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**THREE ESSAYS ON UNEMPLOYMENT
AND SOCIAL ASSISTANCE**

By

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A Thesis

**Submitted to the School of Graduate Studies
in Partial Fulfillment of the Requirements
for the Degree**

Doctor of Philosophy (Economics)

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THREE ESSAYS ON UNEMPLOYMENT AND SOCIAL ASSISTANCE

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Abstract

This thesis is comprised of three essays concerning unemployment and social assistance. The first essay examines the impact of health status on the duration of unemployment spells and finds that individuals with impaired health will have significantly longer unemployment spells. These longer unemployment spells will result in the stock of the unemployed being composed of a larger proportion of individuals with impaired health than the stock of the employed. Hence, it may not be appropriate to interpret the difference between the mortality rates of the unemployed and employed as a health consequence of unemployment as some studies have done. The second essay examines the duration of welfare and off-welfare spells for lone mothers in Ontario from 1990 to 1994. We find that there is significant variation in the distribution of the spell lengths. Personal characteristics, such as the number and age of children, and policy parameters, such as welfare benefit levels, have significant impacts on the duration of spells. We also find evidence of negative duration dependence, that is, the probability of leaving the state decreases as the spell lengthens. However, for welfare spells, the evidence for negative duration dependence is weakest in our most preferred specification. The third essay examines the dramatic increase in the welfare participation rate in Ontario from 1983 to 1994. We are interested in what role benefit levels, minimum wage levels, the labour market conditions, and the UI system played in the rise. We focus on four family types; lone mothers, single males, single females, and couples with children. Our results indicate that there

is significant difference in how the welfare participation rate of each family type changes in response to the four factors we are interested in exploring. Also, we are unable to explain the dramatic increase using these four factors which indicates that other factors were contributed to the increase.

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The third and fourth chapters of this thesis were prepared with the intention of publication jointly with my thesis supervisor, Professor Martin Dooley. I had primary responsibility for data preparation and empirical analysis and played a major role in the writing of the papers.

Three Essays on Unemployment and Social Assistance

Table of Contents

1.	Introduction	1
2.	Health Status and Unemployment Spells	5
	I. Introduction	5
	II. Background	7
	III. Methods	18
	IV. Data	27
	V. Discussion of Results	29
	V.1. Hazard Estimation	29
	V.2. Effect of Hazards on Composition of Stock of the Unemployed	33
	VI. Conclusion	35
	Appendix: Description of Variables	47
3.	Duration of Spells on Welfare and Off-Welfare Among Lone Mothers in Ontario	51
	I. Introduction	51
	II. Review of the Literature	53
	III. Social Assistance in Ontario: The Basic System and Our Data Set	62
	IV. Estimation Strategy	68
	V. Welfare Spells	71
	VI. Off-Welfare Spells	77

VII.	Summary and Conclusion	81
4.	An Analysis of Changes in Welfare Participation Rates in Ontario from 1983-1994 Using Social Assistance Caseload Data	103
I.	Introduction	103
II.	Review of the Literature	104
III.	Social Assistance in Ontario: The Basic System and the MCSS Data Set	108
IV.	Time Series Econometric Procedures	115
V.	Time Series Regression Results and Discussion	120
VI.	A Quasi-Natural Experiment Approach	125
VII.	Conclusion	129
Appendix:	Definition of Demographic Categories in MCSS Data	161
5.	Conclusion	171
	References	176

List of Figures

Chapter 2

Figure 1:	Impact of Unemployment on Health Status	37
Figure 2:	Empirical Hazard for Unemployment Spells	38
Figure 3a:	Empirical Hazard by Reason for Leaving	39
Figure 3b:	Empirical Hazard by Reason for Leaving	40
Figure 4:	Empirical Hazard by Presence of Limitation	41

Chapter 3

Figure 1:	Empirical Hazard Function for On Welfare Spells	85
Figure 2:	Survival Function for On Welfare Spells	86
Figure 3:	Baseline Hazards for On Welfare Spells	87
Figure 4:	Empirical Hazard Function for Off Welfare Spells	88
Figure 5:	Survival Function for Off Welfare Spells	89
Figure 6:	Baseline Hazard for Off Welfare Spells	90

Chapter 4

Figure 1:	Total Caseload and Expenditures	132
Figure 2:	Family Types	133
Figure 3a:	Lone Mothers	134
Figure 3b:	Single Males	135
Figure 3c:	Single Females	136
Figure 3d:	Couples with Children	137
Figure 4:	Unemployment Rate	138

Figure 5:	Employment Population Ratio	139
Figure 6:	UI Generosity	140
Figure 7a:	Lone Mothers	141
Figure 7b:	Single Males	142
Figure 7c:	Single Females	143
Figure 7d:	Couples with Children	144

List of Tables

Chapter 2

Table 1:	Socioeconomic Characteristics of Total Sample and by Reason for Leaving ROE Job	42
Table 2:	Socioeconomic Characteristics of Total Sample and by Presence of a Health Limitation	43
Table 3:	Estimated Coefficients from Four Models	44

Chapter 3

Table 1:	Ontario Assistance Caseload: December, 1983-1994	91
Table 2:	Ontario Social Assistance Benefit Levels and Total Expenditures: 1983-1994	92
Table 3:	Summary Statistics for Welfare Spells and Off Welfare Spells: 1990-1994	93
Table 4:	Estimated Baseline Hazards for Welfare Spells	95
Table 5:	Duration Model Estimates Welfare Spells: With and Without Unobserved Heterogeneity	97
Table 6:	Estimated Baseline Hazards for Off Welfare Spells	99
Table 7:	Duration Model Estimates Off Welfare Spells: Without Unobserved Heterogeneity	101

Chapter 4

Table 1:	Variable Definitions and Regions	145
Table 2:	Descriptive Statistics	146
Table 3:	GLS Regression Dependent Variable: Welfare Participation Rate for Lone Mothers	147

Table 4:	GLS Regression Dependent Variable: Welfare Participation Rate for Single Males	148
Table 5:	GLS Regression Dependent Variable: Welfare Participation Rate for Single Females	149
Table 6:	GLS Regression Dependent Variable: Welfare Participation Rate for Couples with Children	150
Table 7:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 12 Months	151
Table 8:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 11 Months	152
Table 9:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 12 Months	153
Table 10:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 11 Months	154
Table 11:	Abolishment of Man in the House Rule Dependent Variable: Difference in Welfare Participation Rates Experimental Group: Lone Mothers Control Group: Single Males	155
Table 12:	Abolishment of Man in the House Rule Dependent Variable: Difference in Welfare Participation Rates Experimental Group: Lone Mothers Control Group: Single Females	156
Table 13:	October 1991 Change in Definition of Earned Income Dependent Variable: Difference in Welfare Participation Rates Experimental Group: Lone Mothers Control Group: Single Males	157
Table 14:	October 1991 Change in Definition of Earned Income Dependent Variable: Difference in Welfare Participation Rates Experimental Group: Lone Mothers Control Group: Single Females	158

Table 15:	October 1991 Change in Definition of Earned Income Dependent Variable: Difference in Welfare Participation Rates Experimental Group: Couples with Children Control Group: Single Males	159
Table 16:	October 1991 Change in Definition of Earned Income Dependent Variable: Difference in Welfare Participation Rates Experimental Group: Couples with Children Control Group: Single Females	160
Table 1b:	GLS Regression Dependent Variable: Welfare Participation Rate for Lone Mothers	163
Table 2b:	GLS Regression Dependent Variable: Welfare Participation Rate for Single Males	164
Table 3b:	GLS Regression Dependent Variable: Welfare Participation Rate for Single Females	165
Table 4b:	GLS Regression Dependent Variable: Welfare Participation Rate for Couples with Children	166
Table 5b:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 12 Months	167
Table 6b:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 11 Months	168
Table 7b:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 12 Months	169
Table 8b:	Seemingly Unrelated Regression: Dependent Variable: Welfare Participation Rate All Independent Variables Lagged 11 Months	170

Chapter 1

Introduction

This thesis is comprised of three essays related to individuals' activities in and out of the labour market. The first essay examines the impact of impaired health on the duration of unemployment spells. The second essay examines the use of social assistance by lone mothers in Ontario from 1990 to 1994. The third essay examines the growth in the welfare participation rate for four family types in Ontario from 1983 to 1994.

Researchers in health economics have increasingly become aware that policies other than health care spending potentially have an impact on an individual's health¹. In particular, there is concern that a period of unemployment will affect an individual's health. Past research has examined the impact of unemployment on health by measuring the difference in mortality rates between individuals who were unemployed at a point in time and those who were employed. The results from these past studies indicate that the unemployed have higher mortality rates. However, these results could

¹ For example, see Wolfson *et. al.* for an analysis of the relationship between mortality rates and career earnings and the implication for pension and health policy in a Canadian context.

be biased if the stock of the unemployed is composed of more individuals with impaired health than the stock of employed. One reason for this difference in composition is if individuals with impaired health have longer unemployment spells. This essay examines the impact of impaired health on the duration of unemployment spells. We find that individuals with impaired health have longer unemployment spells and, therefore, comprise a larger proportion of the unemployed than of the employed. Therefore, the previous estimates of the impact of unemployment on mortality rates are overestimates.

The second essay examines the use of social assistance by lone mothers in Ontario. There have been recent, substantial changes to the social assistance system in Ontario, but little research examining who uses the program and how they do so. We are interested in the distribution of welfare and off-welfare spell lengths and the impact of personal characteristics and policy parameters on the duration of spells. We are particularly interested in testing for the presence of negative duration dependence; that is, does the probability of leaving welfare decrease as the spell continues. We have used a unique data set supplied by the Ministry of Community and Social Services to study these issues.

Our examination of the distribution of the spell lengths reveals considerable variation for both welfare and off-welfare spells. The estimated impacts of personal characteristics on spell lengths are generally as expected. We also find the expected results for policy parameters and labour market conditions. Our estimated baseline hazards indicate that negative duration dependence is present in our sample for both

types of spells. These results indicate that there may be identifiable groups of long-term users towards whom policies could be directed. Also, we have strong evidence that once an individual is off welfare there is a decreasing probability of returning as the length of the spell increases.

The third essay examines the trends in the welfare participation rate for four family types: lone mothers, single males, single females, and couples with children. During this period, there was a dramatic increase in the welfare participation rates for all four family types studied as well as an increase in benefit levels, changes to the UI system and changes in the labour market conditions. We use the same data set as in the second essay combined with additional information obtained from Statistics Canada publications to analyse the impact of the various explanatory factors on the welfare participation rate. We pooled the time-series for nine regions in Ontario for this purpose. We also used a quasi-experiment approach to isolate the impact of two policy changes that would be expected to affect the welfare participation rate for one family type, but not others.

Our results from the pooled time-series analysis indicate that the impact of the explanatory variables varies significantly between family types. The quasi-experiment approach examines two policy changes. The first occurred in November 1987 when the 'man-in-the-house' rule was abolished. This policy change allowed lone mothers to apply for social assistance even if they were living with a man who was not the father of their children. This policy change should only affect lone mothers and singles can be used as a control group. The second policy change occurred in October 1991,

when the definition of earned income was changed. Childcare expenses could now be deducted in full from earned income. This policy change should only affect families with children and singles can be used as a control group. Our results indicate that these policy changes did not have significant differential impacts on the family types. The thesis concludes with a summary chapter.

Chapter 2

Health Status and Unemployment

I. Introduction

Health economics is currently redefining the role of both health and economic policy. Traditionally, health policy has focused on the role of health care in maintaining health status, but the primacy of health care in health policy has been questioned. Other factors such as position in the social hierarchy or social networks might be equally, or even more, important. Health status is too complicated to be explained by a simple model of health care.

One socioeconomic factor that has been examined for its impact on health status has been unemployment. A causal relationship between unemployment and health status has implications for economic policy. Any decision made by the government that has an impact on the unemployment rate requires an understanding of the full social costs of unemployment. If an increase in the unemployment rate reduces health status then the change in health status needs to be considered when making decisions. Previous papers have examined this issue with both aggregate and

micro-level data sets using a variety of econometric techniques. Using a unique data set, we instead examine the effects of health status on employment, specifically the impact of impaired health on the duration of unemployment spells. The implication for the results reached in previous work is that selection bias into the stock of unemployed may be an important problem. In order to accurately measure the social cost of unemployment, this selection bias needs to be acknowledged.

The methodology of this paper proceeds in two stages. First, the impact of impaired health on the duration of unemployment spells is estimated using a duration analysis framework. Second, given that there is a difference in the duration of unemployment spells by health status, the implied differences in the composition of the stock of unemployed and the stock of employed is estimated. The results show that impaired health significantly increases the length of unemployment spells and, therefore, the fraction of the stock of unemployed with impaired health is greater than for the stock of employed. These results indicate that there is a selection bias into the stock of unemployed that needs to be considered when measuring the impact of unemployment on health status.

The next section of this paper presents a discussion of the previous literature on the relationship between unemployment and health. The third section outlines the theoretical model used to analyse the issue and presents the econometric model that will be used. In the fourth section the data is described. The fifth section discusses the results. The sixth section concludes the paper.

II. Background

The literature on the relationship between health and unemployment consists of two main streams of research. The seminal paper on unemployment and health by Brenner (1979) motivated the first stream of research which is characterized by the use of aggregate data to estimate the correlation among aggregate variables. The second stream of research uses micro-level data sets to determine the impact of unemployment on an individual's health.

Brenner's hypothesis was that unemployment can affect an individual's health status, both directly and indirectly. Unemployment affects a person's life through changes in income and through increased stress. Lower income can lead to a worse diet or less health care, thereby increasing susceptibility to illness. Increased stress may worsen health directly, possibly even result in suicide, and it may have indirect effects by increasing the consumption of comfort goods such as alcohol or tobacco (See Figure 1). Regional levels of unemployment may also indirectly influence an individual's health though the sign is uncertain. Residence in an area with a high rate of unemployment may increase stress for both employed and unemployed individuals. However, in regions of high unemployment, less stigma may be attached to being unemployed, thereby decreasing the stress for unemployed individuals.

Brenner(1979) began this research by using time-series aggregate data to examine the relationship between national unemployment and mortality rates. He used data from England and Wales for the period 1936-76. To test his hypothesis he

regressed five explanatory variables against age-specific mortality rates. His explanatory variables included: (1) the growth trend of personal income in order to proxy for various influences of economic growth on health status. These influences include improvements in sanitation, nutrition, and education, which are usually positively related to economic growth, (2) the unemployment rate as an indicator of recession and to examine the impact of the loss in income on the nation's mortality, (3) lagged values of the unemployment rate, because the stress caused by unemployment may not have an immediate impact on mortality (an obvious exception is suicide), (4) the annual difference from the economic growth trend and the annual change in the growth rate to examine the impact of rapid economic growth, and (5) the percentage of total government spending spent on public welfare to control for health care spending.

The results from the regressions were as Brenner predicted. The coefficients on the economic growth trend variables were negative indicating that economic growth decreases mortality. The coefficients for the unemployment rate were positive and significant indicating that unemployment increases mortality. The results for the annual difference from the growth trend, the annual change in the growth rate, and the government expenditure were insignificant. These results were similar to the results obtained from U.S. data by Brenner. Brenner concludes that these results were promising because the U.S. and Britain are such different countries.

Brenner's results sparked both interest in the subject and critiques of his work. Wagstaff (1985) summarized the criticisms levelled at Brenner's work into the

following seven categories:

1. **Definition of Variables** - The variables chosen by Brenner did not reflect theory. For example, Brenner used personal disposable income to examine the impact of income on aggregate mortality rates. However, if taxes were increased to finance health expenditures then Brenner's income variable would decrease when it is likely that mortality would decrease. Critics suggested that per capita GDP would be a better measure.
2. **Adequacy and Reliability of Data** - Brenner used unemployment rates from England and Wales, but mortality rates from the entire U.K. The data are not consistent.
3. **Selection of Independent Variables** - Critics argued that Brenner's work has an omitted variable bias. For example, the antibiotic revolution and nutrition improvements occurred at the same times that there were significant falls in the unemployment rate. The unemployment variables may be picking up the impact of these developments.
4. **Time-Series Fallacy** - Brenner's results may be demonstrating a spurious correlation between the two time trends rather than causation.
5. **Strength of Underlying Relationship** - Critics have questioned the validity of the hypothesis. For example, Brenner's results were strongest for infants and seniors. These two groups would be least expected to have a strong result because they are not in the labour force.
6. **Determination of Lag Structure** - Brenner reported results from regressions

with the unemployment rate lagged ten years. He chose ten years by adding lags until their coefficients became insignificant. This procedure is not standard.

7. **Use of Aggregate Data** - Critics argued that no conclusion can be drawn about individual relationships from aggregate data.

Subsequent papers by other authors have responded to these criticisms. The first strand of research has continued to examine the issue using aggregate data, but with more appropriate econometric techniques and data.

McAvinchey (1984) responded to the first six criticisms listed above. In particular, he used data only from Scotland, considered the sensitivity of the results to different estimation methods, and considered male and female mortality separately. The mortality rates were computed for 24 groups, 12 age-groups for both males and females. McAvinchey considered five possible functional forms to describe the relationship between unemployment rates and mortality rates: OLS with variables in levels; restricting the error process to AR(1); restricting the lag structure to an Almon Distributed Lag (ADL); restricting both errors to AR(1) and the lag structure to ADL; and using first-differences. For each group the best suited functional form was determined and used for comparison in the final results. McAvinchey finds that higher unemployment is related to lower mortality for younger age groups and higher mortality for older age groups. This result conflicted with Brenner's result that unemployment is positively related to mortality for all age groups.

McAvinchey arbitrarily lagged the unemployment rate nine periods. There was no discussion of the sensitivity of results to different lag lengths. There were also

significant results for age-groups where no strong impact would be expected because of non-labour force participation. For example, he found a significant negative impact of unemployment on mortality rates of females and males 1-5 years old.

In a second paper, McAvinchey (1988) compared the relationship between unemployment and mortality for five European countries. He had information on age-adjusted mortality rates, unemployment, and income for Germany, France, Italy, Sweden and Ireland from similar time periods. The mortality rates were examined separately for males and females by country. First, more attention was paid to determining the lag structure of the unemployment rate for each group, which was an improvement on his previous paper. The lag structures varied between countries, but not between males and females within countries. Second, the model was estimated for each group using the appropriate lag structure. Overall, unemployment had a negative impact on mortality for all countries except France. However, longer lags of the unemployment rate (seven years) had a positive impact on mortality. McAvinchey concluded that "any rise in mortality rates following unemployment will take a considerable number of years to become apparent."

The strengths of McAvinchey's paper are that the results were consistent across the five countries and that an arbitrary lag structure is not imposed. The results indicate that Brenner's strong findings are not consistent across countries or time.

In two similar papers, Joyce (1989) and Joyce and Mocan (1993) focused on the impact of the unemployment rate on infant health. The hypothesis was that unemployment will directly affect the health of the infant by increasing the stress felt

by the pregnant mother or indirectly by changing the consumption of health inputs. However, employment may increase the risk of premature birth decreasing the health of the infant. The impact of unemployment on infant health is ambiguous *a priori*. Both papers used the incidence of low birth weight as an indicator of infant health. The first paper used monthly data from New York City for 1970-86 and data for the second paper was from the State of Tennessee for 1970-88. The incidence of low birth weight was broken down by race, but the unemployment rate could not be broken down by sex, race, or age. The unemployment rate was included in the regression lagged ten months because only stress felt during the pregnancy was likely to affect the health of the infant. The monthly incidence of low birth weight was regressed on the lagged unemployment rate variables, incidence of low birth weight lagged one month, incidence of prenatal care, and incidence of illegitimacy both for the total sample and by race. Joyce did not find that unemployment affected infant health.

These papers by Joyce and Mocan are the only ones with a justification for specifying the lag structure. Without a theoretical basis for the lag structure the previous papers have had to determine it through somewhat arbitrary methods. If the lag structure used is incorrect the results may be biased if the lag length is underestimated or inefficient if over fitted.

Another paper that has used aggregate data was by Junankar (1991). Using British data, Junankar calculated mortality rates and unemployment rates by social class and region. The mortality rates were regressed on the unemployment rates.

occupational groups, as a proxy for social class, and region, to proxy for region-specific variables such as environment. The results showed a positive relationship between unemployment and mortality rates. Junankar cautioned that there were problems with this approach. First, the high level of aggregation was an issue. Second, the direction of causation was not determined.

A further concern with Junankar's paper was that age was not controlled for and the only unemployment rate considered in the model was the current one. It seems unlikely that unemployment kills immediately. Looking at age-specific mortality rates and including lagged values of the unemployment rate would be valuable future work.

Ruhm (1996) took another look at U.S. data on the relationship between health and unemployment. Ruhm agreed that unemployment is a stressful situation that may decrease health, but argues that there are reasons that health could improve during unemployment. First, employment may be detrimental to health status because of hazardous working conditions or job stress. Second, when unemployed the time cost of seeking medical care falls which may result in increased consumption of medical care. The time cost also falls for other health improving activities such as exercise. Third, individuals who become unemployed in the U.S. may become eligible for Medicaid.

The data was for the 50 states and the District of Columbia for the years 1972-1991. Ruhm used a fixed effects model to examine this relationship to control for constant state-specific effects. The fixed effects model should also reduce the bias from omitted variables. Several dependent variables were used including total

mortality rates, age-specific mortality rates and ten disease specific mortality rates. The unemployment rate was used to proxy for macroeconomic conditions. The percentage of the state population in three levels of educational attainment, the percentage of the state population that was black and Hispanic, and the percentage of the state population that was in one of two age categories were used to control for demographic characteristics.

The results indicated that “the preferred specifications suggest that a one percentage point rise in joblessness is associated with a 0.5% decrease in the total death rate. The one exception is that suicides decline during expansions.” These results contradict Brenner’s findings and are similar to the results obtained by McAviney in his cross-country analysis. McAviney included several periods of the lagged unemployment rates and found that longer lags of unemployment (7 years) were positively related to mortality rates. Ruhm included unemployment lagged one period in one specification and found that the lag was related positively to current mortality. However, the overall impact of unemployment was still negative. Brenner only reported the sum of the coefficients for unemployment rate over the 0-10 year period. He states, though, that “the years of strongest predictive value for total mortality are at lags 1,2 (particularly) and 5.”

Overall, the aggregate data approach has produced mixed results. There is some evidence that, if unemployment increases mortality, there is a long lag until the impact is apparent. Ideally, researchers would use micro-level data to evaluate the impact of unemployment on an individual's health. Unfortunately, micro-level data sets

containing extensive health information are scarce. Some papers have used limited micro-level data sets to examine this issue.

Moser, Fox, and Jones (1984), Moser, Fox, Jones, and Goldblatt (1986), and Moser, Goldblatt, Fox, and Jones (1987) are a series of papers that use a British longitudinal survey from 1971-81 to examine the impact of unemployment on mortality. The first paper examined the difference in mortality rates between men who were "seeking work" (i.e., unemployed) in the week prior to the 1971 census and employed men. It also examined the impact of the husband's unemployment on the wife's mortality rate. The results indicated that the mortality rate over the ten years following the census was significantly higher for men who were unemployed than those who were employed. When social class was considered the difference in the mortality rates decreased by 46%. The results indicated that wives of unemployed men had higher mortality rates than wives of employed men, but the difference was not significant.

The authors were concerned that their results were generated by health-related selection into the unemployed group. Health-related selection occurs if unhealthy individuals are more likely to be unemployed. If this selection occurred, they hypothesize that the mortality of the group would improve over time. Unfortunately, the short time span of their data does not allow for a strong test of this hypothesis.

The second paper extended the analysis to consider the effect of region of residence on mortality rates. Unemployed men had statistically significant higher mortality rates than the standard population in two out of three regions, the difference

in the third region was not statistically significant.

The third paper included information on mortality and unemployment from 1981-83. Moser *et al.* reported a higher mortality rate for unemployed men than for employed. With the new data, they were able to exclude men who were not working because of either permanent or temporary ill health. They concluded that health-related selection was not an issue.

In Iverson *et al.* (1987) another approach is taken to analyse the impact of unemployment on mortality with data from the 1970 Danish Census and the national mortality register. The census data had information on age, sex, marital status, occupation, employment status on the day of the census, geographical region, and housing category. Information on local unemployment rates was available. Mortality information until 1980 was gathered from the national mortality register. The mortality data was a longitudinal panel over ten years.

Iverson *et al.* compared the mortality rates of employed and unemployed individuals by various groups. Using age specific mortality rates, their results indicate a significant difference between employed and unemployed. They examine the impact of occupation, housing category, geographical region, and marital status on the relative mortality rates of unemployed and employed individuals. The four characteristics were insignificant for men. For women, however, geographical region and marital status had significant impacts on the relative mortality rates. Using the municipal unemployment rates on census day, the relative mortality rates were examined to consider the impact of the economic environment. The results indicate

a significant negative relationship between the local unemployment rate and the relative mortality rates for both men and women. The relative mortality rate for the unemployed in an area with a higher unemployment rate is lower than an area with a lower unemployment rate.

Iverson *et al.* point out a number of problems with their study. First, their sample of unemployed individuals is length biased. The census was just a one day survey. There was no information on previous and subsequent unemployment spells. The sample was likely to contain a larger proportion of individuals with longer spells of unemployment because they are more likely to be unemployed on that one day. Second, there may be selection into the sample of unemployed individuals by health status. Individuals who are ill may be more likely to be unemployed and higher mortality rates among the ill is not an unusual occurrence. In the presence of selection bias, the results would not necessarily be indicating that unemployment has a positive effect on mortality rates, but that individuals who are ill are more likely to be unemployed. To test for selection bias, the relative mortality rates in 1970-1975 and 1976-1980 were compared. The hypothesis is that individuals who were already ill in 1970 would be more likely to die in the first five years than in the last five years of the study. If selection bias is present then the relative mortality rate should be lower in the last five years. The same excess mortality rate was found in each period suggesting that selection bias is not a problem. However, the regional analysis suggests that selection bias is present. Areas with low unemployment had higher mortality rates for the unemployed than areas with high unemployment. This result suggests that the

individuals with poor health may become unemployed first.

