output

The final number of blocks is 7

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks

Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output

The balancing property is satisfied

This table shows the inferior bound, the number of treated
and the number of controls for each block

Inferior	treat_48		Total
of block	0	1	
of pscore			

.2	124	63	187
.4	329	256	585
.6	49	82	131
.65	84	270	354
.7	155	542	697
.8	178	852	1,030

Total	919	2,065	2,984

Note: the common support option has been selected

End of the algorithm to estimate the pscore

```
*****
Estimation of the ATT with the nearest neighbor matching method
Random draw version
*****
```

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
2065	624	-0.062	0.021	-2.928

Note: the numbers of treated and controls refer to actual nearest neighbour matches

```
*****
Estimation of the ATT with the radius matching method
*****
```

The radius is .0001

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
533	417	-0.076	0.040	-1.899

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
```

The radius is .0005

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
1611	773	-0.052	0.024	-2.165

Note: the numbers of treated and controls refer to actual matches within radius


```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .001
```

ATT estimation with the Radius Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
1926	855	-0.053	0.019	-2.733

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .01
```

ATT estimation with the Radius Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
2065	919	-0.043	0.018	-2.410

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .1
```

ATT estimation with the Radius Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
2065	919	-0.025	0.019	-1.324

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the kernel matching method
*****
```

ATT estimation with the Kernel Matching method
 Bootstrapped standard errors

Bandwidth=0.001

n. treat.	n. contr.	ATT	Std. Err.	t
2065	919	-0.054	0.021	-2.517

```
*****
Estimation of the ATT with the kernel matching method
*****
```

ATT estimation with the Kernel Matching method
 Bootstrapped standard errors

Bandwidth=0.01

ATT estimation with the Kernel Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
2065	919	-0.042	0.016	-2.565

SLID Sample

```
*****
Algorithm to estimate the propensity score
*****
The treatment is treat
```

treat	Freq.	Percent	Cum.
0	464	41.50	41.50
1	654	58.50	100.00
Total	1118	100.00	

Estimation of the propensity score

```
(sum of wgt is 5.0229e+05)
Iteration 0: log likelihood = -764.43966
Iteration 1: log likelihood = -695.96295
Iteration 2: log likelihood = -695.3938
Iteration 3: log likelihood = -695.39355
```

Probit estimates	Number of obs	=	1118
	Wald chi2(21)	=	80.30
	Prob > chi2	=	0.0000
Log likelihood = -695.39355	Pseudo R2	=	0.0903

treat	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
age	.0094762	.0058657	1.62	0.106	-.0020204	.0209727
sex	-.0619113	.1956317	-0.32	0.752	-.4453424	.3215198
fcomp1	-.0269368	.1434274	-0.19	0.851	-.3080494	.2541758
fcomp2	.2110264	.1575621	1.34	0.180	-.0977897	.5198425
fcomp4	-.2209591	.3010076	-0.73	0.463	-.8109232	.369005
edu1	-.1236396	.2010847	-0.61	0.539	-.5177584	.2704792
edu3	-.1712465	.1888436	-0.91	0.365	-.5413732	.1988802
edu4	.0972827	.2478026	0.39	0.695	-.3884016	.5829669
prov2	-.5682807	.2015464	-2.82	0.005	-.9633043	-.1732571
prov3	-.4010883	.1994515	-2.01	0.044	-.792006	-.0101705
prov4	-.6147034	.2138251	-2.87	0.004	-1.033793	-.1956138
prov5	-.5926422	.1878391	-3.16	0.002	-.9608001	-.2244843
can	.5688163	.1971091	2.89	0.004	.1824896	.955143
season	.0668904	.1302956	0.51	0.608	-.1884842	.3222651
qt2	.0441148	.1412924	0.31	0.755	-.2328133	.3210429
qt3	.6080709	.1512591	4.02	0.000	.3116085	.9045332
fsize2	.0073482	.1441102	0.05	0.959	-.2751027	.2897991
fsize3	.3480987	.1536069	2.27	0.023	.0470346	.6491628
fsize4	.1563223	.1876373	0.83	0.405	-.2114401	.5240847
ur_jend	-.0587674	.0164332	-3.58	0.000	-.0909759	-.0265589
blue_wk	.606134	.1611146	3.76	0.000	.2903552	.9219128
_cons	-.575251	.5531575	-1.04	0.298	-1.65942	.5089177