This paper extends the previous research by specifically examining the potential problem of a selection biased sample. If individuals with impaired health have longer unemployment spells then they are more likely to be in a sample of the stock of unemployed. When considering the social cost of unemployment, it should be remembered that the results from previous studies are probably over-estimates.

III. Methods

The literature reviewed in the previous section illustrated the different approaches to estimating the impact of unemployment on health status. Ideally, a longitudinal data set that measures health status at an initial point in time and then follows individuals through their life cycle measuring subsequent health status and amounts of unemployment would supply an estimate of this impact. Unfortunately, such a data set does not exist. The microdata sets used to examine the impact of unemployment on health status may contain a disproportionate number of individuals with impaired health. Such a bias would exist if individuals with impaired health status are more likely to become unemployed or if they are less likely to leave unemployment. In either case, the fraction of the stock of unemployed composed of individuals with impaired health would be greater than in the stock of the employed.

This paper focuses on the impact of impaired health on the likelihood of leaving unemployment. The first step is to estimate the impact of impaired health on

the duration of unemployment. The second step is to estimate the impact of the longer unemployment spells on the composition of the stock of unemployed.

In order to estimate the impact of impaired health on the duration of unemployment, the hazard function needs to be estimated. The hazard function is the number of spells that end at time t as a proportion of spells that lasted past time $t-1$. The hazard function for each group depends on the value of remaining unemployed versus the value of becoming employed. The value of remaining unemployed is a function of personal characteristics (z) and the length of the unemployment spell (T^u):

$$V_t^u = V^u(z, T^u).$$

The value of being employed is assumed to be:

$$V_t^e = V^e(z, w(t)),$$

where w is the net benefit of employment. The offered wage is assumed to arrive according to a Poisson process with a constant arrival rate of ν . The probability of leaving unemployment at time t is equal to:

$$\lambda(z, w, T^u) = \nu * \text{Prob}[V^e(z, w(t)) > V^u(z, T^u)]. \quad (1)$$

This equation defines the hazard rate.

The analysis of the hazard function begins by examining the empirical hazard rate function. The empirical hazard rate function is defined as the number of spells that ended at time t as a proportion of the number of spells that lasted longer than time $t-1$. The analysis of the hazard rate function must be taken beyond the empirical functions as they assume that the population is homogenous. The characteristics of the household and health status included in the theoretical model would be ignored.

The Prentice-Gloeckler-Meyer (PGM) piece-wise constant proportional hazard procedure is used to obtain estimates of the baseline hazard function and coefficients.¹ The advantages of the PGM procedure are that no assumptions about the shape of the baseline hazard function are necessary and that it is relatively easy to control for one type of unobserved heterogeneity. Blank (1989) explicitly reports the difference in the estimated shape of the baseline hazard for welfare spells according to the assumed parameterization of the baseline hazard function. Her results show that the imposition of incorrect assumptions about the shape of the baseline hazard function can bias tests of duration dependence, that is, the manner in which the hazard rate varies with the length of the spell.

Failure to control for unobserved heterogeneity can also bias tests of duration dependence. Only in the presence of such controls can one begin to distinguish between changes in the hazard for individuals of given characteristics (“state dependence”) and changes in the composition of the surviving sample of unemployed (“heterogeneity”). Lancaster (1979) demonstrates that the presence of unobserved heterogeneity may bias the shape of the baseline hazard towards exhibiting negative duration dependence. There are limitations to the PGM approach however. One limitation is that the shape of the baseline hazard function is assumed to be the same for everyone. A related limitation is that the covariates are assumed to shift the baseline proportionately but not to affect its shape.

¹ See Prentice and Gloeckler (1978), Meyer (1988), or Meyer (1990) for further descriptions of this procedure.

First, a proportional hazard model with no unobserved heterogeneity is specified as:

$$h_i(t, z_i, \beta) = h_0(t) \exp(z_i' \beta),$$

where h_i is individual i 's hazard rate, z_i is a vector of individual i 's characteristics, β is the parameter vector to be estimated, and $h_0(t)$ is the baseline hazard function to be estimated. The baseline hazard is divided into intervals and the hazard rate is assumed to be constant over the interval. The decision concerning the number and length of the pieces must balance a desire for functional flexibility (more pieces) and convergence time and estimator precision (fewer pieces). Our choice has been guided both by the specifications of previous researchers and by our own empirical hazard functions. The baseline hazard is divided into twenty-three intervals. The width of an interval is the difference between the final months of successive intervals. The hazard rate is not estimated for the last interval. If we let j represent the ordering of the intervals and t_j the endpoints of the interval then the following table describes the intervals of the baseline hazards:

Definition of baseline hazard intervals			
Interval	Final Month	Interval	Final Month
1	1	13	19
2	2	14	23
3	3	15	27
4	4	16	31
5	5	17	36
6	6	18	41
7	7	19	46
8	8	20	51
9	9	21	56
10	10	22	61
11	13	23	∞
12	16		

The probability that person i 's spell does not end in an interval given that it lasted until the beginning of that interval is:

$$\begin{aligned} \text{Prob}[T_i \geq t_j | T_i \geq t_{j-1}] &= \exp\left[-\int_{t_{j-1}}^{t_j} h_i(u, z_i, \beta) du\right] \\ &= \exp[-\exp(z_i/\beta + \gamma(t_j))]. \end{aligned} \quad (2)$$

where $\gamma(t_j) = \ln \int_{t_{j-1}}^{t_j} h_0(u) du$ and T_i is individual i 's spell length. The product of the probabilities in equation (2) from $t_j = 1$ to t_i , the interval that contains T_i , is the survival function at t_i denoted as $S(t_i; z_i)$. The log-likelihood function can be constructed by conditioning on right censoring because it is assumed that censoring is exogenous. The probability of individual i having an uncensored spell that ends in interval i , given

that the spell is uncensored, is:

$$S(t_{i-1}; z_i) - S(t_i; z_i). \quad (3)$$

Given that a spell is to be censored at interval i , the probability of individual i surviving to interval i is:

$$S(t_{i-1}; z_i). \quad (4)$$

Using equations (3) and (4), the log-likelihood function can be written as:

$$\begin{aligned} L(\gamma, \beta) &= \sum_{i=1}^N \log(\delta_i(S(t_{i-1}; z_i) - S(t_i; z_i)) + (1 - \delta_i)S(t_{i-1}; z_i)), \\ &= \sum_{i=1}^N (\delta_i \log(1 - \exp(-\exp(\gamma(k_i) + z_i' \beta))) - \sum_{t_j=1}^{k_{i-1}} \exp(\gamma(t_j) + z_i' \beta)), \end{aligned} \quad (5)$$

where $\delta_i=1$ if not right censored, $k_i=\min[t_i, C_i]$, and C_i is the censoring time.

By assuming that the unobserved heterogeneity takes a multiplicative gamma form, the hazard function becomes:

$$h_i(t, z_i, \beta, \theta_i) = \theta_i h_0(t) \exp(z_i' \beta), \quad (6)$$

where θ_i is a random variable that is assumed to be independent of z_i and follow a gamma distribution with a mean normalized to one and a variance of σ^2 . A gamma distributed variable has a non-negative support which gives a closed form expression for the likelihood function. The log-likelihood function can then be written as:

$$\begin{aligned} L(\gamma, \beta, \mu) &= \sum_{i=1}^N \log \left(\int \exp(-\theta \sum_{t_j=1}^{k_{i-1}} \exp(\gamma(t_j) + z_i' \beta)) d\mu(\theta) \right. \\ &\quad \left. - \delta_i \int \exp(-\theta \sum_{t=1}^{k_i} \exp(\gamma(t) + z_i' \beta)) d\mu(\theta) \right) \end{aligned} \quad (7)$$

The log-likelihood function is obtained by conditioning on the unobserved θ and integrating over its distribution. The log-likelihood then becomes:

$$L(\gamma, \beta, \sigma^2) = \sum_{i=1}^N \log \left((1 + \sigma^2 \left(\sum_{t_j=1}^{k_{i-1}} \exp(\gamma(t_j) + z_i' \beta) \right)) \right)^{-\frac{1}{\sigma^2}} - \delta_i \left(1 + \sigma^2 \left(\sum_{t_j=1}^{k_i} \exp(\gamma(t_j) + z_i' \beta) \right) \right)^{-\frac{1}{\sigma^2}} \quad (8)$$

The estimated coefficients from the PGM procedure will give us an estimate of the impact of impaired health on the duration of unemployment. The next step, given that individuals with impaired health status have longer unemployment spells, is to determine the composition of the stock of the unemployed by health status. Let us begin by considering the flow into unemployment for group i . Group i 's share of the flow into unemployment is denoted s_i and is equal to:

$$s_i = N_i(0,t)/N(0,t) \quad (9)$$

where $N(x,t)$ denotes the number of individuals that are in the x th month of unemployment at time t and the subscript i denotes the group. So, group i 's share of the flow into unemployment is equal to the number of individuals in group i entering unemployment at time t as a proportion of the total number of individuals entering unemployment at time t . Next, define group i 's share of the stock of unemployment as σ_i and equal to:

$$\sigma_i = U_i(t)/U(t) \quad (10)$$

where $U(t)$ refers to the number of unemployed at time t . In the steady state, where the flow into and out of unemployment are constant, it can be shown that $U(t)$ is equal to the sum, over the groups, of the number of individuals entering unemployment from

the i th group times the average duration of the i th group's spells. Combining the definitions for the entrance and stock shares, equations (9) and (10) and assuming the steady state gives:

$$\sigma_i = s_i * D_i(t)/D(t), \quad (11)$$

where $D(t)$ refers the average completed duration of the unemployment spells.

In order to compare the difference in the shares of the flow into unemployment and the shares of the stock of unemployment, the average duration needs to be derived. The baseline hazard function has been estimated using the PGM procedure. Now the average duration needs to be determined. The estimated baseline has been divided into intervals each one of which is assumed to have a constant hazard rate which simplifies the calculations. The overall average duration is the weighted sum of the average duration within each interval with the weight equal to the probability of a spell ending in that interval. The assumption of a constant hazard rate within each interval imposes an exponential density function on the spell lengths within each interval. Using equation (2), the probability that a spell, for an individual with characteristics z , ends within an interval given that the spell lasted until the beginning of the interval is:

$$\begin{aligned} 1 - \text{Prob}[T \geq t_j \mid T \geq t_{j-1}] &= 1 - \exp\left[-\int_{t_{j-1}}^{t_j} h(u, z, \beta) du\right] \\ &= 1 - \exp\left[-\exp(z'\beta) + \gamma(t_j)\right]. \end{aligned} \quad (12)$$

The unconditional probability that a spell ends within an interval is equal to the product of the probability that the spell ends in the current interval given that it lasted until the beginning of the interval and the probability that the spell did not end in any

previous interval given that it lasted until the beginning of the previous intervals.

Using equation (12), the unconditional probability that a spell ends within an interval

is:

$$\text{Prob}[t_j \geq T \geq t_{j-1}] = (1 - \exp[-\exp(z' \beta + \gamma(t_j))]) \prod_{j=1}^{t_{j-1}} (\exp[-\exp(z' \beta + \gamma(j))]). \quad (13)$$

This probability is the weight that will be assigned to the average duration for each

piece.

The average length of the spells that end within an interval is:

$$E(T|t_j \geq T \geq t_{j-1}) = \int_{t_{j-1}}^{t_j} T f(T|t_j \geq T \geq t_{j-1}) dT \quad (14)$$

where,

$$f(T|t_j \geq T \geq t_{j-1}) = \frac{f(T|T > t_{j-1}, T < t_j)}{1 - \text{Prob}[T \geq t_j | T \geq t_{j-1}]}, \quad t_{j-1} \leq T \leq t_j \quad (15)$$

Using equation (12), equation (15), and the constraint that the hazard is constant over

the interval, equation (14) becomes:

$$E(T|t_j \geq T \geq t_{j-1}) = \frac{t_{j-1} - (t_j)(\exp(-\exp(\gamma(t_j))))}{1 - \exp(-\exp(\gamma(t_j)))} + \frac{t_j - t_{j-1}}{\exp(\gamma(t_j))} \quad (16)$$

The sum, over all intervals of the hazard function, of the product of the probability of a spell ending within an interval, equation (13), and the average duration of spells that end within each interval, equation (16), gives the average duration for all spells. This average duration can then be used in equation (11) to determine the stock share for each group. The impact of the longer unemployment spells by individuals with impaired health status on the stock of unemployed can then be examined.

IV. Data

The data used to consider this question is from the Canadian Out of Employment Panel (COEP) 1995 survey. This survey was commissioned by Human Resources Development (HRD) Canada. The COEP 1995 survey sample is from individuals who received a Record of Employment (ROE) during either one of two cohorts, January 29 to April 1 or April 23 to June 3, and had a Social Insurance Number ending in "5". A ROE must be issued whenever a job separation occurs. Individuals were interviewed two times for the COEP data set. They were interviewed at approximately 36 and 62 weeks after the job separation for which the ROE was issued. The two interviews allowed the actual duration of unemployment to be determined up to 62 weeks at which point the data was censored. The data set was then merged with UI administrative data and income tax records for the previous five years. Individuals living in the North West Territories or the Yukon were excluded due to small sample size.

This paper focuses on the unemployed in the survey. Individuals who indicated that they are no longer in the labour force (therefore, not unemployed) were excluded from the study. The individuals excluded on this basis include the retired, students, homemakers, and women on maternity leave (excluded 824 individuals). Individuals who did not have a spell of unemployment were also excluded (excluded 722 individuals). The results presented are conditional on having a spell of unemployment. Individuals were also excluded if they were over the age of 64 (excluded 17

individuals) and if their income was not between 0 and \$150,000 (excluded 20 individuals). A further 476 individuals were excluded because of missing values. The final sample includes 5817 individuals.

Two variables in the data set were used to proxy for health status. First, the main reason the ROE job ended was asked in the interview. One potential reason for the job termination was illness or injury. A job termination because of illness or injury indicates an impaired health status. Second, individuals were asked if they were “limited in the kind or amount of activity that [they] can do at work because of a long-term physical condition, mental condition or health problem”. A limitation of this kind would also indicate a health impairment.

Table 1 presents the composition of the sample by various socioeconomic status variables and by the reason the ROE job ended. An asterisk beside a variable name indicates that the joint test of that the means for each group are equal was rejected at the 5% significance level. The majority of the sample were laid off (72%), 19 percent quit, 6 percent left because of illness or injury and 3 percent were dismissed. Of particular importance is the difference in socioeconomic status between the individuals that left for different reasons. The groups have different means for the various variables. The only variables for which the joint test was not rejected are the proportion of the group that have completed high school and the proportion of the group that have a child under 6 years old. The reported spell length accounts for censoring by estimating an expected duration for censored spells and assigning the estimated spell length to any censored spells. The expected duration for censored

spells is the observed length (62 weeks) plus one over the estimated hazard for the penultimate interval. This estimate is the expected duration given that the spell lengths follow an exponential distribution over the last interval.

Table 2 compares the socioeconomic composition of individuals who report they have a health limitation and those who report they do not. An asterisk beside a variable name indicates that the difference between the two groups is significantly different from zero at a 5% significance level. Individuals who report a limitation are older, less educated, have a lower income, are more likely to have left the ROE job because of illness and less likely to have quit or been laid off than those who do not report a limitation. Twenty-seven percent of individuals with a limitation left their ROE job because of illness or injury compared to only four percent of those without a limitation.

V. Discussion of Results

V.1. Hazard Estimation

Figures 2, 3, and 4 show the empirical hazard function for the entire sample, by reason for leaving ROE job, and by presence of a health limitation, respectively. The empirical hazard function illustrates the proportion of the sample having a spell at time t that ended their spell by time $t+1$. In Figure 2, the empirical hazard is declining over the first 15 weeks and then it is relatively flat. There is a spike at

around 19 weeks that may be due to the end of benefits. This issue needs to be examined more carefully. Figure 3a shows dramatically different empirical hazard functions for the different reasons for leaving the ROE job. Individuals who quit the ROE job have a hazard that is very high in the first week and then declines over the next seven weeks. Figure 3b shows the same empirical hazards as Figure 3a, but with the first week of the quits excluded because this group's high initial hazard does not allow Figure 3a to reveal the shapes of the other groups' hazards. Figure 3b shows that individuals who were either laid off or dismissed have a declining hazard function while individuals who left because of illness or were dismissed have very noisy hazard functions. Figure 4 shows that individuals without a health limitation have a different empirical hazard than individuals with a limitation. Both groups have declining hazards, but individuals without a health limitation appear to have a higher probability of finding employment.

The impact of the independent variables on the hazard function were estimated. The appendix contains the definitions of each independent variable. The estimated baseline hazard is for a male, aged 36, married, without a child under six, with more than a high school education, who is not a visible minority, whose job ended in cohort one, and whose average annual income over the previous five years was \$17,000. The estimated baseline hazard corresponds to individuals who left a job that was full-time, not covered by a union contract, industrial occupation, expected to return to the job and not seasonal. Table 3 presents the results from four specifications. In order to examine the impact of impaired health status on the hazard

function, two forms of the independent variables for health status were used. First, indicators for whether there was both a health limitation and left the ROE job because of illness, just a health limitation, or just left the ROE job because of illness were used. The omitted category for these specifications is an individual who does not have a health limitation and did not leave their job because of illness. Second, indicators for the presence of a health limitation and for the reason for leaving the ROE job were used. The omitted category in these specifications is an individual that does not have a health limitation and who was laid off. Each set of independent variables was used in an estimation that did not control for unobserved heterogeneity and one specification that did.

Estimated coefficients for several of the personal characteristics were similar across all specifications. Age had a negative and significant impact on the probability of leaving unemployment. Average income over the last five years had a positive and significant impact on this probability. Marital status, sex, and having a child under six did not consistently have significant impacts.

Some of the estimated coefficients for personal characteristics changed across the specifications. The interaction between female and presence of a child under six was significant when there was control for unobserved heterogeneity and the coefficient for visible minority was no longer significant. In the specification that used the interaction terms for health status, the coefficient for having less than a high school education was not significant while it was in the other specification.

The estimated coefficients for the characteristics of the ROE job had a greater

variability between specifications than the personal characteristics except for occupation which is generally consistent across specifications. Having left a part-time job indicated a higher probability of ending an unemployment spell, but was only significant in specifications that controlled for unobserved heterogeneity. The ROE job being a seasonal job did not have a significant impact except in the specification that controlled for unobserved heterogeneity and used the interaction variables for health status. Being covered by a union contract in the ROE job had a positive and significant impact except when both controlling for unobserved heterogeneity and using the interaction variables for health status.

The specifications that control for unobserved heterogeneity indicate that it exists and, therefore, the more accurate specifications control for unobserved heterogeneity.

The coefficients of the variables for health status are fairly consistent across specifications. In the specifications which use the interactions terms, the coefficients for having a health limitation or having a health limitation and leaving the ROE job because of illness were negative and significant regardless of whether the specification controlled for unobserved heterogeneity. The interaction term for leaving the ROE job because of illness was negative, but only significant in the specification that controlled for unobserved heterogeneity. In the specifications that used a dummy variable for the presence of a health limitation and the reason for leaving the ROE job, the coefficients for the presence of a health limitation and leaving the ROE job because of illness were always negative and significant. These results indicate that impaired health status leads

to a lower probability of leaving unemployment, therefore, longer unemployment spells.

V.I. Effect of Hazards on Composition of Stock of the Unemployed

To examine the impact of longer unemployment spells of individuals with impaired health status on their share of the stock of unemployed, we must make some simplifying assumptions. First, we assume a steady state, including that the composition of the flow into unemployment is constant over time. Second, we assume all individuals are homogenous except for their health status. In this world there are four groups; individuals who left a job because of illness but do not have a health limitation(I), individuals who have a limitation but did not leave their job because of illness (L), individuals who are both ill and limited (B), and individuals who are neither (N). Their shares of the flow into unemployment are 3.6%, 5.7%, 2.1%, and 88.6% respectively. The shares of the flow are taken directly from the data which is a random sample of the flow into unemployment. Using equation (13), equation (16) and the estimated coefficients from the specification that used the interaction terms and controlled for unobserved heterogeneity and holding constant the value of the unobserved heterogeneity at one², the predicted average durations in weeks are:

² The predicted average durations were also estimated by integrating over the distribution of the unobserved heterogeneity. The final estimate of each groups' share of the stock was similar to the results, but the predicted average durations were unrealistically large. This result implies that the gamma distribution may not be the correct assumption for the distribution of the unobserved heterogeneity.

$$\begin{aligned}
 D_N(t) &= 1.970 \\
 D_L(t) &= 2.577 \\
 D_I(t) &= 3.278 \\
 D_B(t) &= 3.551
 \end{aligned}$$

The predicted average duration for the total sample is 2.085. The estimated stock shares are then:

$$\begin{aligned}
 \sigma_N &= 83.7 \\
 \sigma_L &= 7.00 \\
 \sigma_I &= 5.70 \\
 \sigma_B &= 3.60
 \end{aligned}$$

Although individuals with lower health status comprised 11.4% of the flow into unemployment, they account for 16.3% of the stock of unemployed, which is 43% higher than their entrance share.

What are the implications for a study that has compared mortality rates of the stock of employed and unemployed? Assume that individuals with high health status have lower mortality rates than those with impaired health status, but that there is no difference in mortality rates between employed and unemployed individuals. Also assume that there is no selection into the flow into unemployment by health status so that the composition of the stock of employed is the same as the flow out of it. These restrictions imply that the estimate of the impact is a lower bound in some sense. In this case the predicted mortality rate for the stock of employed is:

$$MR_E = (0.886)*MR_H + (0.114)*MR_{IH}$$

where the proportion of the stock in each health status is from the data. The predicted mortality rate for the stock of unemployed is:

$$MR_U = (0.837)*MR_H + (0.163)*MR_{IH}$$

where the proportion of the stock in each health status is from the estimated share when the differences in the durations is taken into account. The difference between the mortality rates is:

$$\begin{aligned} MR_U - MR_E &= (-0.049) * MR_H + (0.049) * MR_{IH} \\ &= (0.049) * (MR_{IH} - MR_H). \end{aligned}$$

Even if unemployment has no impact on health status, a difference in the mortality rates between employed and unemployed approximately equal to 5% of the difference in mortality rates between healthy and not healthy individuals will exist. The implication for the studies reviewed in Section II is that the estimates of the impact of unemployment on health status are at least over-estimates if not possibly spurious results.

VI. Conclusion

Several studies have been conducted to determine the impact of unemployment on mortality or health status. The hypothesis is that unemployment decreases health status. A relationship could be observed between employment status and mortality rates for three reasons. First, unemployment does decrease health status. Second, individuals with impaired health status are more likely to become unemployed and, therefore, comprise a larger proportion of the stock of unemployed. Third, individuals with impaired health are more likely to remain unemployed and, therefore, will comprise a larger proportion of the stock of unemployed. This paper focused on

the third issue. Are individuals with impaired health more likely to remain unemployed?

Using a longitudinal data set that interviews individuals after a job separation, duration analysis was used to estimate the effect of health status and other socioeconomic factors on the length of unemployment spells. Two proxies for ill health were examined in this paper: having left a job because of illness and reporting a health limitation. Hazard rates were estimated for the sample. The PGM procedure was used allowing for a possible correction for unobserved heterogeneity. Having quit a job due to illness or reporting a health limitation had a significantly negative impact on the hazard rate. That is, the probability of finding employment at any point in time is lower if the individual quit due to illness or had a health limitation. In particular, individuals who reported both a health limitation and left their job because of illness had extremely long unemployment spells.

The stock of unemployed will be comprised of a larger proportion of individuals with impaired health than the stock of employed because of the longer unemployment spells of these individuals. The implication for previous research is that a relationship between unemployment and mortality rates could be observed, however, it is possible that this relationship is spurious. To accurately measure the social cost of unemployment the results in this paper need to be taken into account.