Note: the common support option has been selected
The region of common support is [.04658343, .8841608]

Description of the estimated propensity score
in region of common support

Estimated propensity score				

	Percentiles	Smallest		
1%	.116041	.0465834		
5%	.1587395	.0561395		
10%	.2082163	.0603328	Obs	1118
25%	.3217682	.0826598	Sum of Wgt.	1118
50%	.4367883		Mean	.4439448
		Largest	Std. Dev.	.1715576
75%	.5694174	.8625614		
90%	.682898	.8645329	Variance	.029432
95%	.7396715	.8775688	Skewness	.1425513
99%	.8272249	.8841608	Kurtosis	2.438804

The final number of blocks is 7
The balancing property is satisfied

This table shows the inferior bound, the number of treated
and the number of controls for each block

Inferior	treat		
of block	0	1	Total
of pscore			

.0465834	59	40	99
.2	184	181	365
.4	104	151	255
.5	63	111	174
.6	35	99	134
.7	16	55	71
.8	3	17	20

Total	464	654	1118

Note: the common support option has been selected

```
*****
Estimation of the ATT with the nearest neighbor matching method
Random draw version
*****
```

ATT estimation with Nearest Neighbor Matching method (random draw version)
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
654	282	-0.119	0.041	-2.915

Note: the numbers of treated and controls refer to actual nearest neighbour matches

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .0001
```

ATT estimation with the Radius Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
92	85	-0.184	0.102	-1.795

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .0005
```

ATT estimation with the Radius Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
339	292	-0.120	0.055	-2.167

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .001
```

ATT estimation with the Radius Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
446	378	-0.127	0.040	-3.186

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .01
```

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
641	462	-0.103	0.028	-3.713

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the radius matching method
*****
The radius is .1
```

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
654	464	-0.097	0.028	-3.536

Note: the numbers of treated and controls refer to actual matches within radius

```
*****
Estimation of the ATT with the kernel matching method
*****
Bandwidth=0.001
```

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
654	464	-0.106	0.039	-2.719

```
*****
Estimation of the ATT with the kernel matching method
*****
Bandwidth=0.01
```

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
654	464	-0.118	0.032	-3.726

APPENDIX D

Technical Note for Reverse-Order Decomposition

Family equivalent income distribution in reverse-order conditioning sequence can be expressed as

$$\begin{aligned}
 f_t(Y) &= f(Y | t_Y = 97, t_{X|S,L,I} = 97, t_{S|L,I} = 97, t_{L|I} = 97, t_I = 97) \\
 &= \int \int \int f(Y | X, S, L, I, t_Y = 97) dF(X | S, L, I, t_{X|S,L,I} = 97) dF(S | L, I, t_{S|L,I} = 97) \\
 &\quad \cdot dF(L | I, t_{L|I} = 97) dF(I, t_I = 97)
 \end{aligned} \tag{D1}$$

The counterfactual density of family income in 1997, holding constant “other attributes X,” “family structure S,” and “immigration factors L, I” at their 1980 levels, is

$$\begin{aligned}
 f_t(Y) &= f(Y | t_Y = 97, t_{X|S,L,I} = 80, t_{S|L,I} = 80, t_{L|I} = 80, t_I = 80) \\
 &= \int \int \int f(Y | X, S, L, I, t_Y = 97) dF(X | S, L, I, t_{X|S,L,I} = 80) dF(S | L, I, t_{S|L,I} = 80) \\
 &\quad \cdot dF(L | I, t_{L|I} = 80) dF(I | t_I = 80) \\
 &= \int \int \int f(Y | X, S, L, I, t_Y = 97) dF(X | S, L, I, t_{X|S,L,I} = 97) \frac{dF(X | S, L, I, t_{X|S,L,I} = 80)}{dF(X | S, L, I, t_{X|S,L,I} = 97)} \\
 &\quad \cdot dF(S | L, I, t_{S|L,I} = 97) \frac{dF(S | L, I, t_{S|L,I} = 80)}{dF(S | L, I, t_{S|L,I} = 97)} \cdot dF(L | I, t_{L|I} = 97) \frac{dF(L | I, t_{L|I} = 80)}{dF(L | I, t_{L|I} = 97)} \\
 &\quad \cdot dF(I | t_I = 97) \frac{dF(I | t_I = 80)}{dF(I | t_I = 97)} \\
 &= \int \int \int f(Y | X, S, L, I, t_Y = 97) dF(X | S, L, I, t_{X|S,L,I} = 97) dF(S | L, I, t_{S|L,I} = 97) \\
 &\quad \cdot dF(L | I, t_{L|I} = 97) dF(I | t_I = 97) \\
 &\quad \cdot \lambda_{X|S,L,I}(X, S, L, I) \cdot \lambda_{S|L,I}(S, L, I) \cdot \lambda_{L|I}(L, I) \cdot \lambda_I(I)
 \end{aligned} \tag{D2}$$

Equation (D3) shows that the re-weighting function for the immigration factor is equal to the probability of observing an immigrant employed full time in the 1980 sample versus the 1997 sample, multiple by the population ratio:

$$\lambda_I(I) = \frac{dF(I | t_I = 80)}{dF(I | t_I = 97)} = \frac{\Pr(t_I = 80 | I)}{\Pr(t_I = 97 | I)} \cdot \frac{\Pr(t_I = 97)}{\Pr(t_I = 80)}. \quad (D3)$$

Similarly, the re-weighting function for mother tongue and duration of residency characteristics of immigrants, conditional on a full-time employment rate, is

$$\lambda_{L,I}(L, I) = \frac{dF(L | I, t_{L,I} = 80)}{dF(L | I, t_{L,I} = 97)} = \sum_{c=1}^4 L_c \frac{\Pr(L = c | I, t_{L,I} = 80)}{\Pr(L = c | I, t_{L,I} = 97)}. \quad (D4)$$

The re-weighting function for family structure, conditional on immigration factors, is

$$\lambda_{S,L,I}(S, L, I) = \frac{dF(S | L, I, t_{S,L,I} = 80)}{dF(S | L, I, t_{S,L,I} = 97)} = \sum_{c=1}^4 S_c \frac{\Pr(S = c | L, I, t_{S,L,I} = 80)}{\Pr(S = c | L, I, t_{S,L,I} = 97)}. \quad (D5)$$

Both re-weighting functions in (D4) and (D5) can be estimated through multinomial logit estimation. Finally, using a simple property, the re-weighting function for other attributes $\lambda_{X|S,L,I}(X, S, L, I)$ can be expressed as

$$\begin{aligned} \lambda(X, S, L, I) &= \lambda(X | S, L, I) \cdot \lambda(S | L, I) \cdot \lambda(L | I) \cdot \lambda(I) \\ &= \lambda(I | L, S, X) \cdot \lambda(L | S, X) \cdot \lambda(S | X) \cdot \lambda(X) \end{aligned} \quad (D6)$$

Rearranging equation (D6) and the $\lambda_{X|S,L,I}(X, S, L, I)$ can be obtained by the product of the complete set of primary-order weights, divided by the product of three reverse conditional weights (D5), (D4), and (D3):

$$\lambda_{X|S,L,I}(X | S, L, I) = \frac{\lambda_{I|L,S,X}(I | L, S, X) \cdot \lambda_{L|S,X}(L | S, X) \cdot \lambda_{S|X}(S | X) \cdot \lambda_X(X)}{\lambda_{S,L,I}(S | L, I) \cdot \lambda_{L,I}(L | I) \cdot \lambda_I(I)} \quad (D7)$$

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