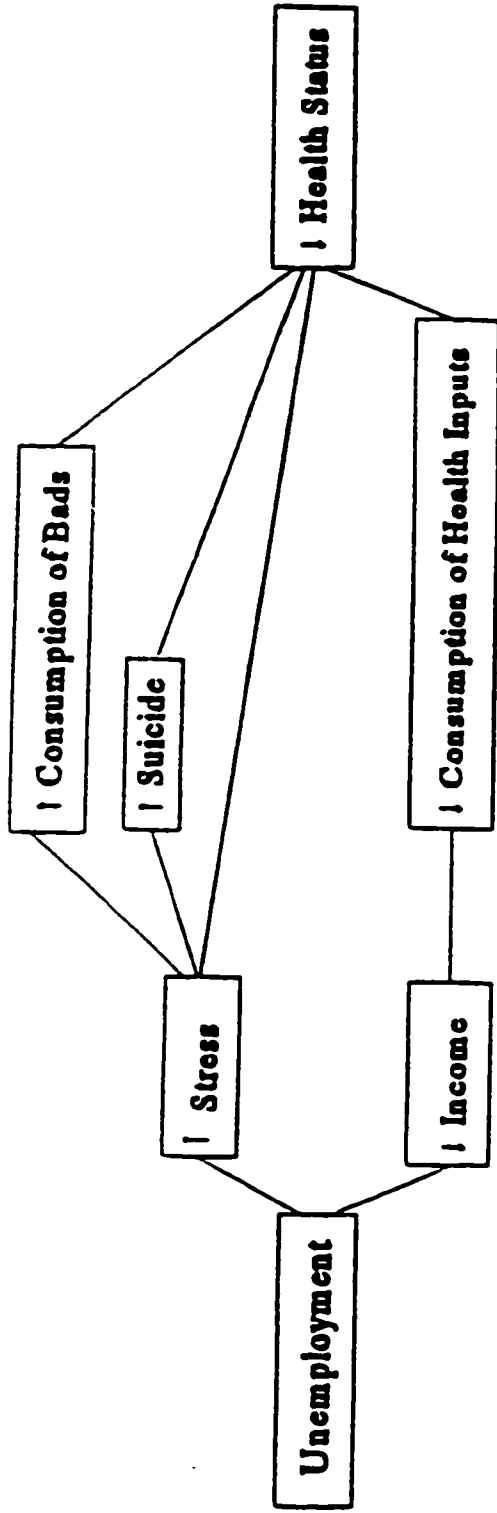


Figure 1 Impact of Unemployment on Health Status

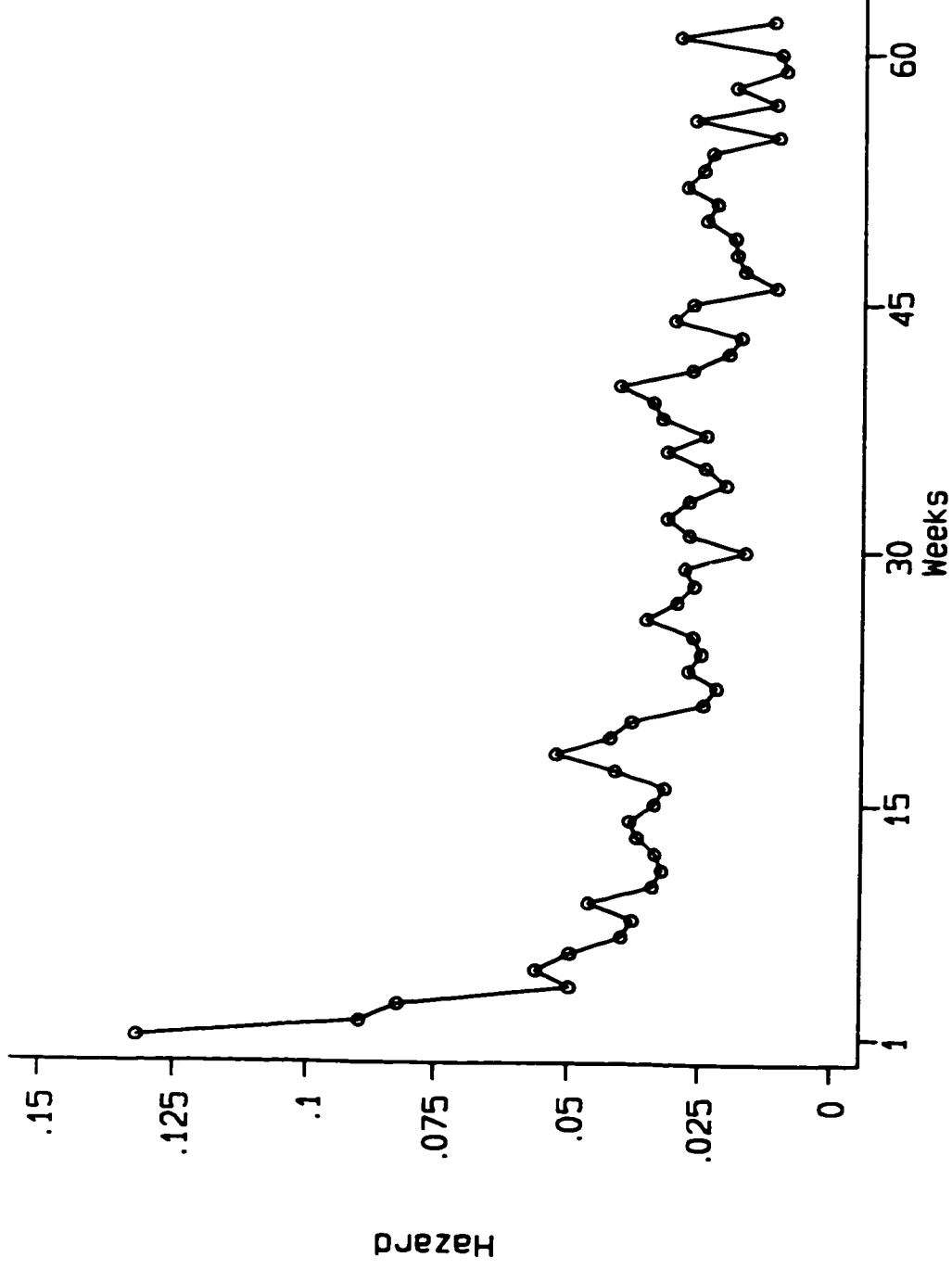


Fig.2 Empirical Hazard for Unemployment Spells

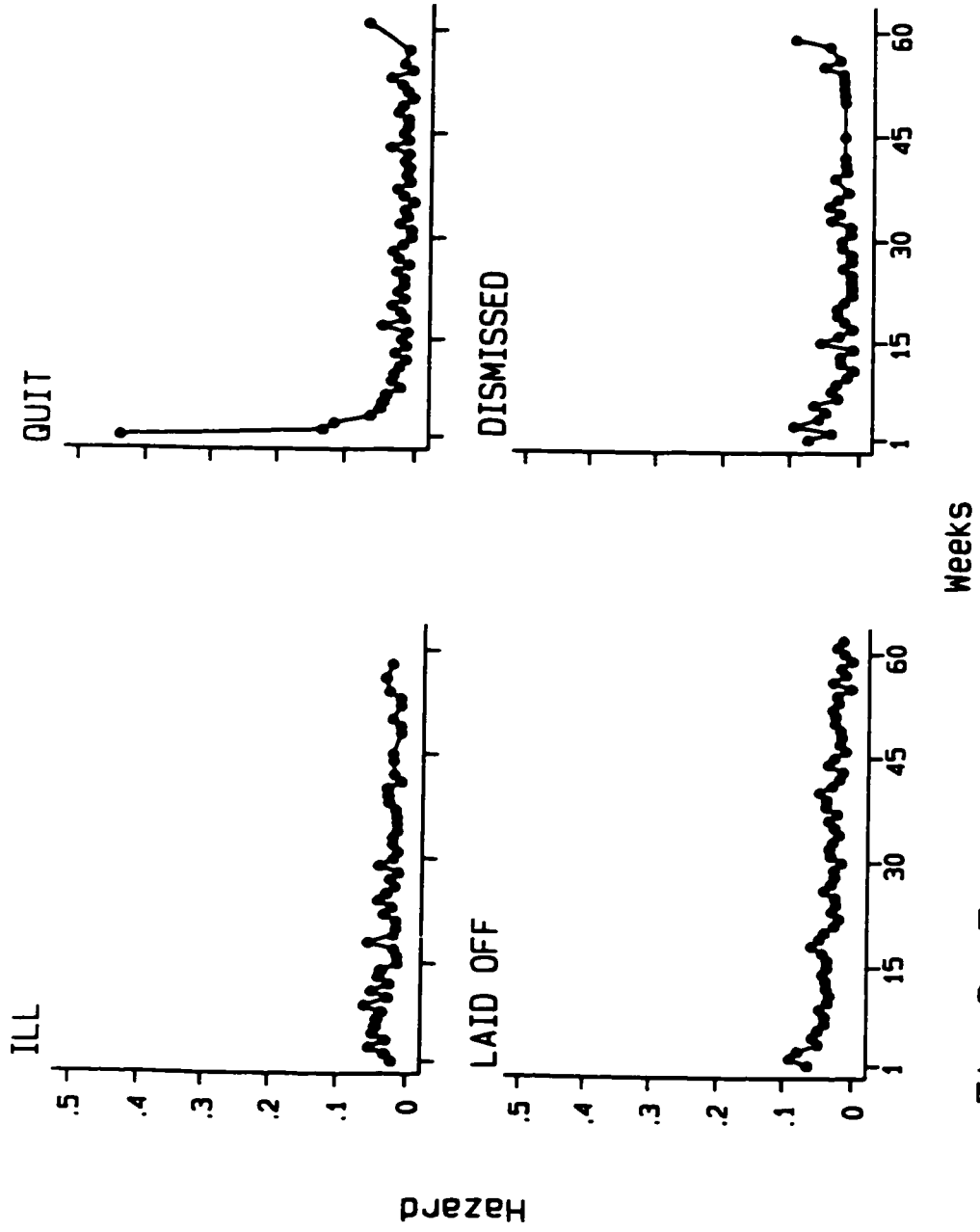


Fig 3a Empirical Hazard by Reason for Leaving

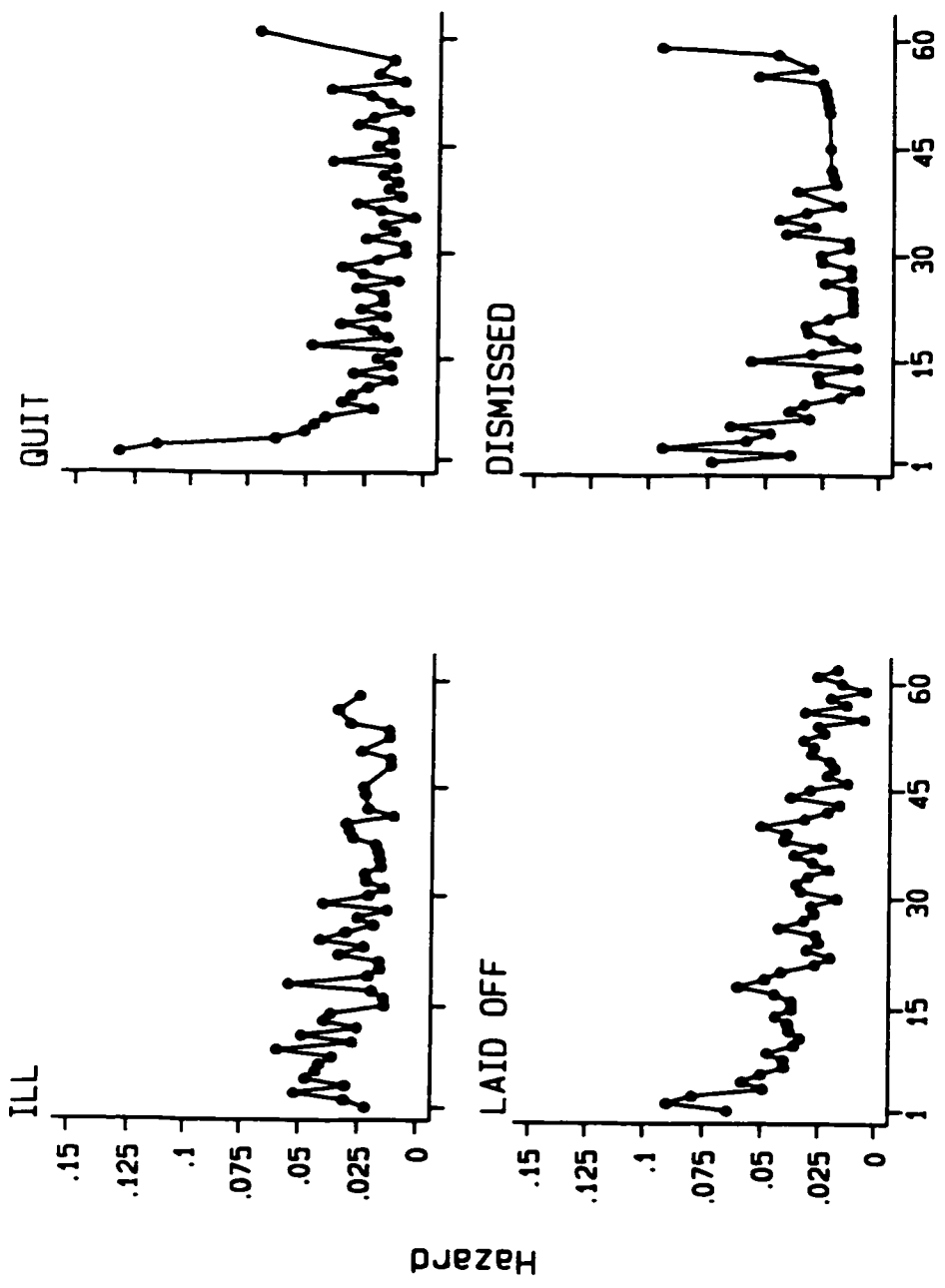


Fig 3b Empirical Hazard by Reason for Leaving

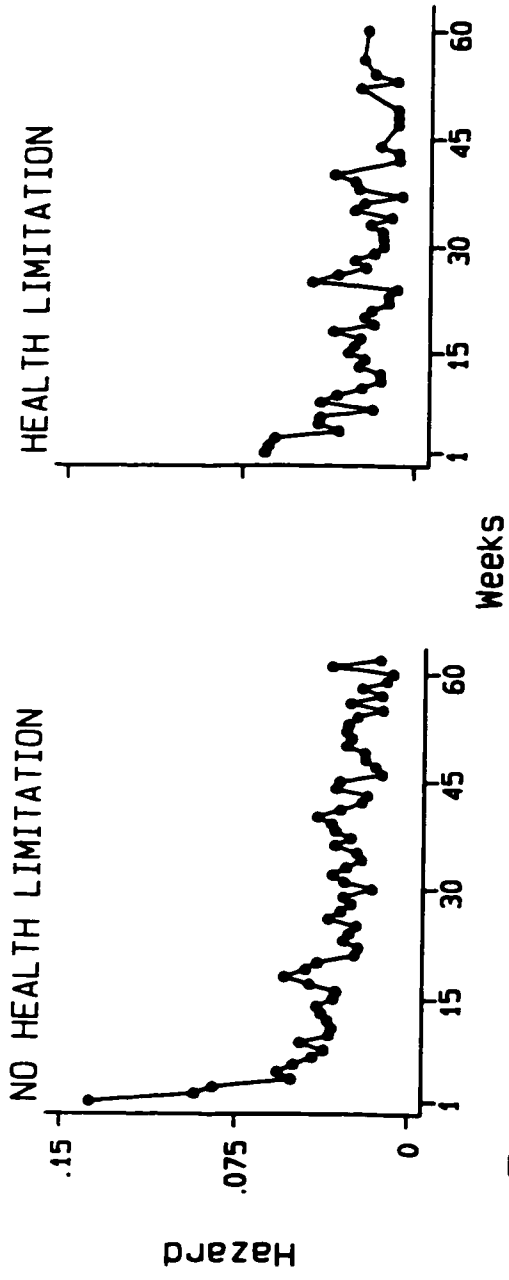


Fig. 4 Empirical Hazard by Presence of Limitation

Table 1
Socioeconomic Characteristics of Total Sample
and by Reason for Leaving ROE Job
(Entries are Percentages unless otherwise indicated)

Characteristics	Total	Ill	Quit	Laidoff	Dismissed
Age(years)*	36	40	31	28	33
Married*	61	66	52	64	42
< High School*	26	34	17	28	28
High School	31	32	30	31	28
Female*	39	55	41	38	34
Visible Minority*	19	23	16	20	17
Income (1,000's)*	22	21	20	23	18
Full Time*	72	70	66	73	75
Children under 6	19	19	20	19	18
Union Contract*	32	31	14	37	11
Expect to Return*	54	79	12	65	16
Previous UI Claim*	59	57	23	69	44
Seasonal Job*	28	9	11	35	7
Cohort 2*	52	51	56	51	40
Professional*	9	9	12	8	10
Clerical*	3	2	4	3	2
Service*	6	4	2	7	0
Primary Industry*	5	13	4	4	5
Industrial*	77	72	78	78	83
Limited*	8	37	5	6	11
Spell Length (Weeks)	24	34	18	25	33
OBSERVATIONS	5817	334	1108	4198	177
*indicates that joint test of the equality of the means across the reasons was rejected at a 5% significance level.					

Table 2			
Socio-economic Characteristics For Total Sample and by Presence of a Health Limitation			
(Entries are Percentage unless otherwise indicated)			
Characteristics	Total	Health Limited	Not Health Limited
% of Total Sample	100	8	92
Age(years)*	36	40	36
Married	61	62	61
< High School*	26	36	25
High School	31	31	31
Female	39	42	39
Visible Minority	19	23	19
Income(\$1000's)*	22	20	22
Full Time	72	70	72
Children under 6	19	19	19
Union Contract	32	29	32
Expect to Return	54	62	53
Previous UI Claim	59	56	59
Seasonal Job	28	25	28
Cohort 2	52	47	52
Professional	9	7	9
Clerical*	3	1	3
Service	6	7	6
Primary Industry	5	6	5
Industrial	77	79	77
REASON: Ill*	6	27	4
Quit*	19	12	20
Laid off*	72	57	73
Dismissed	3	4	3
Spell Length (Weeks)	24	35	23
OBSERVATIONS	5817	457	5360

Table 3				
Estimated Coefficients from Four Models				
Variables	Interaction Terms		Separate Dummy Variables	
	Without Un. Het.	With Un. Het.	Without Un. Het.	With Un. Het.
Personal Characteristics				
Age(10 years)	-0.015 (.000)	-0.336 (.000)	-0.013 (.000)	-0.016 (.002)
Income (Log)	0.122 (.000)	0.762 (.000)	0.128 (.000)	0.448 (.000)
Not Married	-0.079 (.010)	-0.260 (.090)	-0.068 (.023)	-0.224 (.024)
Female	0.040 (.135)	0.453 (.020)	0.045 (.111)	0.225 (.038)
Female*Presence of a Child under 6	-0.170 (.012)	-1.643 (.000)	-0.167 (.013)	-1.093 (.000)
Child under 6	-0.021 (.333)	0.522 (.050)	-0.023 (.316)	0.187 (.130)
Not Completed High School	-0.088 (.015)	-0.436 (.031)	-0.098 (.008)	-0.403 (.001)
Completed High School	.004 (.455)	0.012 (.477)	0.014 (.352)	-0.049 (.343)
Visible Minority	-0.137 (.000)	-0.259 (.109)	-0.137 (.000)	-0.211 (.043)
Cohort 2	0.095 (.001)	0.132 (.223)	0.089 (.001)	0.050 (.305)

Table 3 Continued				
Variables	Interaction Terms		Separate Dummy Variables	
	Without Un. Het.	With Un. Het.	Without Un. Het.	With Un. Het.
ROE Job Characteristics				
Previous Job Part-time	0.050 (.085)	0.817 (.000)	0.016 (.334)	0.316 (.008)
Covered by Union Contract	0.159 (.000)	-0.061 (.384)	0.183 (.000)	0.364 (.001)
Not Expected to Return to Previous Job	-0.116 (.000)	1.782 (.000)	-0.225 (.000)	-0.193 (.048)
No Previous UI Claim	-0.004 (.446)	1.823 (.000)	-0.096 (.002)	.0271 (.015)
Seasonal	-0.013 (.346)	-0.481 (.005)	0.036 (.146)	-0.251 (.011)
Professional	-0.119 (.016)	-0.724 (.021)	-0.108 (.025)	-0.482 (.006)
Clerical	0.030 (.360)	-0.895 (.077)	0.119 (.078)	0.315 (.155)
Service	-0.144 (.014)	-0.494 (.082)	-0.101 (.064)	-0.437 (.031)
Primary Industry	-0.235 (.001)	-1.334 (.001)	-0.190 (.004)	-0.820 (.000)

Table 3 Continued				
Variables	Interaction Terms		Separate Dummy Variables	
	Without Un. Het.	With Un. Het.	Without Un. Het.	With Un. Het.
Health Status Indicators				
Not Ill but Health Limitation	-0.130 (.022)	-0.994 (.002)	---	---
Ill but No Health Limitation	-0.011 (.442)	-2.592 (.000)	---	---
Ill and Health Limitation	-0.945 (.000)	-4.889 (.000)	---	---
Ill	---	---	-0.0190 (.004)	-1.013 (.000)
Quit	---	---	0.555 (.000)	3.796 (.000)
Dismissed	---	---	-0.137 (.066)	-0.196 (.243)
Health Limitation	---	---	-0.288 (.000)	-0.726 (.000)
Variance	---	13.620 (.000)	---	5.288 (.000)

The omitted category for personal characteristics is a male, aged 36, married, without a child under 6, more than a high school education, not a visible minority, cohort 1, and income of \$17,000. The omitted category for the ROE job characteristics is a full-time job, not covered by a union contract, industrial occupation, expected to return to ROE job, and year-round. The omitted category for the health status is either no health limitation and did not leave the ROE job because of illness or no health limitation and was Laid off.

Appendix: Description of Variables**Age:**

A continuous variables measured as the age in 1995 in units of ten years.

Marital Status:

A discrete variable which equals one if not either married or common-law.

The category includes never married, divorced, separated, and widowed.

Education:

A discrete variable divided into three categories. The first category is less than completed high school. The second category is at least completed high school, but no university education. The third category at least some university education.

Not Full-time:

A discrete variable which equals one if the previous job was a not full-time position.

Visible Minority:

A discrete variable which equals one if the individual answered yes to the question "By virtue of your ethnic origin are you a visible minority in Canada?".

Child under 6:

A discrete variable which equals one if there is at least one child under the age of one living in the household.

Union Contract:

A discrete variable which equals one if the individual was covered by a union contract in the previous job.

Occupation:

A discrete variable divided into five categories. The professional category includes officials and administrators, government, other managers and administrators, management and administration related, physical and life sciences, maths, stats, system analysis, architects and engineers, architecture and engineering related, social sciences and related, religion, university and related, elementary, secondary and relate, other teaching and related, health diagnosing and treating, nursing, therapy and related, medicine and health related, and artistic and recreational. The clerical category includes stenographic and typing, bookkeeping, account recording, and related, office machine and E.D.P. operators, material recording, scheduling and distributing, receptions, information, mail and message distribution, and library, file, correspondence, other clerical and related. The services category includes sales, commodities, sales, services and other sales, protective service, food and beverage preparation and related lodging and accommodation, personal, apparel and furnishing services, and other service occupations. The primary industry category includes farmers, other farming, horticultural and animal husbandry, fishing, hunting, trapping and related, forestry and logging, mining and quarrying including gas and oilfield. The industrial occupation category includes food, beverage and related, other processing occupations, metal shaping and forming occupations, other machining occupations, metal products, N.E.C, electrical, electronic and related equipment, textiles, furs and leather goods, wood products, rubber, plastics and other related, mechanics and repairmen, except electrical, excavation, grading, paving and related, electrical power,

lighting and wire, communications equipment, erecting, installing and repairing, other construction trades, motor transport operators, other transportation equipment operators, material handling, other crafts and equipment operators.

Expect to Return to Previous Job:

A discrete variable which equals one if the individual expected to return to the previous job when it ended.

Previous UI Claim:

A discrete variable which equals one if the individual had any UI claims in the previous five years.

Seasonal Job:

A discrete variable which equals one if the previous job was seasonal.

Income:

A continuous variable which is the natural logarithm of the average of the individual's total reported income over the previous five years.

Cohort Two:

A discrete variable which equals one if the individual was in cohort 2. Cohort 1 was defined as individuals that had a job end between January 29 and April 1. Cohort 2 was defined as individuals that had a job end between April 23 and June 3.

Region:

All results included controls for the region in which the individual was residing. The four regions were the Atlantic provinces, Quebec, Ontario, the Western provinces. The omitted category was Ontario.

Limited:

A discrete variable which equals one if the individual answered yes to the question “Are you limited in the kind or amount of activity that you can do at work because of a long-term physical condition, mental condition or health problem?”

Reason for Leaving Previous Job:

A discrete variable divided into four categories. Individual were asked what the primary reason for leaving the previous job. The four categories used are illness or injury, quit, dismissed or fired, and laid off .

Chapter 3

Duration of Spells On Welfare and Off-Welfare Among Lone Mothers In Ontario

I. Introduction

This paper provides one of the first in-depth looks at the dynamics of social assistance use in Ontario. Specifically, we study the duration of both welfare spells and off-welfare spells among lone mothers during the first half of the 1990's. This subject is timely for at least two reasons. First, social assistance policy reform has been high on the agenda in Ontario and in other provinces. This concern reflects in part the rapid growth in the welfare expenditures during the 1990's, but it has earlier roots in the recovery of the 1980's when there was no decline in the welfare caseload despite a large drop in unemployment. A second reason arises from our focus on lone mothers. Such families contain a large and growing fraction of poor children whose problems have been the subject of much recent discussion. They are the most reliant on welfare of any family type except for the disabled, yet relatively little is known about their patterns of social assistance use especially in Ontario.

Several studies have used data from a single cross-section or a time-series of cross-sections to study the welfare participation of Canadian lone mothers. These

studies have generally found the expected associations of welfare participation with personal characteristics, labour market indicators and policy parameters. Though informative, most survey data can not answer several questions of key interest to policy makers. What determines the length of time which lone mothers spend on welfare? After leaving welfare, which lone mothers are most likely to return to the rolls and how soon? Is there evidence of welfare dependence, that is, a “welfare trap”? For example, does the likelihood that a lone mother will leave welfare decline as her spell gets longer? Do individuals with great SA use in the past have a greater likelihood of returning to the rolls or of a longer spell on welfare spell if they do return?

Several recent papers have used caseload data from British Columbia and Quebec to answer some of the above questions. We begin the task for Ontario in this paper using administrative data made available to the authors by the Ministry of Community and Social Services (MCSS). Specifically, we analyse the link between the duration of spells both on welfare and off welfare, and a series of factors including personal characteristics, the client’s history of welfare use, the duration of the current spell, labour market conditions and SA benefit levels.

Section II of the paper contains a brief review of the literature. The Ontario welfare system and the data used in this study are discussed in Section III. Section IV presents our estimation strategy. The empirical estimates for welfare spells and off-welfare spells are discussed in Sections V and VI, respectively. Section VII is a summary and conclusion.

II. Review of the Literature

The literature on welfare use can be divided into two sections, the first of which is older and larger: studies of the probability of welfare participation and studies of the length of welfare spells. A brief review of the comparative statics of welfare participation will be helpful prior to a discussion of the literature. [See Charette and Meng (1994) for a detailed, graphical exposition.] Two welfare policy parameters influence the budget set: the guarantee and the tax rate. The guarantee or basic assistance is the welfare payment if the client has no other source of income. The national average for a lone mother with one child was \$11,000 in 1991 (National Council of Welfare 1992). The implicit (or negative) welfare tax is zero on some minimal level of monthly earnings referred to as the “earned income exemption” or “set aside”. This ranged in value from \$30-\$200 per month in 1991. The tax on earnings beyond the exemption or “marginal tax rate” ranges from 75% to 100% (National Council of Welfare 1993). The “break even” is the level of earnings at which the welfare payment is reduced to zero which, in a simple system, is equal to the “earned income exemption” + (basic assistance/ “marginal tax rate”).

The probability that a randomly selected individual qualifies for social assistance is an increasing function of the level of basic assistance and the earnings exemption, and a decreasing function of the marginal tax rate. Individuals with higher hourly wages will reach the break even at fewer hours of market work, thereby making the probability of welfare participation a decreasing function of market wages.

As documented below, most studies have also found that the probability of welfare participation is greater for lone mothers who are poorly educated, never married and have larger numbers of younger children. In this paper, we assess the impact of many of these same variables on the length of welfare spells and off-welfare spells among those lone mothers whom one observes on welfare for at least one month during our sample period.

Would we expect the same qualitative links as in the previous paragraph between the number of months spent on welfare (within a fixed time frame) and both policy parameters and personal characteristics? For a random sample of individuals, the answer is yes. What of welfare spell length? This is more complicated by the fact that intensive welfare use may come in the form of either infrequent long spells or frequent short spells. However, in a random of individuals for whom the most common spell length would be zero months, we would generally expect the answer to be yes. Our administrative sample, however, is limited to actual clients and our estimated coefficients may be influenced by the non-random nature of selection into the data set. For example, one would expect an increase in basic assistance to have two effects: (1) lengthen the welfare spells of those persons already on welfare and (2) increase the proportion of the overall population that ever starts a welfare spell, that is, shows up in our sample. If the second effect adds persons to the sample with welfare spells which are shorter than those of veteran welfare clients, then average observed spell length among all clients could decrease. This same problem is true of the predicted effects of other independent variables and for off-welfare spells.

Unambiguous predictions are difficult to make for a sample of clients which is precisely the type of data most commonly used, normally because it is the only suitable data available, in duration studies such as ours.

A key policy issue of interest in welfare policy is that of dependence. Does past use of the welfare system alter the likelihood of future use? There are a variety of mechanisms through which such effects might occur, e.g., skill atrophy or acquisition (schooling), employers' perceptions of clients' skills (stigma), knowledge of the welfare system, preferences, etc. The term duration dependence refers to a situation in which the probability of leaving welfare, i.e. terminating the spell, changes as the spell proceeds. Lagged duration dependence refers to a situation in which the length of the current spell varies with the length of the previous spell(s). Detecting the presence of duration dependence is complicated by the possibility of "unobserved heterogeneity". For example, as a welfare spell proceeds, the exit probability of the surviving clients may change either because their individual characteristics are changing ("state dependence") or because the composition of the sample of surviving clients are changing ("heterogeneity"). Lancaster (1979) demonstrates that the presence of unobserved heterogeneity may bias the shape of the baseline hazard towards exhibiting negative duration dependence.

Our review will focus on the U.S. and Canadian literature. The most notable difference between the systems is that the U.S. Aid for Families with Dependent Children (AFDC) has been mainly directed at lone-parent families. In Canada, there are no formal demographic welfare requirements. Given the focus of this paper on

lone mothers in Ontario, however, this distinction is less important than otherwise might be the case.

Moffitt (1992) provides an excellent survey of the U.S. literature. With respect to welfare participation, he focuses on the impact of variation in the guarantee or basic assistance because there is no inter-state variation in welfare tax rates and there have been only two major tax changes over time. Moffitt distinguishes between the mechanical and behavioural impacts of changes in the guarantee. The former arise because a rise in the guarantee will increase the break-even level of earnings. As a result, more families will qualify for welfare even if their market work is unchanged. The behavioural impact refers to the fact that an increase in the break-even may induce some families, who are close but still above the new break-even, to reduce their hours of market work in order to qualify for welfare. He reports that the mechanical effect is substantial, as one would fully expect, but that the behavioural effect is very modest.

There have been several Canadian studies of welfare participation. Allen (1993), Charette and Meng (1994), and Christofides, Stengos, and Swindisky (1997) all use a single cross-section. Dooley (1996) uses a time series of cross sections. These studies generally find the likelihood of welfare participation has a statistically significant association of the expected sign with policy parameters (welfare benefit levels and implicit tax rates), personal characteristics (potential wages, education, marital status and the numbers and ages of children) and labour market conditions. None of these studies distinguish between the mechanical and behavioural effects of

policy changes.

Plant (1984) provides an early U.S. study of welfare dependence with data from the Seattle and Denver Income Maintenance Experiments (SIME/DIME). Plant asserts that if welfare does not create a dependence then the proportion of the control group with income below the SIME/DIME breakeven point(s) should be no smaller than the proportion of the treatment group that participates in the experimental welfare scheme(s). He finds no difference in these proportions during the experiment and, therefore, little support for the existence of a welfare trap. Further tests reveal that the reason for persistent welfare participation is the correlation in low earnings across time periods.

Feaster, Gottschalk, and Jakubson (1987) examine the impact of the Omnibus Budget Reconciliation Act (OBRA) on welfare spell length among AFDC recipients in Wisconsin. OBRA tightened eligibility rules and raised the tax-back rate on earnings in January of 1982. Two samples of AFDC cases were used, one which included recipients from September 1980 to September 1981 (pre-OBRA) and one which included recipients from September 1981 to September 1982 (pre- and post-OBRA). Their results indicate that the mean duration of a welfare spell is three months shorter after OBRA. The authors further find that this spell-shortening effect was concentrated among those recipients in the second sample that were working in the market prior to OBRA (between September 1981 and January 1982) and that there was no significant effect among those recipients who were not working in the market during this same period.

O'Neill, Bassi and Wolf (1987) analyse the patterns of AFDC use with 11 years of data from the National Longitudinal Study(NLS) of Young Women. They define a spell as a sequence of years in which an individual reports any positive amount of welfare during the year. This definition is quite different than the usual one of a sequence of months (the typical administrative unit) on welfare. Their estimated hazard rate does decline with the length of the spell, but this could be due to unobserved heterogeneity for which the authors were unable to control. They find that the majority of spells last less than two years, but there are a significant number of spells which last longer than two years. The longer term recipients are disproportionately likely to have large numbers of young children, low wage rates, limited schooling and work experience, and to be from a black, female-headed families in states with high benefit levels.

Blank (1989) uses a sample of female household heads from the control group of the SIME/DIME experiment to study the duration dependence. Her specification permits there to be two (endogenously determined) groups of clients due to unobserved heterogeneity. For one group, she estimates that the probability of leaving welfare increases over the first eight months of the spell and then decreases beyond that point. For the second group, the hazard rises only slightly at the start of the spell is then constant. She concludes that support for negative duration dependence is much weaker in her data than in previous research.

There have been two Canadian studies of welfare spell duration among lone mothers both of which use provincial welfare caseload data. Barrett (1996) uses a ten

percent random sample of welfare clients between 1980 to 1992 in British Columbia. He estimates a piece-wise constant proportional hazard model for welfare spells among lone parents and single women and men.¹ (Off-welfare spells are not considered.) For lone mothers, he finds that welfare exit rates are negatively related to potential welfare benefits, the unemployment rate, and the number of children, and are positively related to the minimum wage and mother's age. This last result may reflect the age of the children, which is unknown in these data, rather than the age of the parent.

Barrett tests for one form (gamma distributed) of unobserved heterogeneity and finds evidence for this among lone parents. Even with controls for unobserved heterogeneity, he also finds support for negative duration dependence and negative lagged duration dependence, the latter defined as the total number of months on welfare during the sample period prior to the current spell. He does not find support for what he labels "occurrence dependence" which is defined as the number of previous spells during the sample period. This may reflect the fact that the spells must be short in order for there to be numerous spells within a twelve year time frame.

Barrett concludes that welfare may act as a "trap" which has "scarring" or "stigmatizing" effects on the clients. However, unobserved characteristics also appear to play an important role in welfare use and, until more information is available on welfare recipients, it is difficult for policy makers to target the groups most vulnerable

¹ Cragg and Barrett (1998) use the same data source and include married couples but limit their analyses to empirical hazard functions.

to state dependence. Barrett did not analyse off-welfare spells.

Fortin, Lacroix and Thibault (1997) use a random sample of all single parents who were on welfare at least once between 1979 and 1993 in Quebec. Their estimated hazard functions include personal characteristics, potential welfare benefits, the implicit welfare taxation rate², the “generosity” of the unemployment insurance (defined as the ratio of the maximum number of weeks a claimant may receive UI to the minimum number of weeks worked needed to qualify for UI) and the rate of coverage of UI. They used the same piece-wise constant proportional hazard model as Barrett to estimate duration models for both welfare and off-welfare spells.

They find evidence of negative duration dependence within welfare spells but, unlike Barrett, they were unable to control for unobserved heterogeneity because these models did not converge. They also found, as did Barrett, that the welfare exit rates are negatively related to potential welfare benefits, the unemployment rate, and the number of children (either pre-school or school-age) and positively related to parental age. Unlike Barrett, they found that welfare exit rates are positively related to the provincial minimum wage and parental education (the latter variable was not available for B.C.). Fortin et al. used several variables which Barrett did not. The exit rate decreases with the welfare tax rate and increases with the generosity of the UI system. They were not able to identify the impact of UI coverage in their welfare spell model.

² The implicit welfare taxation rate is defined as “the increase in taxes net of transfers as a percentage of labour income facing a welfare recipient accepting a minimum wage job.”

Fortin et al. also provide one of the few estimated duration models for off-welfare spells. The hazard of returning to welfare decreases with the age of the client but only after age 30. More education lengthens off-welfare spells but only for clients under 30. Surprisingly, the exit rate is not significantly associated with potential welfare benefits or with the number and ages of children. The exit rate back onto welfare is positively affected by the unemployment rate and the minimum wage and is negatively associated with the generosity and coverage of the UI system.

In summary, Canadian studies of welfare use among lone mothers have generally found the expected association of spell length with both personal characteristics, policy parameters and labour market conditions. The early studies with administrative data clearly indicate the importance of longitudinal data for assessing some of the highest profile policy questions such as the existence or not of various possible forms of “welfare dependency”. Future studies may wish to analyse alternative measures of “welfare dependency” such as the proportion of some fixed time frame spent on welfare. During a four-year period, for example, the key policy issue may well be the determinants of the total number of months spent on welfare. Future studies will also need to link administrative data with other data sets in order to provide a more complete picture of responses to policy changes and to assess the interaction between systems such as welfare and UI.

III. Social Assistance in Ontario: The Basic System and Our Data Set

Short term financial assistance in Ontario is provided by municipalities under the terms of the General Welfare Assistance (GWA) Act. The provincial government administers a program of long-term assistance under the Family Benefits Act (FBA). GWA clients are categorized according to "reason for assistance" such as "inability to find regular employment" or and "lack of principal family provider". FBA clients are categorized according to "case classification" such as "disabled" or "sole support parent". Some lone mothers receive only GWA or FBA during an entire spell but switches from GWA to FBA are common. Indeed, a three month "waiting period" on GWA before switching to FBA was required of most unwed, separated and deserted lone parents prior to October 1991. In our estimation sample, 45% of spells involved a switch from GWA to FBA, only 2% involved a switch from FBA to GWA, 40% were solely (the uncensored portion) GWA and 14% were solely FBA.

Table 1 provides basic caseload information for our sample period, 1983 through 1994. The final column shows that the total caseload grew from 3.7% to 8.0% of the population age 15 and over. The total number of recipients (clients plus dependents) grew from 5.2% to 12.1% of the total population. Most of this growth occurred from 1990 on, but it is still notable that the caseload grew as a fraction of the population even during the strong recovery of the late 1980's when the unemployment rate fell from 11% to 7%. The proportion of clients who are lone parents grew from 30% to 37% during the 1980's but shrank back to 30% during the

1990's.

Table 2 provides information concerning annual benefit levels. In 1983, the FBA benefits for a lone parent with two children were the same as the GWA benefits for a couple with two children. By 1994, the former had grown by 45% and the latter had grown by 65%. Most of this growth in benefit levels occurred prior to 1990. Real benefit levels changed little during the 1990's until the cuts initiated by the current government in 1995. The final column of Table 2 shows the quadrupling of real social assistance expenditures which underlies much of the concern with welfare policy in Ontario.

Our data set contains a record for most individuals who received welfare in Ontario for one or more months during the period January 1983 to December 1994. We have annual values for demographic characteristics such as marital status and number of dependents under age 22. We have monthly values for welfare-specific variables such as level of welfare income and of other sources of income, and the reason for assistance. We have values at first encounter and at last encounter with the social assistance system during the data period for the variables schooling and county/municipality of residence. Finally, we have several unchanging variables such as date of birth and sex.

There are two significant gaps in our data. The first is that we have no GWA data for persons in ten counties/regional municipalities/districts which account for

approximately 15% of the population of Ontario.³ The second gap is that we are missing substantial amounts of data for the years 1983-1989. In the case of FBA, we are missing data for ten (non-consecutive) months during this seven year period. For GWA, monthly data are only available for March, June, September and December of (most of) the years during this period. Hence, GWA data are missing for two-thirds of the months prior to 1990. These gaps imply that we lack complete information for many welfare spells of either of the following types: (1) spells which occurred in those regions for which GWA data are not available (at any point in time) and (2) spells which commenced prior to 1990 in any part of the province. Therefore, we have chosen to restrict our estimating sample to those spells which commenced after 1989 and which occurred in areas for which we have GWA data.

Welfare Spells and Off-Welfare Spells. The estimates presented in this paper are based on the “two-month rule” which Barrett (1996) used to define spells with the BC data. A new welfare spell begins only after two successive months in which no cheque is issued and ends only when one encounters the next two successive months in which no cheque is issued.⁴ Barrett’s rationale was that a non-trivial proportion of what appear to be one-month, off-welfare spells (a single month with no cheque,

³ These are Bruce, Elgin, Hamilton-Wentworth, Huron, Manitoulin, Oxford, Peel, Perth, Peterborough and Rainy River.

⁴ We observe the actual cheque amount for each month on welfare. In a few cases, this amount is negative or zero which means that the cheque has been temporarily “blocked” for administrative reasons, e.g., information concerning the number of dependents is missing. MCSS considers such persons to be part of the regular caseload and so do we.

preceded and followed by one or more months with a cheque) were in fact administrative or coding errors rather than true spell terminations. In results not presented here, we also used the “one-month rule” adopted by Fortin, Lacroix and Thibault (1997) under which a welfare spell is any sequence of one or more months in which a cheque is issued and an off-welfare spell is any sequence of one or more months in which a cheque is not issued. The two rules for spell definition yield very similar proportional hazard model estimates due to the fact that few lone mothers in our data have single isolated months either on welfare or off welfare.⁵

Lone Mothers. We classified as a lone mother any woman between the ages of 18 and 59 who met either demographic criteria or case classification criterion.⁶ Our demographic criteria are that the client be unmarried (registered or common-law) with one or more dependents under the age of 22. The case classification criteria are that the woman be either (i) an FBA client classified as

⁵ Our earliest welfare spell (using the two month rule) starts in March 1990 because GWA data are missing for November and December of 1989. A new welfare spell starts in March 1990 if a cheque is issued in that month but not in January and February of 1990. Our earliest off-welfare spell starts in April 1990 and occurs if a cheque is issued in March 1990 but there is no cheque in January and February (so that a new welfare spell starts in March) and no cheque in April and May (so that the new welfare spell lasts only one month) of 1990. Under the two-month rule, a welfare spell can last one month but an off-welfare spell must be at least two months long. This is because no welfare spell stops until one encounters two (or more) consecutive months off-welfare.

⁶ We also excluded lone mothers who receive only supplementary aid, special assistance, or aid for a foster or handicapped child. Also, henceforth we will use the term “case classification” when referring to both FBA and GWA categories even though “reason for assistance” is the term officially used for the latter.

“single parent” or (ii) a GWA client who has one or more dependents under age 22 and is classified as “lacks of principal family provider”.⁷

Each of the above criteria for lone motherhood has a drawback. The demographic criteria may miss some *de facto* lone mothers may who are legally married.⁸ The case classification criteria may miss some GWA lone mothers whose category is not “lack of principal family provider” but rather, for example, “unable to find employment”. Therefore, we classified as a lone mother any client who met either criteria during any month of the spell. For the off-welfare spells, we classified as a lone mother any client who met either criteria during any month of the preceding welfare spell. In our sample, 89% of the spells met both criteria, 10% met only the demographic criteria, and 1% met only the case classification criteria.

Summary Statistics. Our estimation sample is a 10% random sub-sample of all records that met the criteria described in the two previous sections. Table 3 provides descriptive statistics. The maximum welfare spell length is 58 months. The mean welfare spell length is 17 months (with no adjustment for censoring) and 47% of all welfare spells are censored. Off-welfare spells can be up to 57 months long, they average 17 months in length and 67% are censored.

We constructed two measures of previous welfare use, the first of which is the

⁷ One must have a dependent under age 22 to be classified as an FBA “sole support parent”. Such is not the case with a GWA client who “lacks a principal family provider”. Hence, we added the criterion of “has one or more dependents under age 22” for the latter.

⁸ See Dooley (1996) for a discussion of this issue in the context of the Survey of Consumer Finances.

number months on welfare between 1983 and the current spell. This averaged 7 months for welfare spells and 16 months for off-welfare spells. The second is a dummy variable for any months on welfare between 1983 and the current spell. Thirty-nine per cent (39%) of our welfare spells were not a first spell during the 1983-1994 period. By definition, this variable had a value of 100% for off-welfare spells. The next three rows of Table 3 indicate that, within the 1990-1994 period, most of our welfare and off-welfare spells were first spells.

Welfare clients are a bit younger than ex-clients (off-welfare spells) due in part to the fact that one must complete a welfare spell in order to start an off-welfare spell in our sample.⁹ We have the client's level of education at first encounter and at last encounter with the welfare system between 1983 and 1994, but values are missing for about 25% of our sample. We used the schooling value at the last encounter unless it was missing in which case we used the value for education at the first encounter if present. As Table 3 indicates, our sample of non-missing values was about evenly divided between those who have and have not completed high school.

Almost one-half of the mothers had only one child and less than one-fifth had three or more. Just over one-half of the mothers had a preschool age child and about 20% of the lone mothers in our sample were never married. We classified a mother as "not employable" if her FBA "case classification" or GWA "reason for assistance" was poor health or disability. This monthly value was a time-varying covariate in the

⁹ We describe the frequencies in Table 3 as though they refer to clients but they actually refer to spells. The former are easier to discuss and the two sets of frequencies are very similar.

welfare spell analysis. For the off-welfare spells, we classify a client as employable or not employable according to the last month of the most recent welfare spell. As Table 3 shows, very few (3-4%) clients begin either type of spell as “not employable”.

Welfare benefits vary with family size and we followed Barrett in measuring this variable on a per capita (family member) basis. The most likely alternative to social assistance for many is a minimum wage job. We used the potential earnings from a full-time (140 hours per month) job at the minimum wage. We measured this variable on a per capita basis also in order to reflect the typical choice set of the mothers in our data.

Our labour market variables are the unemployment rate (for males age 20-59) and the help wanted index both of which are available for six different regions: Toronto, Hamilton (no observations in our estimation sample), London, Ottawa, Sudbury and the rest of the province. We used all except Hamilton for which we have no GWA data. We know the region of residence of each client at the time of first contact and last contact with the welfare system during the sample period. In order to assign labour market variable values in each month, we assigned a client whichever regional value (first or last contact) was closest in time to the month in question.

IV. Estimation Strategy

The theoretical model underlying our estimation strategy assumes that individuals remain on welfare if the value of that state is greater than the value of the

alternative state. Processes which could cause the relative values of these states to change over time include the arrival of a wage offer, a potential mate or another child.

The value of staying on welfare is defined as:

$$V_t^w = V^w(z(t), b(t), T^w)$$

where $z(t)$ is a vector of personal characteristics at time t , $b(t)$ is the potential benefits at time t , and T^w is the length of the welfare spell. The value of being off-welfare is defined as:

$$V_t^o = V^o(z(t), w(t), T^o),$$

where $w(t)$ is the value of earned income when off welfare and T^o is the length of time off welfare. Comparing these values and assuming that opportunities for leaving welfare arrive at some constant rate, v , according to a Poisson process, gives the hazard rate:

$$\lambda_t(z(t), b(t), w(t), T^w) = v * Prob[V^o(z(t), w(t), T^o) > V^w(z(t), b(t), T^w)]. \quad (1)$$

We follow Barrett and Fortin et al. in using the Prentice-Gloeckler-Meyer (PGM) piece-wise constant proportional hazard procedure to estimate the baseline hazard function and the coefficients for personal characteristics, policy parameters and labour market conditions [Prentice and Gloeckler (1978), Meyer (1988), or Meyer (1990)]. The PGM procedure requires no assumptions about the shape of the baseline hazard and allows control for one type of unobserved heterogeneity. A limitation of the PGM approach is that the covariates are assumed to shift the baseline but not to affect its shape. The proportional hazard model with unobserved heterogeneity assumed to take a multiplicative gamma form is the following:

$$h_i(t, z_i(t), \beta, \theta_i) = \theta_i h_0(t) \exp(z_i(t)' \beta), \quad (2)$$

where h_i is individual i 's hazard rate, $h_0(t)$ is the baseline hazard function to be estimated, $z_i(t)$ is a vector of individual i 's characteristics which can vary through time, β is the parameter vector to be estimated and θ_i is a random variable that is assumed to be independent of $z_i(t)$ and follow a gamma distribution with a mean normalized to one and a variance of σ^2 .

The baseline is divided into intervals and the hazard rate is assumed to be constant within each interval. The decision concerning the number and length of the pieces must balance a desire for functional flexibility (more pieces) and convergence time and estimator precision (fewer pieces). Our choice has been guided both by the specifications of previous researchers and by our own empirical hazard functions. The baseline hazard is divided into nineteen intervals for welfare spells and into fourteen intervals for off-welfare spells. The chart below provides the final month for each interval. The interval length is the difference between the final months of successive intervals. For example, the length of the fourteenth welfare interval is 5 (=21-16) months.

Definition of Intervals for Baseline Hazard					
	Final Month:			Final Month:	
Interval	Welfare	Off-Welfare	Interval	Welfare	Off-Welfare
1	1	2	11	11	27
2	2	3	12	13	38
3	3	4	13	16	49
4	4	5	14	21	∞
5	5	6	15	27	
6	6	9	16	35	
7	7	10	17	45	
8	8	11	18	55	
9	9	12	19	∞	
10	10	17			

Estimates of this model both for welfare and off-welfare spells are presented in the next two sections. We experimented with fewer intervals and found that the coefficient estimates for the other independent variables changed little. See Chapter 2 for further details concerning the estimation procedure.

V. Welfare Spells

We present our empirical estimates for welfare spells in this section. All of these are based on the two-month rule (see Section III) for spell termination. Figures 1 and 2 present the Kaplan-Meier empirical hazard function and survival function for the on welfare spells. The empirical hazard function is the ratio of exits to the number

of spells still ongoing for each month defined as:

$$h(t) = d_t/n_t.$$

where n_t is the number of spells still ongoing at time t and d_t is the number of exits at time t . The survivor function is the percentage of spells still ongoing at each month defined as:

$$S(t) = \prod_{j|j < t} ((n_j - d_j)/n_j)$$

The hazard rate in Figure 1 falls off sharply during the first ten months of the spell and declines very slowly or not at all thereafter. Figure 2 reveals considerable variation in spell length. Approximately 30% of the spells end within 5 months and 50% of the spells are over within 20 months. More than 30% however, are still ongoing at 55 months.

The estimates of the proportional hazard models for welfare spells are presented in Figure 3 and Tables 4 and 5. We present the estimates for four different specifications: with and without the mother's level of education and with and without controls for unobserved heterogeneity.¹⁰ Education is missing for over one-third of the observations and inclusion of this variable reduces our sample size from 20,139 to 14,918. As a check, we also estimated the hazard function using the education sample but omitting the schooling variables from the model. The resulting estimates

¹⁰ Another set of specifications were attempted. These specifications included a dummy variable if the month was after October 1991. In October 1991, the second part of the Steps To Employment Program was introduced which decreased the tax-back rate and allowed the full amount of child care to be deducted from gross income in the calculation of benefits. This dummy variable was not significant in the welfare spells and not enough of the off-welfare spells ended before October 1991 for any effect to be identified

(not shown here) are very similar to those presented in Tables 4 and 5 with this same sample.

The parameter estimates are fairly stable across all four specifications shown in Table 4 and Table 5 but there are exceptions which we note below. In results not shown here, likelihood ratio tests reject the null hypothesis of no heterogeneity for both specifications (with and without schooling) with p-values of less than .01.

The baseline hazard estimates are presented in Table 4 and are graphed in Figure 3. The actual coefficients estimated are equal to the natural logarithm of the coefficients reported in Table 4. For this baseline hazard, we assigned the following values to the other independent variables. The spell is the first one (in 1990-1994) which occurs in the 4th quarter for a mother aged 32 who is previously married, employable, with no previous welfare use, grade 12-13 schooling and one dependent child age 6-21. The unemployment rate is 9.0, help-wanted index is 110, the benefit level is 460, and the minimum wage earnings is 316.

The shape of the baseline hazard provides a test of duration dependence within the spell. The bottom panel of Table 4 provides Wald statistics for tests of the null hypothesis that the hazard in month A is equal to the hazard in month B against the alternative that the hazard in month A is greater than the hazard in month B. The tests for the first three specifications (columns) generally indicate the presence of negative duration dependence at least during the first year of the spell.

The support for negative duration dependence is less obvious in column (4) when we control for schooling and unobserved heterogeneity. As the bottom rows of

Table 4 show, we are unable to reject the hypothesis of no difference between the hazard in the first and third months and between the hazards in the ninth and fourteenth months. In results not shown here, we also conducted step by step comparisons of the baseline hazards prior to the fourth month and after the ninth month. In each case, we were unable to reject of hypothesis of no difference. This was even true of the sharp increase in the baseline hazard at the last step, i.e., we were unable to reject the null hypothesis that the last two steps are equal. These results highlight the potential importance of controlling for unobserved heterogeneity.

The remaining hazard coefficients for the welfare spells are in Table 5. As in Table 4, we have also chosen to present the anti-logarithms of the actual coefficients for ease of interpretation. Each coefficient in Table 5 indicates the proportional shift in the baseline hazard as predicted by the indicated change in the independent variable. Hence, a coefficient of 1.10 represents a ten percent shift up in the hazard (shorter spell) and a coefficient of 0.90 represents a ten percent shift down (longer spell). The baseline hazard implies a mean spell length of 8.8 months if one assumes a constant hazard beyond the sample period. A ten percent shift up (down) in the hazard implies a mean spell length of 7.9 (9.8) months. A fifty percent shift up (down) in the hazard implies a mean spell length of 5.5 (17.4) months.

Older lone mothers consistently have higher hazards (shorter spells). A schooling level of Grade 9 or less is strongly associated with longer spells but this educational category characterizes a small and rapidly diminishing proportion of the population especially younger persons (Dooley 1996). Post-secondary education is

associated with shorter spells. A joint test (not shown here) of the hypothesis that all of the schooling coefficients are equal to zero rejects the null with a p-value of less than .01. The status of never-married is strongly associated with longer welfare spells. This result is consistent with all previous studies cited in Section II which show that never married lone mothers are much more likely to use welfare and to have longer spells than are previously married mothers even in the presence of controls for age and education. More children significantly lengthens the welfare spell which is consistent with the heavier home responsibilities in a larger family. Another interpretation of this effect is that welfare benefits are worth more to larger families because payments vary with family size whereas market wages do not. Note, however, that we adjust both our welfare benefit and minimum wage earnings measures for family size.

The presence of pre-school children is associated with longer spells. The BC data available to Barrett did not contain the age of children. The measures used by Fortin, Lacroix and Thibault with the Quebec data were the number of children under 6 and the number of children age 6-17. Both effects were significantly negative (longer spells for younger children) and, consistent with our results, the coefficient for the number of preschool children was much larger than that for school age children. We can not replicate their model because we only know the age of the youngest child.

There are only a few lone mothers who are classified as non-employable due to poor health or disability. Those that are, however, have a much lower hazard than

those who are not so classified.¹¹ The coefficients for welfare benefits are quite robust and indicate that higher benefits are associated with a lower hazard and longer spells. The expected effect of minimum wage earnings on the hazard is ambiguous for well known reasons. Higher wages, if available, make market work more attractive but the effect of a legislated increase may be to limit job opportunities for welfare clients. Our estimates in Table 5 indicate a positive impact of minimum wage earnings on the hazard rate. As expected, a higher unemployment rate is associated with a lower hazard rate and longer welfare spells. However, the coefficients for the help-wanted index are not significantly different from zero.

The variable for the number of previous months of welfare is a test of lagged duration dependence which we interacted with age because younger clients have had less opportunity for a previous welfare spell. Note that the expected sign of this coefficient is not unambiguous. Past reliance on welfare may well make it more difficult to find a job because of skill atrophy or stigma which would cause a longer current spell. However, a large number of previous months can also be accumulated by persons with frequent short spells which would lead to the opposite prediction. Unfortunately, we were not able to include a measure in our model for the number of spells prior to 1990 due to the gaps in the data during this period. In any event, the number of previous months of welfare use is strongly and negatively associated with the hazard rate in Table 5. Controlling for unobserved heterogeneity actually increases

¹¹ Some provinces classify lone parents with very young children as “unemployable” and this was true of the lone mothers in Barrett’s study with B.C. data.

the (absolute) size of this coefficient slightly thereby confirming the existence of negative, lagged duration dependence. There is no evidence, however, that the impact of this variable varies with the age of the client.

We also include two dummy variables which indicate if the spell is the second or third (or higher order) spell within the sample period as a test of what Barrett refers to as “occurrence dependence”. We find that both coefficients are significantly positive as did Barrett. Our sample period is less than five years long and, as a result, average spell length must be relatively short for any mother with multiple spells.

Our quarterly dummy variables confirm that the hazard rate is distinctly higher in the second and third quarters than in the fourth quarter. The evidence also indicates that the first quarter hazard is higher than that for the last quarter. Finally, the next-to-last row of Table 5 provides an estimate of the variance in the unobserved determinant of the welfare hazard. The coefficients in columns (2) and (4) are both significantly different from zero which rejects the hypothesis of no unobserved heterogeneity as did the likelihood ratio tests cited earlier in this section.

VI Off-Welfare Spells

We present our estimates for off-welfare spells in this section beginning with the empirical hazard and survival functions in Figures 4 and 5. The empirical hazard falls off sharply during the first ten months of the spell and thereafter declines very slowly or not at all. The empirical survival function reveals that approximately 25%

of ex-clients return to welfare within the first 10 months. Beyond that point, the survival function becomes relatively flat and about 60% of ex-clients are still off welfare after 4 years.

The estimates of the proportional hazard models for off-welfare spells are presented in Figure 6 and Tables 6 and 7. We report the results from only the two specifications that do not control for unobserved heterogeneity. The log-likelihood function is a function of the variance of the unobserved heterogeneity and constraining the value of this variance to be positive results in the log-likelihood being maximized at zero. This result indicates that unobserved heterogeneity is not present in our sample of off-welfare spells.

The baseline hazard coefficients are graphed in Figure 7 and reported in Table 6. We assigned the same values to the other independent variables as in the case of the welfare baseline hazard with the exception of past months on welfare which is now set equal to 14. Both specifications indicate the presence of negative duration dependence during most of the first year of the spell but not beyond that point. The baseline hazard implies a mean off-welfare spell length of 32.3 months if one assumes a constant hazard beyond the sample period. A ten percent shift up (down) in the hazard implies a mean spell length of 30.5 (34.3) months. A fifty percent shift up (down) in the hazard implies a mean spell length of 24.6 (46.4) months.

The remaining proportional hazard coefficients are in Table 7. Older lone mothers consistently have lower hazards (longer spells) but none of the schooling variables have significant coefficients. Furthermore, a joint test of the hypothesis that

all of the schooling coefficients are equal to zero fails to reject the null (p -value = .75). Never-married lone mothers are more likely to return to welfare (higher hazard) which is consistent with our findings from previous section and the literature in general.

Our expectation was that larger numbers of children would be associated with a higher likelihood of returning to welfare, but the estimated coefficient implies just the opposite. (Fortin et al. estimated coefficients for the number of children under 6 and the number of children age 6-17, neither of which were significantly different from zero.) One possible explanation for this finding is selection bias, i.e., those mothers with large families who do manage to leave welfare are a highly selective subset of all clients and possess (unobserved) characteristics that make a return to social assistance very unlikely. This hypothesis is unfortunately not testable with currently available data.

Another possible explanation for the family size coefficients arises from the possibility that the birth of an additional child may prompt a return to welfare in some cases because this raises the value of home-time and lowers the net value of market work due to child care costs. Such additional births while off-welfare may be more likely among those ex-clients who have relatively few children and, therefore, less incentive to limit family size which would be consistent with our coefficient estimate.¹²

¹² Of the lone mothers whom we observe to return to welfare, 7% have more children upon return than at the end of their previous spell. Of the 7% that return with an additional child, 79% had 1-2 children at the end of their previous spell. Unfortunately, we lack the data to make the appropriate comparisons because we do not know the (post-welfare) fertility history of those mothers with censored off-welfare spells.

The presence of a child under age 2 is strongly associated with a higher probability of a return to welfare as a simple, static model of welfare participation would predict, but the presence of a child age 2-5 is not. As expected, the lone mothers who are classified as non-employable due to poor health or disability have a higher likelihood of a return to social assistance.

The coefficients for welfare benefits imply, as expected, that higher benefit levels make a return to social assistance more likely. Higher minimum wages are associated with longer off-welfare spells which is consistent with the finding in Table 5 that higher minimum wages lead to shorter welfare spells. Higher levels of unemployment, as expected, are associated with a faster return to welfare but the coefficients are not significant. The coefficients for the help-wanted index are statistically significant but have the unexpected effect of making a return to welfare more likely.

The coefficients for the number of previous months on welfare have a positive sign (more previous months means a faster return to welfare) which is consistent with our finding of negative lagged duration dependence for welfare spells. The p-values for the linear term are large, but the coefficients for the interaction with age are significant. This implies that negative lagged duration dependence (more past use means a quicker return to welfare) may characterize the older lone mothers who have terminated spells. The significantly, positive coefficients for the higher order (2nd, 3rd or higher) spells imply that persons who have had multiple spells are more likely to return to welfare than are persons who have had only one spell. This is consistent

with our findings in the previous section in that persons who manage to have more than one spell within a five year time period are likely to be persons who have frequent short welfare spells. Finally, our quarterly dummy variables confirm that a return to welfare is more likely in the third quarter. Interestingly, this was also one of the two quarters in which an exit from welfare was most likely.

VII. Summary and Conclusion

This paper provides a first look at the dynamics of social assistance use among lone mothers in Ontario. We use an administrative data set provided by the Ontario Ministry of Community and Social Services to analyse the relationship between the duration of spells, both on welfare and off welfare, and a series of factors including the clients' personal characteristics, their history of welfare use, the duration of current spells, labour market conditions and social assistance benefit levels.

The empirical hazard and survival functions reveal considerable variation in the length of welfare spells. Approximately 30% of the spells end within 5 months and 50% of the spells are over within 20 months. However, over 30% are still ongoing at 55 months. Our proportional hazard estimates strongly confirm the presence of unobserved heterogeneity in welfare spells. Three of the four specifications which we estimate also indicate the presence of negative duration dependence (the likelihood of leaving welfare falls as the spell proceeds) during the first year of the spell. The support for this finding, however, is weakest in our preferred specification. Our results

also confirm the existence of negative lagged duration dependence, that is, the current spell is longer for lone mothers with more months of welfare receipt in previous spells. However, the magnitude of this effect is quite small.

Most of the other welfare spell coefficients have significant effects of the expected sign. Welfare spells tend to be longer for those lone mothers who are younger, poorly educated, never married, not employable and for those who have larger numbers of pre-school children. Spell lengths also increase with the level of potential welfare benefits and the unemployment rate, and to decrease with the level of the minimum wage. The magnitude of most of the effects are sizable especially in the case of welfare benefits, schooling, marital status and family size.

The empirical survival functions for off-welfare spells reveal that 25% of ex-clients return to welfare within the first 10 months. The survival function becomes relatively flat beyond that point, however, and about 60% of ex-clients are still off welfare after 4 years. Our proportional hazard estimates reveal that there is no strong evidence of unobserved heterogeneity in the case of off-welfare spells. There is support for the presence of negative duration dependence (the likelihood of returning to welfare declines as the spell proceeds) during the first year. There is some evidence of positive lagged duration dependence (more months of welfare receipt in previous spells means a faster return to welfare) but only among older lone mothers and the size of the effect is again quite small.

Off-welfare spells tend to be shorter (the return to welfare more rapid) for those lone mothers who are older, never married, not employable and who have very

young children. Higher welfare benefits also appear to hasten the return to welfare. Off-welfare spells are longer when the minimum wage is higher. We also find that the return to welfare is more likely when a mother has a smaller number of children. This last and unexpected result may be due to the selective nature of our sample, but this finding clearly calls for more investigation.

What are the most important policy implications of our findings? We find mixed evidence concerning the key question of the scarring or stigmatizing effects of welfare, that is, for a “welfare trap”. There is evidence that the likelihood of exiting welfare declines during the first year of a spell. The support is weakest, however, in our preferred specification. There is more consistent evidence that the likelihood of returning to welfare declines during the first year off the rolls. Clients with more total months of prior welfare do appear to have somewhat longer future spells on welfare and to return more quickly to the rolls once they leave, but the magnitude of this effect is very small. Finally, the length of both welfare and off-welfare spells is very sensitive to the levels of welfare benefits.

Our results indicate the need for further work in the following areas. (1) Additional parameters should be incorporated into our analysis including measures of the coverage and adequacy of the (un)employment insurance system and of aggregate labour demand. (2) Consideration should be given to alternative measures of welfare dependency such as the proportion of a fixed window of time that is spent on welfare which reflects both the likelihood of starting a spell and the spell length. This measure would also permit the use of our data for the 1983-1989 period. (3) We need to

analyse the spell duration of other groups such as young singles and couples. (4) A competing hazard model would help us to distinguish among different reasons for leaving welfare and possibly provide insight into the unobserved heterogeneity which our study has confirmed.

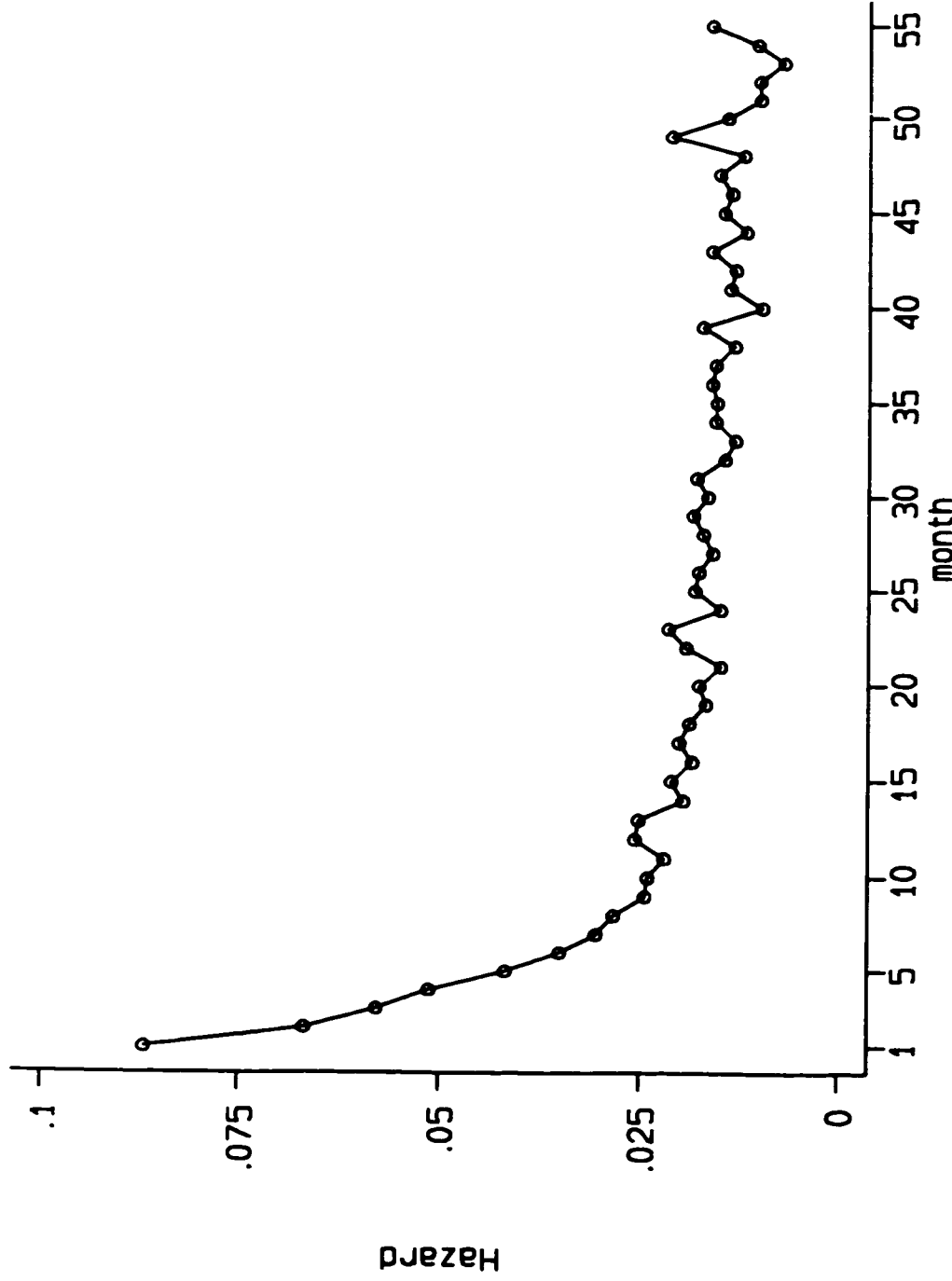


Fig. 1 Empirical Hazard Function for On Welfare Spells

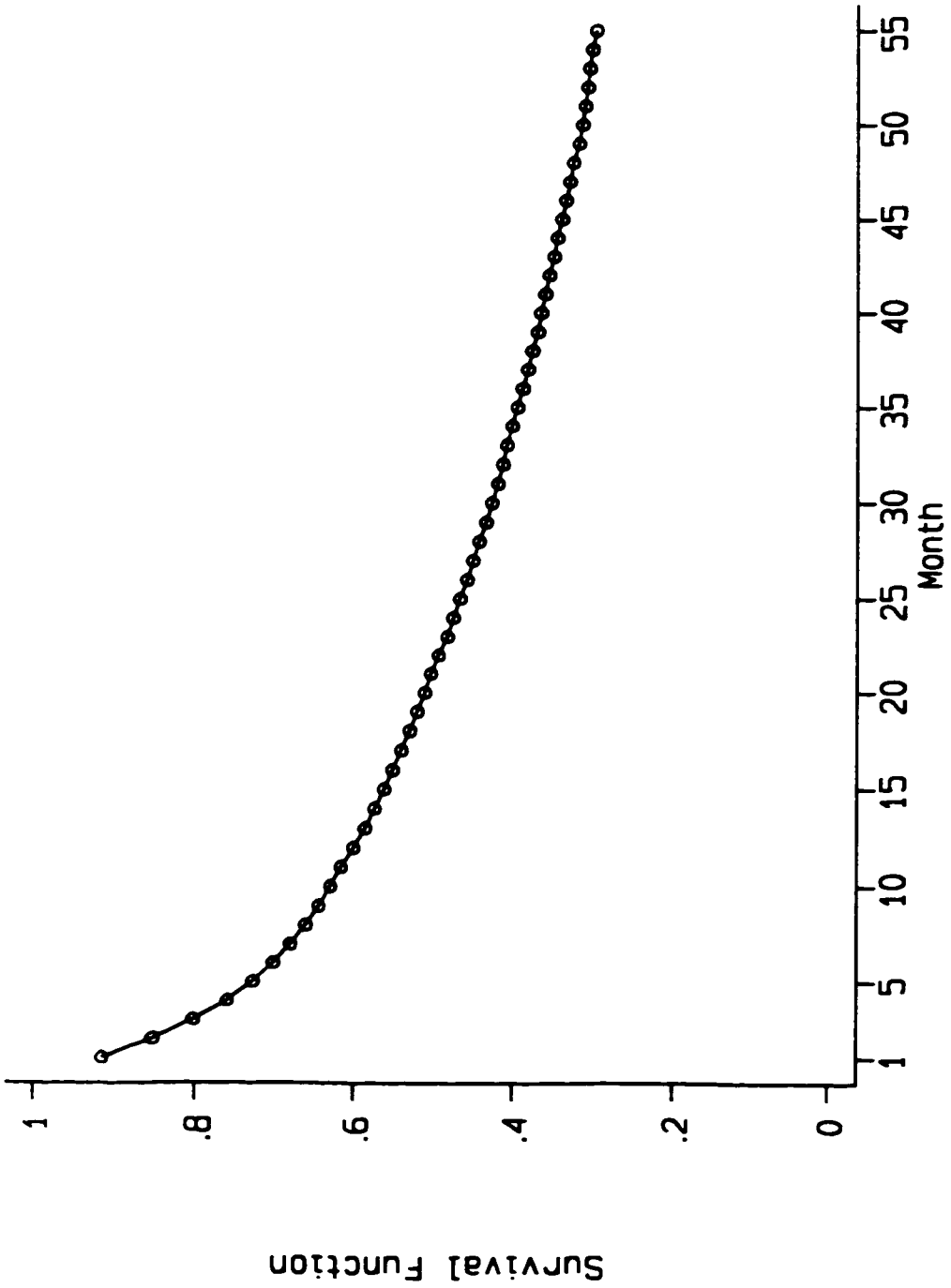


Fig 2. Survival Function for On Welfare Spells

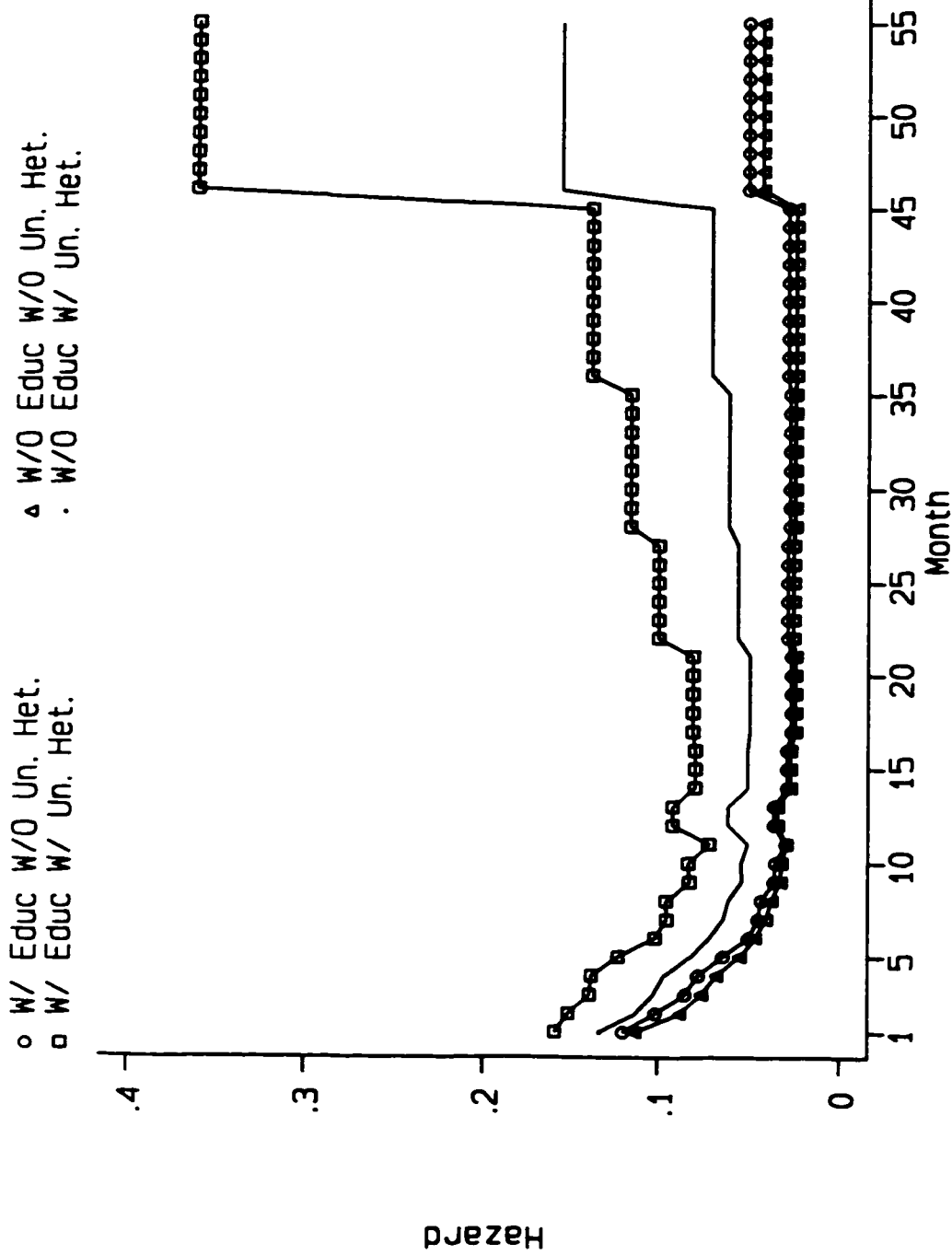


Fig.3 Baseline Hazards for On Welfare Spells

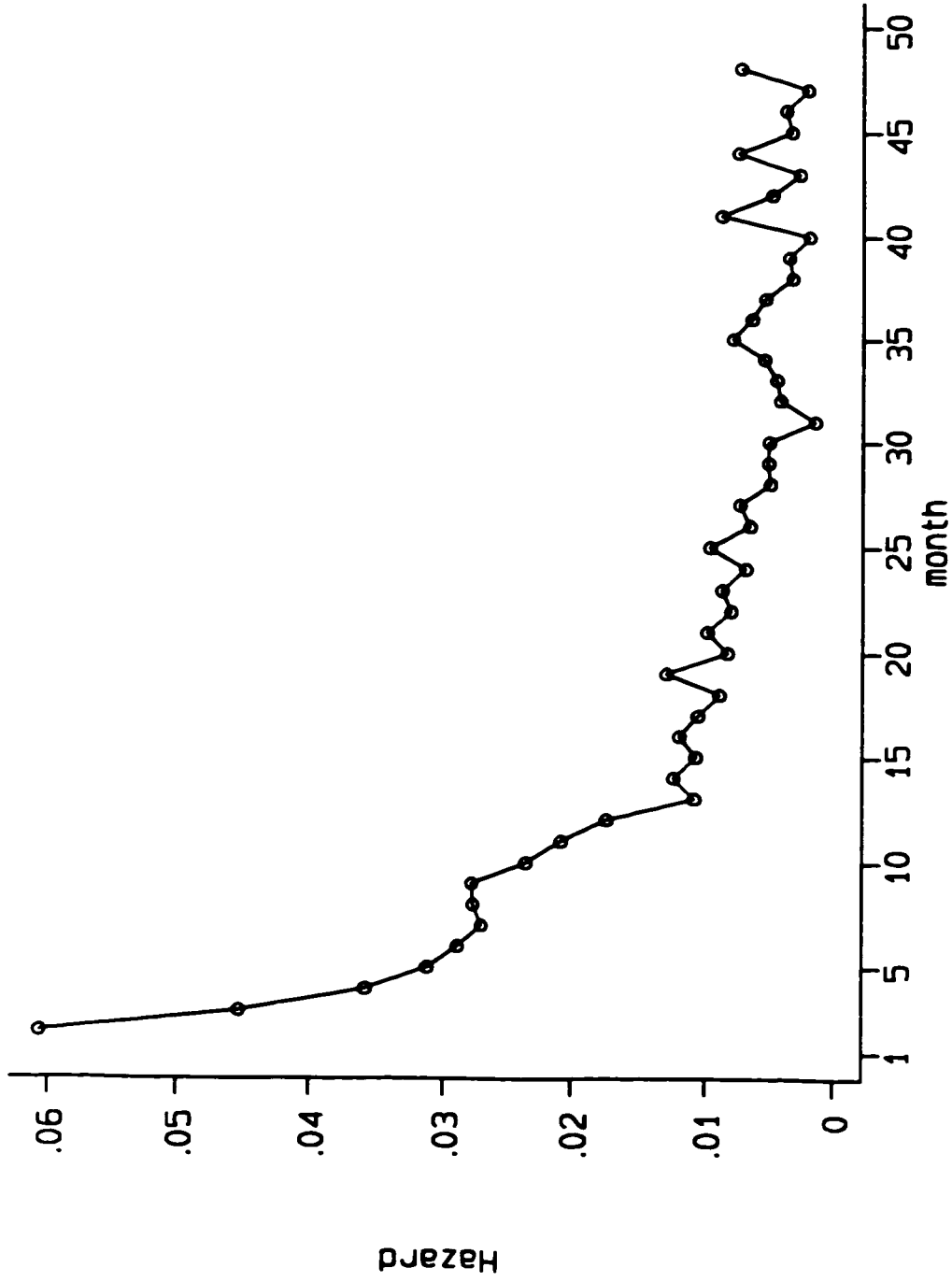


Fig 4. Empirical Hazard Function for Off Welfare Spells

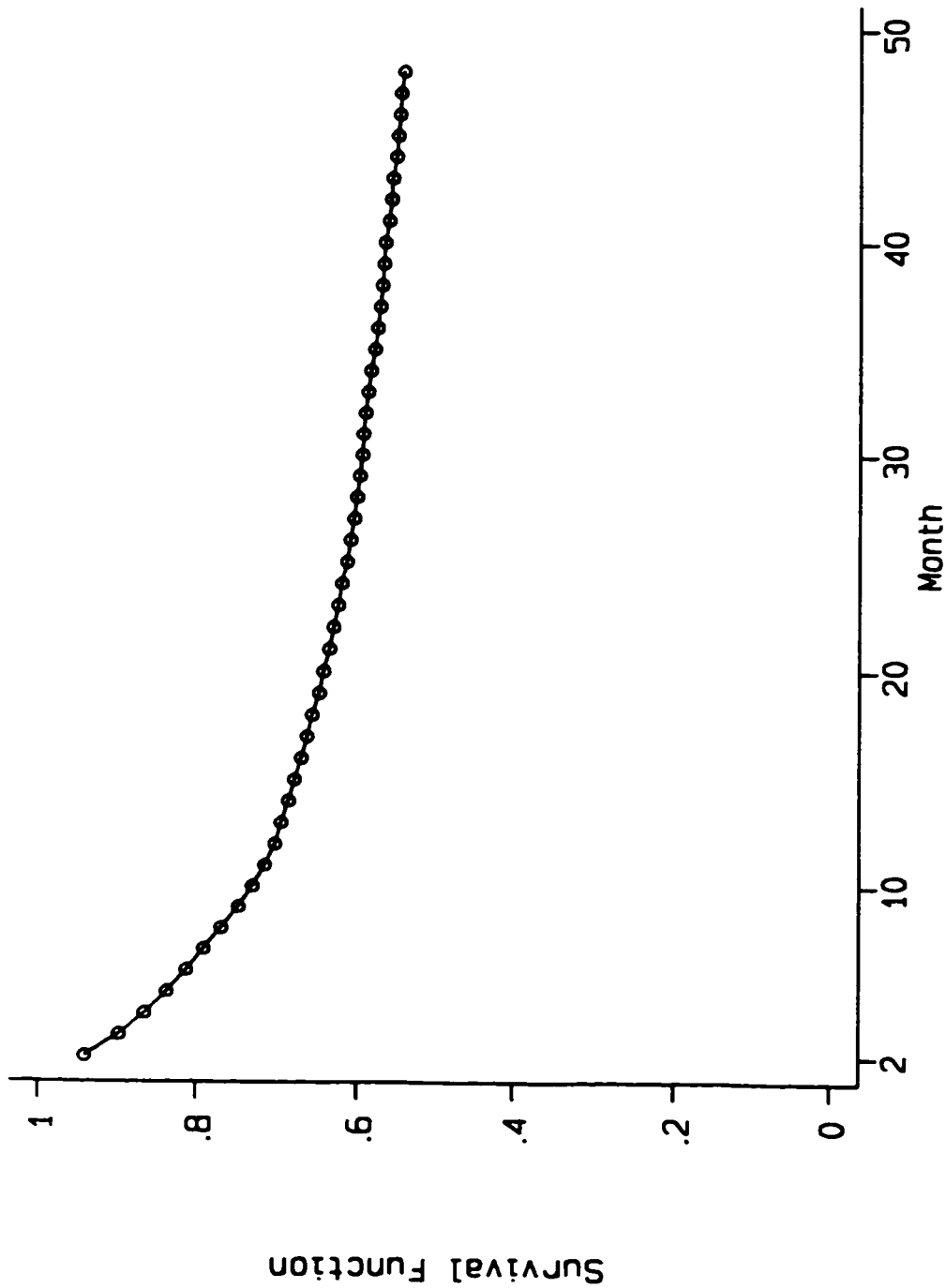


Fig 5. Survival Function for Off Welfare Spells

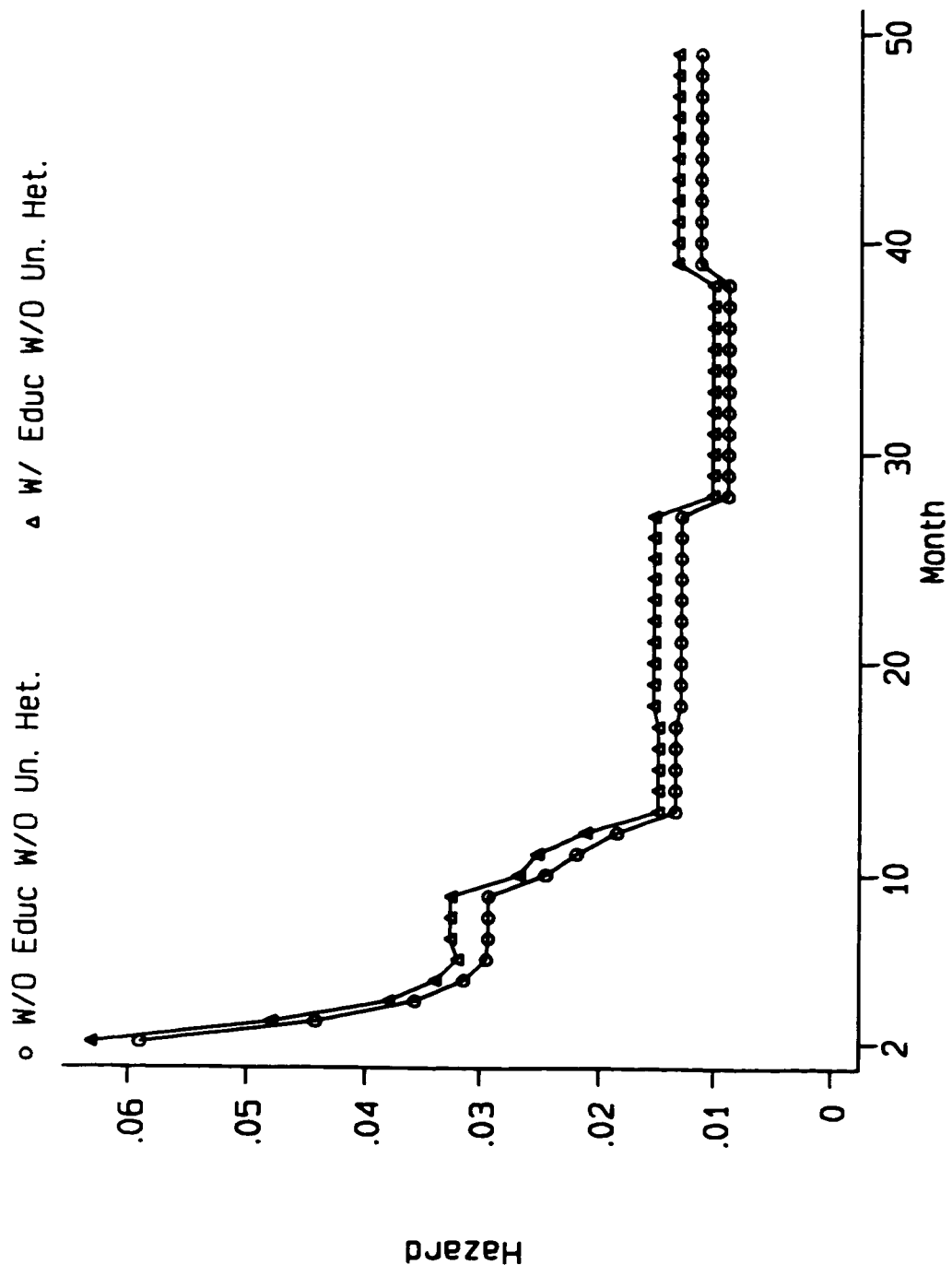


Fig.6 Baseline Hazard for Off welfare Spells

Table 1							
Ontario Assistance Caseload: December, 1983-1994							
Year	FBA	GWA	Single Persons	Lone Parents	Other Families	Total Cases	Total Cases/ Pop., Age 15+
Number of Cases							
1983	137,099	113,282	135,846	76,640	37,895	250,381	3.7%
1984	146,798	110,859	140,962	79,034	37,661	257,657	3.7%
1985	152,356	112,738	143,777	81,859	35,775	261,411	3.7%
1986	159,348	114,186	149,955	90,975	32,604	273,534	3.8%
1987	168,659	112,342	151,909	97,927	31,165	281,001	3.9%
1988	180,498	118,229	155,598	105,167	37,962	298,727	4.1%
1989	196,522	128,588	164,963	119,021	41,126	325,110	4.3%
1990	225,582	192,499	214,870	147,609	55,601	418,081	5.5%
1991	271,333	292,898	295,424	185,361	83,446	564,231	7.3%
1992	299,315	337,801	326,427	211,850	98,794	637,116	8.0%
1993	317,112	358,800	na	197,011	na	675,912	8.4%
1994	327,106	332,800	na	198,571	na	659,906	8.0%
Distribution of Cases							Recipients/ Pop.
1983	55	45	54	31	15	100	5.2%
1984	58	42	55	31	14	100	5.2%
1985	58	42	55	31	14	100	5.1%
1986	58	42	55	33	12	100	5.3%
1987	60	40	54	35	11	100	5.4%
1988	60	40	52	35	13	100	6.1%
1989	60	40	50	37	13	100	6.2%
1990	54	46	52	35	13	100	7.8%
1991	48	52	52	33	15	100	10.5%
1992	47	53	51	33	16	100	11.8%
1993	47	53	na	29	na	100	12.4%
1994	50	50	na	30	na	100	12.1%

Source: Inventory of Income Security Programs in Canada, Health and Welfare Canada

Table 2			
Ontario Social Assistance Benefit Levels and Total Expenditures: 1983-1994 (\$1990)			
Year	Annual Benefit Level		Total Expenditures
	One Parent With 2 Children	Two Parents With 2 Children	(millions)
1983	10,932	10,851	1,365
1984	11,761	11,792	1,567
1985	12,101	12,137	1,677
1986	12,735	13,719	1,770
1987	13,552	14,383	1,888
1988	13,778	15,216	2,113
1989	13,850	15,102	2,279
1990	15,193	17,791	2,609
1991	15,553	18,201	3,386
1992	15,839	18,150	4,752
1993	15,821	18,112	5,637
1994	15,828	17,952	6,055

*Sources. Benefit levels from The Ontario Gazette-Regulations. Expenditures from Public Accounts of Ontario as cited in Sabatini (1996).

Table 3		
Summary Statistics for On-Welfare and Off-Welfare Spells		
	First Month of On-Welfare Spell	First Month of Spell Off-Welfare Spell
Spell Length (months)	17	17
% of Spells Censored	47%	67%
Number of Months of Previous Welfare Use Since 1983	7	16
Any Welfare Previous Use	39%	100%
1st Spell in Period	77%	80%
2nd Spell in Period	17%	16%
3rd or Higher Spell in Period	5%	4%
Age of Lone Mother		
<25	18%	13%
25-34	47%	48%
35-44	28%	33%
>44	7%	8%
Education (frequency of non-missing values in parentheses)		
Less than Grade 9	11% (15%)	11% (15%)
Grade 10 or 11	24% (33%)	25% (33%)
Grade 12 or 13	27% (36%)	26% (35%)
Some Post Secondary	12% (16%)	13% (17%)
Missing Values for Education	26%	25%

Table 3 Continued		
	First Month of On-Welfare Spell	First Month of Spell Off-Welfare Spell
One Child Under Age 22	48%	47%
Two Children	34%	35%
3 or More Children	18%	18%
Age of Youngest Child <2	28%	17%
Age of Youngest Child 2-5	31%	35%
Age of Youngest (Dependent) Child 6-21	41%	48%
Never Married	23%	20%
Not Employable (Disabled)	4%	3%
Maximum Monthly Welfare Benefits/Family Size (1990\$)	461	462
Minimum Wage Earnings/Family Size (140 hours per month)	304	310
Unemployment Rate	8.8%	9.1%
Help Wanted Index	112	105
Sample Size	20139	10732

Table 4				
Estimated Baseline Hazards for Welfare Spells				
	Without Education		With Education	
Time	No Heterogen.	Heterogeneity	No Heterogen.	Heterogeneity
1	0.113 (0.007)	0.134 (0.011)	0.120 (0.009)	0.159 (0.017)
2	0.088 (0.006)	0.112 (0.010)	0.101 (0.008)	0.152 (0.018)
3	0.076 (0.005)	0.103 (0.010)	0.085 (0.007)	0.139 (0.019)
4	0.068 (0.005)	0.097 (0.011)	0.078 (0.006)	0.138 (0.021)
5	0.055 (0.004)	0.082 (0.010)	0.064 (0.005)	0.123 (0.020)
6	0.047 (0.003)	0.072 (0.009)	0.050 (0.004)	0.102 (0.018)
7	0.041 (0.003)	0.064 (0.009)	0.045 (0.004)	0.095 (0.018)
8	0.038 (0.003)	0.062 (0.009)	0.044 (0.004)	0.096 (0.019)
9	0.033 (0.003)	0.054 (0.008)	0.036 (0.004)	0.082 (0.017)
10	0.032 (0.003)	0.055 (0.009)	0.035 (0.004)	0.083 (0.018)
11	0.030 (0.003)	0.051 (0.008)	0.030 (0.003)	0.072 (0.016)
12-13	0.035 (0.003)	0.062 (0.010)	0.036 (0.003)	0.092 (.020)
14-16	0.027 (0.002)	0.051 (0.009)	0.029 (0.003)	0.079 (.019)
17-21	0.025 (0.002)	0.050 (0.009)	0.027 (0.002)	0.081 (0.021)

Table 4 Continued				
	Without Education		With Education	
	No Heterogen.	Heterogeneity	No Heterogen.	Heterogeneity
22-27	0.026 (0.002)	0.057 (0.011)	0.029 (0.002)	0.100 (0.029)
28-35	0.025 (0.002)	0.062 (0.014)	0.028 (0.002)	0.116 (0.038)
36-45	0.028 (0.002)	0.079 (0.021)	0.029 (0.003)	0.153 (0.058)
46-55	0.048 (0.005)	0.173 (.057)	0.052 (0.007)	0.399 (0.188)
Comparison	Wald Statistics			
1 to 3	8.72**	5.60**	6.66**	2.31
3 to 6	7.94**	6.38**	6.73**	4.64**
6 to 9	4.87**	3.69**	3.82**	2.42**
9 to 14	2.34**	0.74	2.08	.35
<p>The actual coefficients estimated are equal to the natural logarithm of the coefficients reported in these tables. The standard errors (in parentheses) in this table are calculated from the estimated standard errors by the following non-linear transformation: $\text{var}(g(x))=(dg(x)/dx)' \text{var}(x)(dg(x)/dx)$.</p> <p>*The Wald Statistic is for the test of the null hypothesis that the hazard in month A is equal to the hazard in month B against the alternative that the hazard in month A greater than the hazard in month B. The test statistic has a normal distribution under the null, therefore, the critical value for a one tailed test at the 1 percent confidence level is 2.326.</p> <p>**Reject the null</p>				

Table 5				
Duration Model Estimates on Welfare Spells				
With and Without Unobserved Heterogeneity				
Variables	Without Education		With Education	
	(1)	(2)	(3)	(4)
	No Heter.	Heterog.	No Heter.	Heterog.
Age/10	1.114* (.020)	1.171* (.030)	1.112* (.023)	1.198* (.040)
Education: Less than Grade 10	---	---	0.931* (.032)	0.879* (.045)
Grade 10 or 11	---	---	0.991 (.027)	1.011 (.040)
Some Post Secondary	---	---	1.099* (.036)	1.107* (.053)
Never Married	0.746* (.021)	0.701* (.026)	0.786* (.025)	0.731* (.033)
Two Children	0.810* (.062)	0.662* (.068)	0.749* (.066)	0.544* (.071)
Three or More Children	0.670* (.080)	0.474* (.077)	0.610* (.084)	0.362* (.074)
Youngest Child Under 2	0.875* (.030)	0.861* (.035)	0.858* (.034)	0.825* (.042)
Youngest Child 2 to 5	0.973 (.025)	0.962 (.031)	0.959 (.029)	0.938 (.038)
Not Employable (Health/Disability)	0.681* (.038)	0.656* (.041)	0.690* (.045)	0.648* (.048)
Potential Benefits/Family Size (\$00)	0.593* (.047)	0.542* (.051)	0.656* (.062)	0.584* (.068)
Minimum Wage Earnings/Family Size (\$00)	1.518* (.010)	1.449* (.113)	1.295* (.101)	1.179 (.118)
Unemployment Rate	0.956* (.009)	0.949* (.010)	0.953* (.011)	0.948* (.012)

Table 5 (continued)				
	Without Education		With Education	
	(1)	(2)	(3)	(4)
	No Heter.	Heterog.	No Heter.	Heterog.
Help-Wanted Index /10	1.001 (.008)	1.006 (.009)	0.995 (.009)	0.999 (.010)
Number of Past Months on Welfare /10	0.978* (.008)	0.972* (.010)	0.980* (.010)	0.967* (.013)
Age * Number of Past Months	0.993 (.009)	0.997 (.012)	1.003 (.011)	1.001 (.016)
Second Spell	1.129* (.031)	1.158* (.041)	1.082* (.033)	1.082 (.047)
Third or More Spell	1.255* (.061)	1.362* (.088)	1.191* (.064)	1.303* (.010)
First Quarter	1.082* (.033)	1.093* (.034)	1.058 (.037)	1.063 (.038)
Second Quarter	1.152* (.032)	1.149* (.033)	1.153* (.037)	1.145* (.038)
Third Quarter	1.159* (.032)	1.158* (.033)	1.139* (.036)	1.138* (.037)
Sigma (Gamma Heterogeneity)	---	0.787 (.000)	---	1.173 (.000)
Sample Size	20139	20139	14918	14918

*The baseline hazard was estimated for the first spell of a lone mother aged 32, previously married, employable, with no previous welfare use, one school aged child, at an unemployment rate of 9.0, a help-wanted index of 110, benefit level of 460, minimum wage earnings of 550, in the fourth quarter and, when education is included, with grade 12 or 13.

**Variables were included for five regions, but the results are not reported here.

***Values in the parenthesis are standard errors. Asteriks indicate that the coefficient is significantly different from one at a 5% confidence level.

Table 6		
Estimated Baseline Hazards for Off Welfare Spells		
	Without Education	With Education
Time	No Heterogen.	No Heterogen.
1-2	0.030 (0.003)	0.032 (0.003)
3	0.044 (0.004)	0.048 (0.005)
4	0.036 (0.003)	0.038 (0.004)
5	0.031 (0.003)	0.034 (0.004)
6	0.029 (0.003)	0.032 (0.004)
7-9	0.029 (0.003)	0.033 (0.003)
10	0.025 (0.003)	0.027 (0.004)
11	0.022 (0.003)	0.025 (0.003)
12	0.019 (0.002)	0.021 (0.003)
13-17	0.014 (0.001)	0.015 (0.002)
18-27	0.013 (0.001)	0.015 (0.002)
28-38	0.009 (0.001)	0.010 (0.002)
39-49	0.011 (0.002)	0.013 (0.013)

Table 6 Continued		
	Without Education	With Education
Comparison	Wald Statistics*	
2 to 3	4.4**	3.62**
3 to 6	4.8**	4.2**
6 to 9	0.06	-0.2
9 to 13	8.4**	7.3**
13 to 26	0.4	-0.3

The actual coefficients estimated are equal to the natural logarithm of the coefficients reported in these tables. The standard errors (in parentheses) in this table are calculated from the estimated standard errors by the following non-linear transformation: $\text{var}(g(x))=(dg(x)/dx)' \text{var}(x)(dg(x)/dx)$.

*The Wald Statistic is for the test of the null hypothesis that the hazard in month A is equal to the hazard in month B against the alternative that the hazard in month A is greater than the hazard in month B. The test statistic has a normal distribution under the null, therefore, the critical value for a one tailed test at the 1 percent confidence level is 2.326.

**Reject the null.

Table 7		
Duration Model Estimates Off-Welfare Spells without unobserved heterogeneity		
Variables	Without Education	With Education
Age/10	0.845* (.026)	0.864 (.029)
Education: Less than Grade 10	---	1.009 (.058)
Grade 10 or 11	---	0.981 (.045)
Some Post Secondary	---	1.056 (.060)
Never Married	1.150* (.052)	1.205* (.060)
Two Children	0.634* (.062)	0.709* (.081)
Three or More Children	0.500* (.076)	0.625* (.112)
Youngest Child Under 2	1.557* (.083)	1.484* (.087)
Youngest Child 2 to 5	0.995 (.048)	1.006 (.053)
Not Employable (Health/Disability)	1.701* (.135)	1.826* (.157)
Potential Benefits/Family Size (\$100)	2.597* (.311)	2.681* (.375)
Minimum Wage Earnings/Family Size (\$100)	0.270* (.034)	0.289* (.041)
Unemployment Rate	1.010 (.019)	1.015 (.021)

Table 7 (continued)		
	Without Education	With Education
Help-Wanted Index /10	1.089* (.020)	1.080* (.022)
Number of Past Months on Welfare /10	1.017 (.012)	1.015 (.014)
Age * Number of Past Months	1.036* (.015)	1.046* (.017)
Second Spell	1.575* (.070)	1.431* (.070)
Third or More Spell	1.867* (.151)	1.573* (.142)
First Quarter	0.954 (.051)	0.932 (.055)
Second Quarter	1.060 (.051)	1.037 (.061)
Third Quarter	1.106* (.051)	1.144* (.058)
Sample Size	10732	8081
<p>*The baseline hazard was estimated for the first spell of a lone mother aged 32, previously married, employable, with 14 months of previous welfare use, one school aged child, at an unemployment rate of 9.0, a help-wanted index of 110, benefit level of 460, minimum wage earnings 316, in the fourth quarter and, when educated is included, with either grade 12 or 13.</p> <p>**Variables were included for the regions, but the results are not reported here.</p> <p>***Values in the parenthesis are standard errors. Asteriks indicate that coefficient is significantly different from one at a 5% confidence level.</p>		

Chapter 4

An Analysis of Changes in Welfare Participation Rates in Ontario from 1983-1994 Using Social Assistance Caseload Data

I. Introduction

This paper examines changes in the social assistance caseload in Ontario between 1983 and 1994. This period witnessed major changes in Ontario. Between 1989 and 1994, the proportion of the population on welfare increased markedly at (approximately) the same time as social assistance policy went through a major overhaul and the economy experienced a recession, the effects of which were especially harsh in this province. Concern with this issue, however, has earlier roots in the recovery of the 1980's when there was little decline in the welfare caseload despite a large drop in the number of unemployed. The increase in the caseload, and the corresponding increase in expenditures on social assistance, are shown in Figure 1.

Our specific questions in this paper will be three. First, what have been the changes in the proportion of individuals on welfare in each of the following categories: lone mothers, single women, single men and couples with children?

Second, what has been the role of regional labour market conditions in the trends in social assistance use? Third, what has been the role of changes in social assistance and (un)employment insurance policy in the trends in social assistance use?

A major contribution of this paper is that we are able to disaggregate the total caseload by labour force region and family type. The Ontario Ministry of Community and Social Services (MCSS) has made available to the authors an administrative data set which provides partial information concerning welfare use by most clients in the province during this twelve-year period. The individual records provide information concerning the demographic characteristics and region of residence of each client. We use this information to estimate a time-series regression for the welfare participation rate of four different family types in nine regions. We are also able to use the variation across labour force regions in labour market conditions and unemployment insurance program parameters in estimating our regression equations. Section II of the paper contains a review of the literature. The Ontario welfare system and the data used in this study are discussed in Section III. Section IV describes our estimation strategy. The time series regression results are presented in Section V and the results from a quasi-experiment approach are presented in Section VI. Section VII is a summary and conclusion.

II. Review of the Literature

Several recent studies have analysed the growth of social assistance use in

Canada in relation to both labour market conditions and government policy, specifically, social assistance and (un)employment insurance policy. These studies use aggregate data and generally rely upon variation across provinces and over time to identify the association between the welfare caseload and both policy parameters and the economic climate.

Brown (1995) uses data from Quebec, Ontario, Alberta, and British Columbia from the late 1960's through to the early 1990's to study the trends in the welfare caseload. The trends in benefit levels have varied widely between these four provinces. During this period, benefit levels in Ontario increased from one of the lower levels in the country to the highest whereas the opposite was true of Alberta. Benefits in Quebec have increased at a fairly steady rate and those in BC have followed an inverted-U pattern. Brown estimates a straightforward OLS regression of the caseload per 1,000 population on real benefits levels and the number of unemployed per 1,000 population. He finds significantly positive coefficients for both variables.

Stark (1997) expands Brown's analysis in several dimensions. He uses data from 9 provinces (adequate data were unavailable for PEI) for the period 1982-1996 and, in addition to the variables used by Brown, also examines the interaction of social assistance with the (un)employment insurance system. His independent variables are the ratio of the benefit level to the minimum wage, the unemployment rate for men aged 25-44, the minimum number of weeks of insurable employment required for UI (EI) and dummy variables for each province and year.

Both the unemployment rate and the ratio of benefits to minimum wages have

significantly positive coefficients. The minimum required number of weeks of insurable employment also has a positive impact on the caseload but the estimate is not statistically significant. Under OLS assumptions, these three factors can account for most of the variation in social assistance usage. When an AR(1) specification of the errors is assumed, however, the size of these three coefficients decreased substantially as does the proportion of the variation in the dependent variable attributable to these variables. Stark concludes that further investigation is required before conclusive statements can be made about the determinants of growth in social assistance.

Stark also provides a clear discussion of the limitations of his data, especially his measure of social assistance benefits, which is total actual social assistance expenditures divided by the number of cases. This variable may vary over time or across provinces even when the actual benefits paid to any given type of family or individual are constant. For example, if there is a shift in the composition of the caseload towards a type of family that receives higher benefits then, even if the total number of cases stays the same, this measure of benefit levels will increase.

Fortin and Cremieux (1998) use data from Quebec, Ontario, Alberta, and British Columbia for the time period 1977-1996. These authors introduce an independent variable called the UI wage subsidy rate which is calculated as rD/M where r is the UI wage replacement rate, D is the maximum weeks of UI that could be received, and M is the minimum required weeks of insurable employment. Their results indicate that changes in the UI wage subsidy, the unemployment rate, welfare

benefit levels and the minimum wage all have significant impacts. A one percent increase in the unemployment rate is associated with a one percent increase in the welfare participation rate. The changes to the UI program are estimated to have increased the percentage of the population on social assistance by as much as one-quarter. A higher minimum wage appears to increase the percentage on social assistance, i.e., the negative impact on labour demand outweighs the positive attraction of a higher minimum wage to low skill workers. The major increase in benefit levels for Ontario over the 1985-1994 decade is associated with an increase of up to 22 per cent in the social assistance caseload in that province.

Klassen and Buchanan (1997) concentrate on the causes of changes in the welfare caseload in Ontario between 1985 and 1995. Their analysis indicates a weak relationship between labour market conditions, as measured by the employed to population ratio, and the size of the caseload for the time period 1985 to 1989. They postulate that the increasing benefits and looser eligibility conditions kept the caseload constant even though labour market conditions were improving during this era. For 1989 to 1994, they find a much stronger relationship between the caseload and labour market conditions. STEP (Supports to Employment Programs) was a program introduced to lower the benefit reduction (negative tax) rate for clients with earned income. Klassen and Buchanan find evidence that the introduction of STEP in late 1989 and subsequent tightening of STEP eligibility requirements in August 1992 had substantial impacts on welfare participation. Klassen and Buchanan did not, however, control for such variables as changes in benefit levels and the UI system. They also

did not examine the changes in the caseload for different types of families and individuals.

Our current study is limited in that we consider only Ontario. The offsetting strength is that we use detailed data on changes in the caseload (more specifically, welfare participation rates) across nine different regions and among different types of families and individuals. Furthermore, we employ a more extensive set of independent variables and more appropriate econometric techniques than do most preceding studies.

III. Social Assistance in Ontario: The Basic System and The MCSS Data Set

Ontario is one of three provinces which have a two-tier social assistance delivery network. The other two are Nova Scotia and Manitoba. In Ontario, short term financial assistance is normally provided by municipalities under the terms of the General Welfare Assistance (GWA) Act. The provincial government administers a program of long-term assistance under the Family Benefits Act (FBA). Among the most common “reasons for assistance” among GWA clients are “inability to find regular employment”, “temporary ill health” and “lack of principal family provider”. The most common case classifications for FBA clients are disabled, blind and sole-support parent. Some clients, especially single parents, switch from GWA to FBA during the course of a given spell on welfare. Indeed, a three month “waiting period” on GWA before switching to FBA was required of most unwed, separated and

deserted lone parents prior to October 1991. For this reason, we focus on the combined caseload rather than on GWA and FBA separately.

The data set provided to us by MCSS contains a record for most individuals (the exceptions are described below) who received welfare in Ontario for one or more months during the period March 1983 to December 1994. Each record contains the following four types of information. (1) Permanent characteristics such as date of birth and sex. (2) Characteristics which we observe only at the first and last encounters with the social assistance system during the data period. These include level of schooling and area of residence. (3) Demographic characteristics for which we have data in each year in which the person was on welfare. These include marital status and number of dependents under age 22. (4) Economic characteristics for which we have data in each month in which the person was on welfare. These include the level of welfare income, the level of other sources of income, and the reason for assistance.

There are two significant gaps in our data. The first is that we are missing substantial amounts of data for the years 1983-1989. For GWA, monthly data are only available for March, June, September and December of (most of) the years during this period. Hence, GWA data are missing for two-thirds of the months prior to 1990. The only month after 1989 with missing data is August 1992 for which we have no GWA data. In the case of FBA, we are missing data for ten (non-consecutive) months during this seven year period. One of these is March 1983 which means that our sample period begins in June 1983, the first month for which we have GWA and FBA data.

The second data gap is that we have no GWA data for ten census divisions

(counties, regional municipalities or districts) which account for approximately 15% of the population of Ontario throughout our sample period. (See Table 1 for the names of these regions.) As indicated above, we decided to analyse the combined GWA-FBA caseload. In light of this decision and the fact that the overall caseload distribution was shifting towards GWA during our sample period, we thought it best to also exclude the FBA clients in those 10 census divisions for which we lack GWA data.

Labour Force Regions.

Our caseload data are grouped into nine labour force regions for the regression analysis in Sections V and VI. These labour force regions correspond closely to the unemployment insurance regions for which we have values of several of the independent variables in our regressions, specifically, the unemployment rate, the employment/population ratio, the minimum number of weeks of work needed to qualify for (un)employment insurance and the maximum number of benefit weeks for (un)employment insurance. Table 1 indicates the region to which each of the 49 census divisions in the province belongs and identifies each region by the name of the largest city. The ten divisions which are excluded from our analysis due to the absence of GWA data are identified with an asterisk.

We know the census division of residence for each welfare client but only at two points in time: the point of first contact and point of last contact with the social assistance system during the 1983-1994 period. Many of the clients in our sample have only brief periods of contact with the welfare system and many that changed

census division of residence stayed within the same labour force region. For clients who did change labour force region, we used the points of first and last contact to divide the entire (possibly non-continuous) period of contact with welfare system into halves. The client was assigned to the region at the point of first contact for the first half of this period and to the region at the point of last contact for the second half of this period.

Family Types

There was a substantial change in the demographic composition of the caseload over our sample period as indicated by Figure 2. There are two types of cases in the “other” category. One type includes the following “special” categories: handicapped or foster children, special assistance (short term needs), and supplementary aid (welfare is not major source of income). The second type includes those clients whom we have classified as “nonemployable” usually due to disability, poor health or old age. The six identified demographic categories in Figure 2 (lone parents, couples and [childless] singles) are restricted to “employable” clients. Figure 2 indicates that the proportion of cases in the “other” category declined from about 50% to under 40% during the second half of our sample period. Proportionate increases were largest among single males and couples with children. In this paper, we wish to focus on those groups which were both of reasonable size and whose welfare participation could be expected to be relatively sensitive to labour market conditions and policy parameters. For this reason we have chosen to focus on four groups of employable clients: lone mothers, single males, single females and couples with

children.

Welfare Participation Rates

The size of the social assistance caseload is a function of two factors: the size of the total population and the proportion of the population which is on social assistance (the “welfare participation rate”). In order that population growth not mislead our empirical inferences, we focused on the welfare participation rate rather than the absolute caseload size. The MCSS data, however, contain no information about the population not on welfare. For this purpose, we used data from censuses of the population. Statistics Canada (1981, 1986, 1991) publishes census tables of the population by family type and census division. The latter characteristic was needed to exclude the population in those divisions in which we do not have welfare caseload data. (The census public use sample does not identify census division and, therefore, can not be used for this purpose.) For the non-census years in our sample period, we assumed a constant yearly growth rate and then interpolated and extrapolated to estimate the population size of the relevant groups. (The census does publish intercensal estimates but not by census division.)

The family type definitions are consistent across censuses and match closely, but not exactly, with our family type definitions in the MCSS data. For this reason, these welfare participation rates should be viewed as approximations. They are very likely, however, to be better approximations than the welfare participation rate estimates which one obtains from Statistics Canada surveys on which social assistance income is known to be seriously under-reported. See Appendix A for an extensive

description of the family types in both our MCSS and census data sources.

Independent Variables

We are interested in how changes in program parameters and labour market conditions influence these welfare participation rates. The implicit behavioural model behind our estimation is that the decision to use social assistance depends on the level of utility while on social assistance compared to that in alternative states. The utility of these two states, in turn, is a function of a variety of factors including the value of welfare benefits, the availability of other income support programs, and the availability and pay level of jobs.

Formal models (Fortin and Cremieux 1998) typically predict that the likelihood of welfare participation increases with the level of welfare benefits and declines with the adequacy of (un)employment insurance. Specifically, the welfare participation rate is predicted to decrease with the maximum number of weeks that benefits are available, increase as the required weeks of work for eligibility increase, and increase as the replacement rate decreases. With respect to labour market conditions, one would generally expect that welfare participation rates would rise with the unemployment rate and fall with the employment rate (employment/population ratio). The relationship with the minimum wage is less obvious. A higher minimum wage would increase the attractiveness of the labour market to low skill workers, but also may reduce the availability of low wage jobs.

Variable Definitions and Descriptive Statistics

Tables 1 and 2 provides definitions and descriptive statistics for the variables

used in our regression analysis. The first four columns of Table 2 provide the welfare participation rates for each family type. In each case, the trend is quite flat through the 1980's with a sharp increase which starts in 1989-1990 and tapers off in 1993-1994. The next three columns provide the (maximum) level of monthly welfare benefits for each family type (1990 dollars). The lone mother and couple are assumed to have two children but the pattern over time is the same for other family sizes. These benefit levels increase by approximately 20-25% during the 1980's and then sharply rise in 1989-1990. Figures 3a through 3d show the monthly levels of both welfare participation rates and benefit levels for each family type. It is clear that the big increases in both variables occurred in the latter half of this period. The figures also indicate that the correlation between these two variables is not perfect. The benefit level is set Ontario-wide and, so, does not vary between the labour force regions.

The next column of Table 2 contains the potential earnings from a full-time (140 hours per month) job at the minimum wage. This variable shows a slight (5%) increase between 1983 and 1990 and a much larger (20%) increase between 1990 and 1994. The next two columns contain the unemployment rate for the entire labour force and the employment/population ratio for the population age 15 and over. Both variables reflect the recovery of the late 1980's and the severe recession of the early 1990's. The unemployment rate can vary (as shown in Figure 4 and 5) across regions by up to six percentage points and the employment/population ratio by up to fourteen percentage points. These figures show that labour demand began to fall in 1989 corresponding roughly to the start of the dramatic increase in the welfare participation

rate.

The final column in Table 2 contains our measure of the adequacy of the (un)employment insurance system which, following Fortin and Cremieux (1998), we define as the replacement rate times the ratio of the maximum weeks of benefits to the minimum qualifying weeks of work. This value of this variable is almost cut in half over the sample period and as of 1994 varied from a low of 1.3 to a high of 2.2 across the province. Figure 6 shows the variation across the labour force regions in the UI generosity parameter.

IV. Time Series Econometric Procedures

The sample used in our regressions was divided into four family types and nine regions as defined in the previous section. Each family type was analysed separately in a pooled, time-series framework, that is, the regional time series were stacked and then the models were estimated. As well, the family types were combined in a SUR model.

The time trend was split into pieces and separate constants and slopes were estimated for each piece that is, without continuity restrictions. The break points in the time trend correspond to significant changes in eligibility requirements for social assistance. For lone mothers there are four break points and for the other family types there are three. For lone mothers, the first break point is at November 1987 when the “man in the house” rule was abolished. Lone mothers living with men who were not

the father of their children and with whom they had lived for less than three years were now eligible for social assistance in their own right. This change in policy does not apply to the other family types and so we did not include it as a break point in the other regressions.

The second break point for lone mothers and the first for the other family types is at October 1989 when Supports to Employment Program (STEP) was introduced. STEP included significant changes to the definition of earned income. Earned income was now equal to 80% of net income less the earning exemption level and child care costs. Previously, earned income was calculated on 100% of gross earnings with lower exemption levels and child care costs were not deducted. The next break is October 1991 when the definition of income was revised again. Earned income was now equal to 75% of net income less the earnings exemption and all of any child care costs were deducted. The final break in the time trend is August 1992 when the STEP “notch” was implemented. This tightening of eligibility requirements essentially required clients to be on welfare for three months before fully qualifying for the STEP program, that is, the complete set of exemptions from earned income could not be used to qualify initially for social assistance. Separate time trends were estimated for each region.

We have not investigated a random walk hypothesis, for two reasons related to these trend variables. First, little is known about the behaviour of unit root statistics when applied to models such as this model, with several trends with breaks, somewhat complicated covariance structure, and unevenly spaced data. Second, the flexible

trend specification makes it seem likely to us that any non-stationarity has been picked up by the trend variables. Note that the error autocorrelation estimates in Tables 3 to 6 and 1b to 4b, discussed later, never exceed 0.77.

We also needed to determine the lag structure for the independent variables. It seems clear that a change in an independent variable may not only have an immediate impact on the welfare participation rate, but also an impact that persists over time. For example, changes in the UI system may not be expected to have an impact until individuals use up the UI benefits for which they are eligible. Determining the appropriate lag structure for four independent variables can be a somewhat complicated and *ad hoc* process. We have used three different approaches. First, we included all independent variables lagged 12 months, those being the benefit level, the minimum wage level, UI generosity, and the unemployment rate. Second, starting with all independent variables lagged 12 months, we dropped the last lag for all four independent variables simultaneously and then tested the null hypothesis that all four lags were equal to zero. We stopped this procedure as soon as the null hypothesis was rejected at the 5% significance level. This approach restricts the lag length to be the same for each variable. Single males were the only family type for which this approach did not immediately stop at 12 lags. Third, again starting with all variables lagged 12 months, we dropped the last lag for only one variable until the last lag of the variable was significant. Then we began again with all variables lagged 12 months and began the procedure again with the next variable. In this way, separate lag lengths for the four variables are determined and used together in the estimated model.

All lag structures produce similar estimated coefficients and the differences will be noted in the following discussion.

We estimated an ordinary least squares (OLS) regression in order to test for cross-regional heteroscedasticity, cross-regional correlation and autocorrelation. To test for heteroscedasticity, we calculated a Lagrange multiplier statistic (Greene 1993, p. 450). equal to

$$\left(\frac{T}{2}\right)\sum_i \left(\frac{s_i^2}{s^2} - 1\right)^2,$$

where i refers to region i , T to the number of observations in the time series, s_i^2 to the estimated error variance of region i , and s^2 to the estimate of the pooled variance. For all family types, the test was highly significant and indicated the presence of cross-regional heteroscedasticity.

To test for cross-regional correlation, we calculated another Lagrange multiplier statistic (Greene 1993, p. 454) equal to

$$T\sum_{i=2}^M \sum_{j=1}^{i-1} r_{ij}^2,$$

where r_{ij}^2 is the estimated error correlation between regions i and j . For all family types this statistic was also highly significant and indicated a cross-regional correlation in errors.

The potential problem of autocorrelation was more challenging due to the fact that our data are not evenly spaced through time. After 1989, we have an observation every month except August 1992. Prior to 1990, the observations are generally spaced three months apart but sometimes there are larger gaps. We wanted to use all of our data in the analysis including for the estimation of the autocorrelation coefficient.

Therefore, we assumed that the errors from the underlying monthly process followed the AR(1) process,

$$u_t = \rho u_{t-1} + \epsilon_t,$$

where u_t denotes the error at time t and ϵ_t is white noise. This form implies that

$$u_t = \rho^j u_{t-j} + \sum_{i=0}^{j-1} \rho^i \epsilon_{t-i}, \quad j = 1, 2, 3, 4, 6$$

The error term is expressed as a function of the previous observation's error, which is j months earlier than the current observation. To estimate ρ , we obtained the non-linear least squares (NLS) estimate of

$$e_t = \rho I(t,1)e_{t-1} + \rho^2 I(t,2)e_{t-2} + \rho^3 I(t,3)e_{t-3} + \rho^4 I(t,4)e_{t-4} + \rho^6 I(t,6)e_{t-6} + \text{error},$$

where e_t is the OLS residual and $I(t,j)=1$ if the most recent observation prior to t is j months earlier, $I(t,j)=0$ otherwise. This function includes all the observed gaps in our data. We restricted the value of ρ to be constant across regions. The estimated ρ is always highly significant (using heteroscedastic-robust standard errors) in the NLS regressions indicating that autocorrelation is a problem in the data. The estimated ρ is used in a GLS estimator along with estimates of the cross regional heteroscedasticity and correlation to obtain the final regression estimates which are reported in this paper.

We also estimate a SUR model and report the results in this paper. The benefit of using a SUR model is increased efficiency if the error terms are correlated between family types. In the SUR model presented, we have assumed that the error term follows the same AR(1) process for each family type. We have controlled for cross-regional heteroscedasticity and cross-regional correlation within and between family

types. The covariance parameters are estimated in the manner previously described in this section.

V. Time Series Regression Results and Discussion

Tables 3 to 6 present the results from the time series regressions for the different lag structures and two specifications of the UI variables. The estimates of the time trend are not presented. As well, dummy variables for the month were included in the regressions and these results are also not reported. The reported coefficients for the independent variables are the sums of the current and lagged coefficients of each variable and as such represent the long-run impact of a permanent change in the independent variable. Our standard for a significant coefficient was for it to be significant at the 5% significance level.

The coefficient for the welfare benefit level varies in sign and significance between family types. For lone mothers the coefficient is unexpectedly negative and is only significant when the UI variables are included separately. For single males and females, the coefficient is always positive and often significant. For couples with children, the coefficient is always negative and significant. These results do not strongly support our prediction that the coefficient would be positive.

The coefficients for the minimum wage are slightly more consistent between family types. For lone mothers, single males, and couples with children, the coefficient is always negative although for lone mothers it is not always significant. For single

females, the coefficient is not significant. The estimated elasticities are -1.18 for single males and -1.02 for couples with children. A 1% increase in the level of the minimum wage earnings is associated with a decrease of 1.18% in the welfare participation rate for single males and 1.02% decrease for couples with children. Except for single females, these results support a scenario where the incentive effects on the supply side of an increase in the minimum wage outweigh the disincentive effects on the demand side.

The estimated coefficient for the unemployment rate is quite often negative, which is unexpected, and is also not significant. For lone mothers, the estimated coefficient is always positive and is significant when all variables are lagged 12 months and the UI variables are included in a combined form. For single males, the coefficient is generally positive. When the coefficient is negative, it is also not significant. For single females, the coefficient is always negative and not significant except when all variables are lagged 12 months and the UI variables are included separately. For couples with children, the coefficient is always negative and not significant. The insignificant coefficients for the unemployment rate may be due to the fact that the unemployment rate is used to determine the values of the UI variables. To avoid this problem we have also used the employment population ratio.

Generally, using the employment population ratio instead of the unemployment rate had little effect on the coefficients for the other variables, although sometimes the significance changed. The results from the regressions using the employment population ratio are included in Appendix B. The coefficient for the employment

population ratio has the expected sign for lone mothers and is significant when the separate lagged independent variables are included. For single males, estimated coefficient for the employment population ratio is always positive and often significant. These results are unexpected. For single females and couples with children, the coefficient is also unexpectedly positive and significant. Using the employment population ratio does not appear to have changed the estimated coefficients for the other independent variables.

The variables for the UI system were included in the regressions in two different forms. First, they were included combined as the replacement rate times the ratio of the maximum weeks of benefits to the minimum required weeks of work for eligibility. Second, they were included separately. The replacement rate only changed once in our sample period, so in the second specification, we included a dummy variable equal to one if the observation was after April 1993 when the replacement rate decreased from 60% to 57%.

For lone mothers, the coefficient for the combined form of the UI variables is positive and not significant. When the UI variables are included separately, the dummy variable for the change in the replacement rate is positive and significant and the minimum weeks is negative and significant when all variables are lagged 12 months which is an unexpected result. We expected that as the required minimum weeks of work increased, fewer individuals would be eligible for UI and the use of social assistance would increase. These results indicate that there is an interaction between the UI system and welfare, however, we may not be capturing this interaction with the

variables we have used. The dummy variable may be capturing more than the change in the replacement rate such as changes in eligibility rules that occurred at the same time.

For single males, the coefficients for the combined UI variable are positive and significant in each reported lag structure. When the UI variables are included separately, the coefficient for the maximum weeks of benefits is negative and significant, as expected, and the dummy variable for the change in the replacement rate is positive and significant, also as expected. The coefficient for the minimum weeks required to be eligible has an unexpected negative sign and is significant. For single women, the results are similar to single men with two exceptions. One, the coefficient for the change in the replacement rate is not significant. Two, the coefficient for the maximum required weeks of work is not significant when UI variables are included separately with the fewer months lagged. For couples with children, the signs of the coefficients are the same as for the single men and women, however, the only coefficient that is significant in all reported lag structures is the change in the replacement rate. The coefficient for the maximum weeks of benefits is significant for couples with children when the separate lag structure is used.

Figures 7A to 7D graph the actual welfare participation rate, the predicted welfare participation rate from the results presented in this paper, and the predicted welfare participation rate from specifications that do not include a time trend, but do include the breaks. Generally, what is interesting is that the model without the time trends follows the actual rate very well. These graphs indicate that some of the

independent variables are also following a time trend and can capture some of the increase in the welfare participation rate without including a time trend.

Our results from the four specifications of a SUR model are presented in Tables 7 to 10 (the specifications using the employment population ratio are included in Appendix B). The estimated coefficients for the benefit level are similarly mixed as when the family types are estimated separately. Lone mothers and couples have negative and significant coefficients, single males have a positive and significant coefficient, and single females have an insignificant coefficient. Once again, we do not have strong support for our predicted benefit effect except for single males.

The coefficient for the minimum wage earnings displays a similar pattern to the results from the separate regressions. For lone mothers, single males, and couples the coefficient is always negative although not always significant for single males. The coefficient is not significant for single females. These results seem to indicate that the increased work incentive caused by increasing the minimum wage dominates any decreased demand for labour.

The coefficients for the unemployment rate are more consistent between family types in the SUR model. The coefficient is always positive, although for single females it is never significant. Our prediction that a higher unemployment rate should be related to higher a welfare participation rate seems to have some support in this model.

The UI generosity variables have mixed results. The combined form of the variables is positive and significant for lone mothers and single males, which is

unexpected, and negative for single females and couples. When the UI variables are included separately the coefficient on the maximum weeks of benefits has the expected negative sign except for single females. The coefficient for the required minimum weeks of work is negative and significant for lone mothers. This unexpected result explains the coefficient we get when the unemployment policy variables are combined. We have based our predictions on a static model, but a more dynamic model may be necessary to understand the relationship between the UI system and the social assistance system.

There are a few general conclusions that can be drawn from these results. The effect of variables on the welfare participation rate varies between family types. Single males appear to be the only family type that increases participation as benefits increase. Our most consistent result is that an increase in the minimum wage is related to a decrease in the welfare participation rate. There is some evidence that labour market conditions play a role in the welfare participation rate.

VI. A Quasi-Natural Experiment Approach

The time series regression approach discussed in the previous section has two inherent problems that can be controlled for using a quasi-natural experiment approach. First, it is difficult to conclude causation using the time series regression approach. We may only be observing a correlation. For example, it may only be coincidence that benefit levels increased at the same time as the welfare participation

rate. Second, omitted variables may be a particular problem. The independent variables included in our time series analysis may be proxying for omitted variables and the estimated coefficients may not represent the true impact of the independent variable. A quasi-natural experiment is possible when an independent variable changes for one family type (the experimental group) and not for another (the control group). We can then regress the difference in the welfare participation rates between the experimental and control groups on a dummy variable which equals one after the policy change. Under our assumption that any other unobserved changes would affect both family types in the same way, the estimated coefficient captures the impact of the policy change, that is the “difference” in the welfare participation rate. If the estimated coefficient for the policy change is significant then the policy change had a significant impact on the experimental group.

Most of the independent variables we have considered in our time series analysis changed at the same time for all family types. Hence, we are not able to use a quasi-natural experiment approach to estimate the impact of benefit levels, minimum wage levels, unemployment rate, or the UI generosity. However, there were two different changes in policy that were likely to have affected one family type (experimental group) and not another (control group). The first quasi-natural experiment examined is the abolishment of the “man in the house” rule in November 1987. This policy change was included as a break point in the time trend for lone mothers in the previous section. After this change, lone mothers living with men who were not the fathers of their children and with whom they lived less than three years

were now eligible for social assistance in their own right. This change should not have an impact on the welfare participation rate of singles. We expect to see an increase in the difference in the welfare participation rates between lone mothers and singles.

The second policy change occurred in October 1991 when the definition of earned income was changed. Prior to October 1991, earned income was equal to 80% of net income less the earnings exemption and child care costs:

$$\text{Earned income} = .8[\text{Net Earnings} - \text{earnings exemption} - \text{child care costs}].$$

In October 1991, this definition was changed to:

$$\text{Earned income} = .75[\text{Net Earnings} - \text{earnings exemption}] - \text{child care costs}.$$

We would expect an impact for all family types due to the change in the definition of earned income, however, the change in the handling of the child care costs should only affect families with children. Using single males and single females as control groups and lone mothers and couples with children as experimental groups, we should get an estimate of the impact of the change in the handling of child care costs. We would expect the difference in the welfare participation rates between families with children and singles to increase.

Specifically, we are assuming that the welfare participation rate (WP) of the experimental group is a function of the independent variables discussed in the previous section (Ben , MWE , UR , UI), unobserved variables (UV), a time trend ($f(t)$), the policy change (P), and an error term (ϵ);

$$WP_{ERt} = \alpha_{ER} f(t) + \beta_{1E} Ben_{Et} + \beta_{2E} MWE_t + \beta_{3E} UR_{Rt} + \beta_{4E} UI_{Rt} + \gamma P_{Et} + \delta UV + \epsilon_{ERt},$$

where $P_{Et} = 1$ if the observation is after the change in policy (November 1987 or

October 1991) and zero otherwise. The subscript E indicates the experimental group, the subscript R indicates region and the subscript t indicates time. Similarly for the control group;

$$WP_{CRt} = \alpha_{CR} f(t) + \beta_{1C} Ben_{Ct} + \beta_{2C} MWE_t + \beta_{3C} UR_{Rt} + \beta_{4C} UI_{Rt} + \delta UV + \epsilon_{CRt},$$

where the subscript C indicates the control group. There was no policy change for the control group and so P is not included in this equation.

The difference in the welfare participation rates between the two groups, assuming that the independent variables and the unobserved variables have the same impact on the experimental and control groups, is:

$$WP_{ERt} - WP_{CRt} = (\alpha_{ER} - \alpha_{CR}) f(t) + \beta_{1E} Ben_{Et} - \beta_{1C} Ben_{Ct} + \gamma P_{Et} + \epsilon_{ERt} - \epsilon_{CRt}.$$

However, as observed in the previous section, the coefficients are not the same for each family type. In this case, the difference between the groups' welfare participation rate is:

$$WP_{ERt} - WP_{CRt} = (\alpha_{ER} - \alpha_{CR}) f(t) + \beta_{1E} Ben_{Et} - \beta_{1C} Ben_{Ct} + (\beta_{2E} - \beta_{2C}) MWE_t \\ + (\beta_{3E} - \beta_{3C}) UR_{Rt} + (\beta_{4E} - \beta_{4C}) UI_{Rt} + \gamma P_{Et} + \epsilon_{ERt} - \epsilon_{CRt}.$$

The results from both of these specifications will be discussed below.

Tables 11 and 12 present the results from the quasi-natural experiment analysis of the abolishment of the “man-in-the-house” rule. The difference in the welfare participation rate for lone mothers and single males or single females was regressed on the policy change and other independent variables. The specifications which use single males as the control group all have a positive coefficient for the policy change indicating that the welfare participation rate for lone mothers increased, but the

coefficient was only significant when the coefficients on the other independent variables were assumed to be the same for lone mothers and single males. When single females were used as the control group, the coefficient on the policy change was never significant. These results indicate that the abolishment of the “man-in-the-house” rule did not significantly increase the welfare participation rate of lone mothers.

The results are presented in Table 13 to Table 16 for the October 1991 change in the definition of earned income. The coefficient on the policy change is not significant in any specification for both lone mothers and couples with children. These results indicate that the October 1991 change did not have a different impact on the welfare participation rate for families with children versus families without children.

VII. Conclusion

There has been a dramatic increase in the social assistance caseload in Ontario between 1983 and 1994. We have also observed a change in the composition of the caseload. There has been a marked increase in the proportion of the caseload constituted of single males and couples with children and a comparable decline in the proportion of the caseload classified as “nonemployable”. In this paper, we have focused on the changes in the welfare participation rate for four family types; lone mothers, single males, single females, and couples with children. We find that these family types are very different from each other in regards to the response to labour

market conditions and policy parameters.

Single males are the only family type that appears to have a positive and significant relationship between benefit levels and its welfare participation rate. In contrast, lone mothers and couples appear to have a negative relationship between their welfare participation rate and benefit levels. An increase in the minimum wage decreases the welfare participation rate for lone mothers, single males, and couples, while there appears to be no impact for single females. The variables for labour demand, the unemployment rate and the employment population ratio, indicate a negative relationship for lone mothers and couples, when the labour market conditions improve the welfare participation rate decreases, while for single males and females these coefficients are not always significant. The UI variables present a confusing story. The general conclusion is that an increase in the maximum weeks of benefits decreases the welfare participation rate, as expected, and the same for the required minimum weeks of work, which is unexpected. It is possible that a more dynamic model of time allocation could explain this unexpected result.

Using a quasi-experiment approach, we have tried to isolate the impact of policies that affected only one specific family type. Our results indicate weak evidence that the abolishment of the “man-in-the-house” rule increased the welfare participation rate for lone mothers relative to singles. We found no support for the hypothesis that the October 1991 change in the definition of earnings increased the welfare participation rate for families with children more than for families without children.

Our attempts to explain the dramatic increase in welfare participation rates

have clearly met with mixed success. Several extensions of this research may prove helpful. The last recession was especially hard on young workers and it may be illuminating to estimate our regressions for specific age groups. One barrier is that the census population data, which are needed to calculate the welfare participation rates, are not completely available by age, family type and region. Another especially interesting step would be to incorporate data for 1995 and 1996 when large benefit cuts and other important welfare policy reforms were introduced by the current provincial government. These data may be made available in the relatively near future.

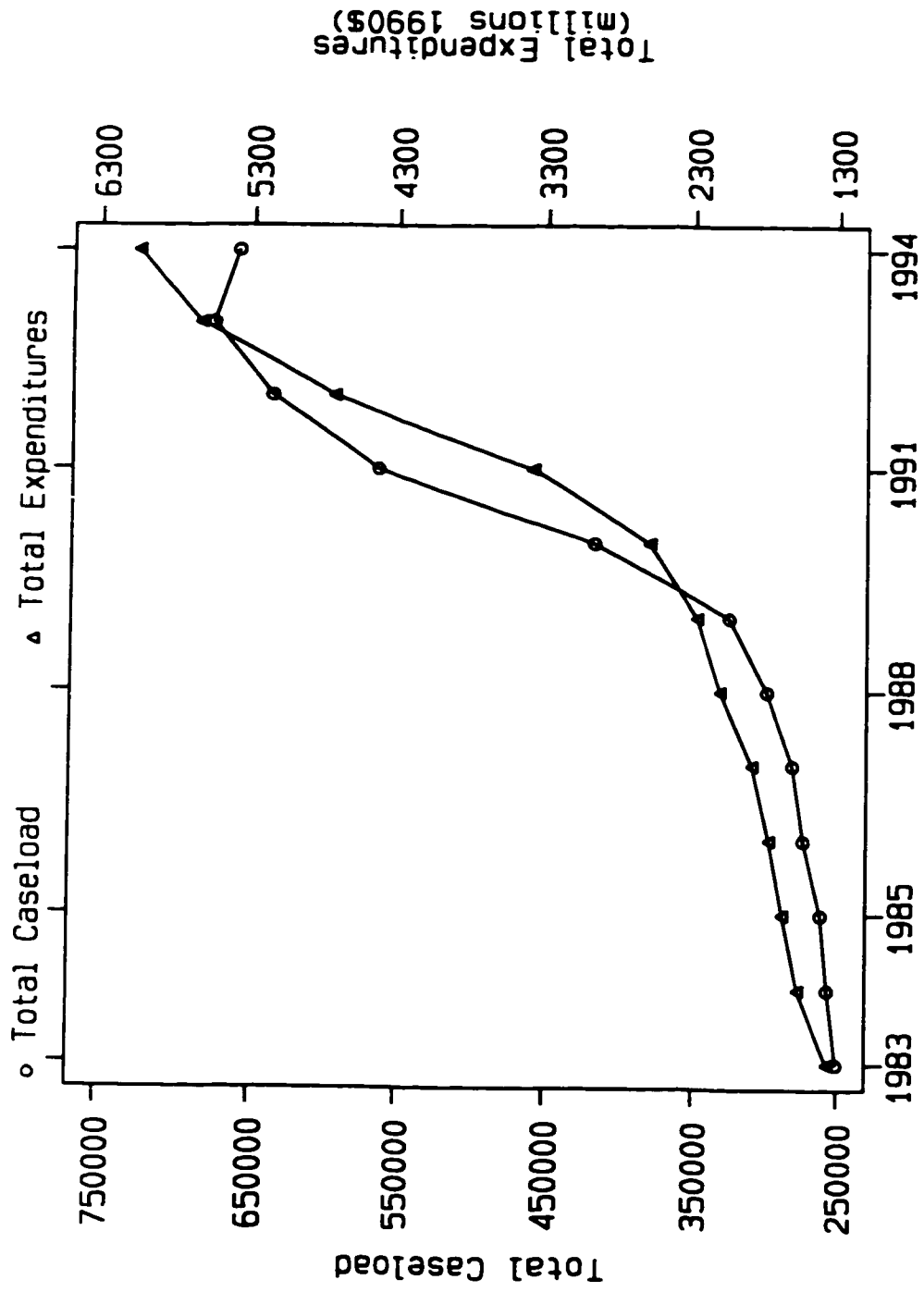


Figure 1. Total Caseload and Expenditures

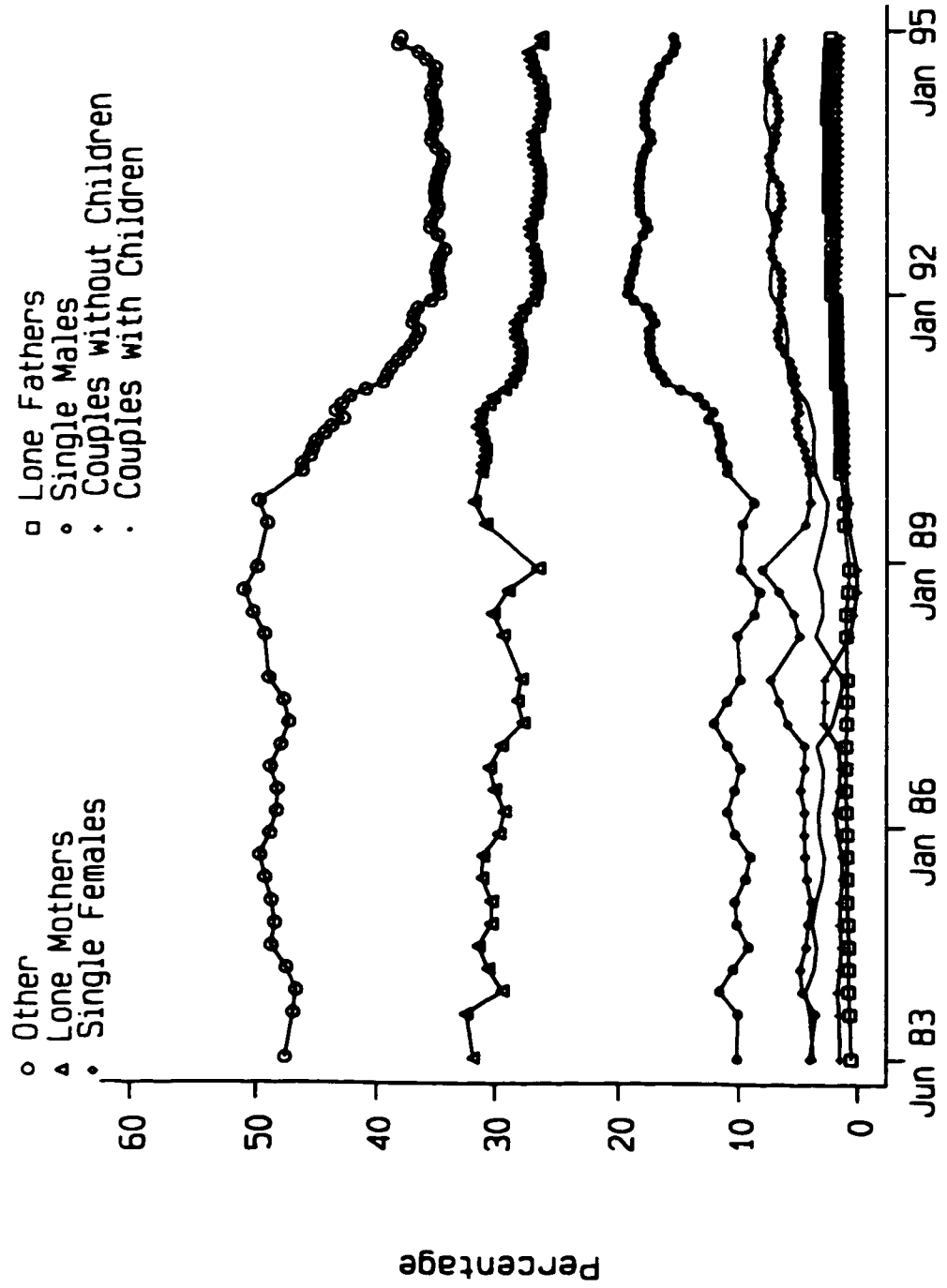


Figure 2. Family Type as Percentage of Total Caseload

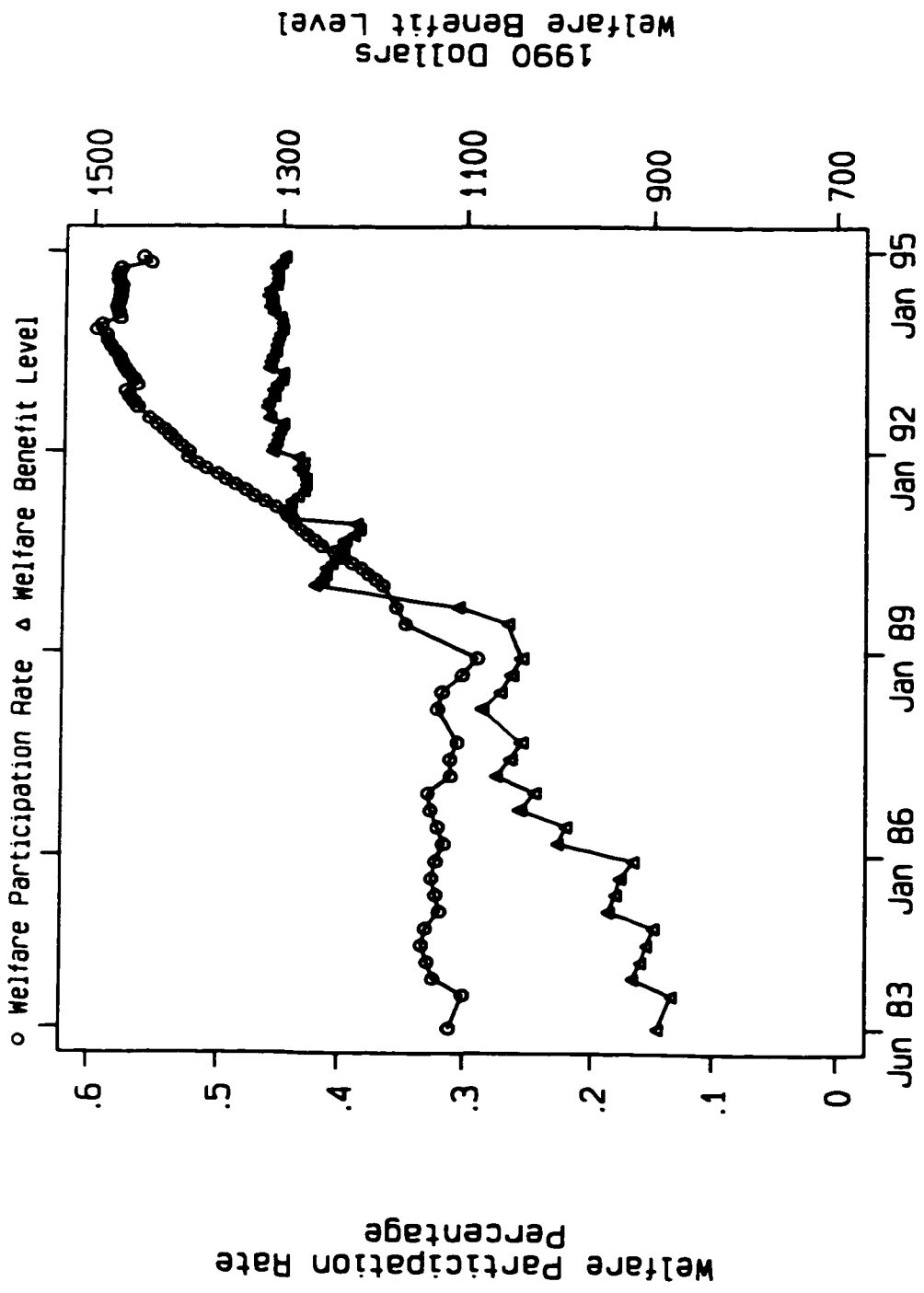


Figure 3A. Lone Mothers

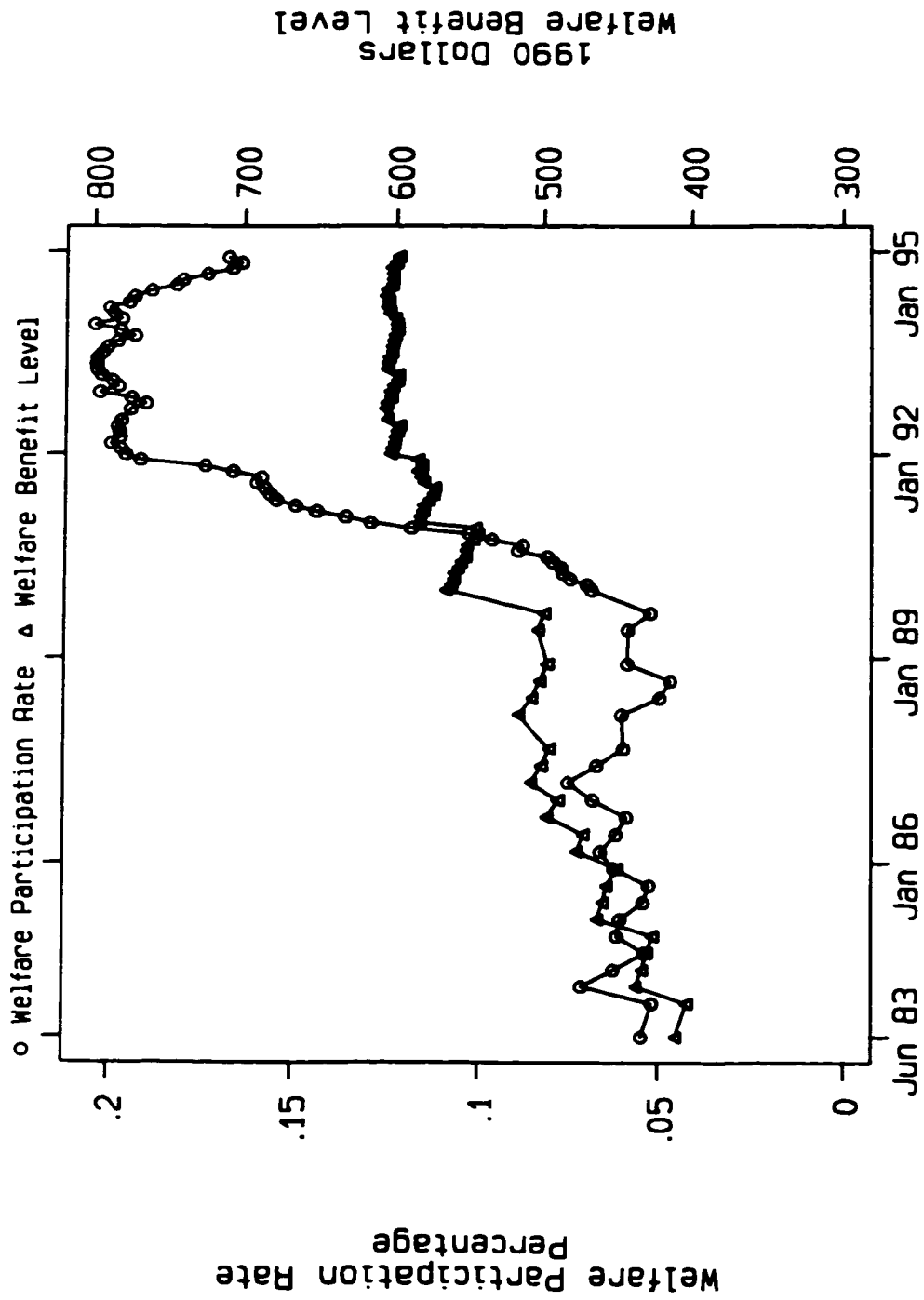


Figure 3B. Single Males

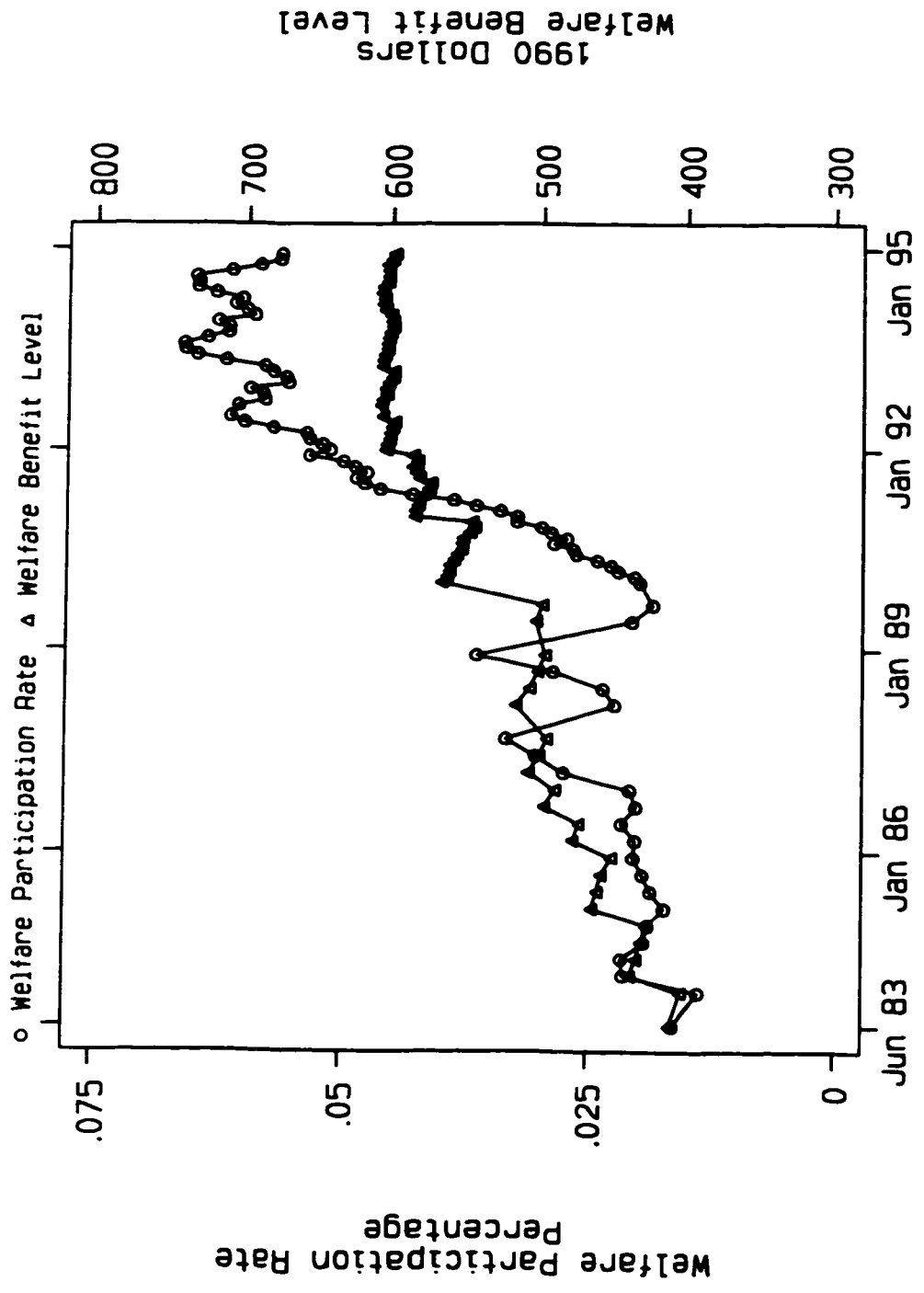


Figure 3C. Single Females

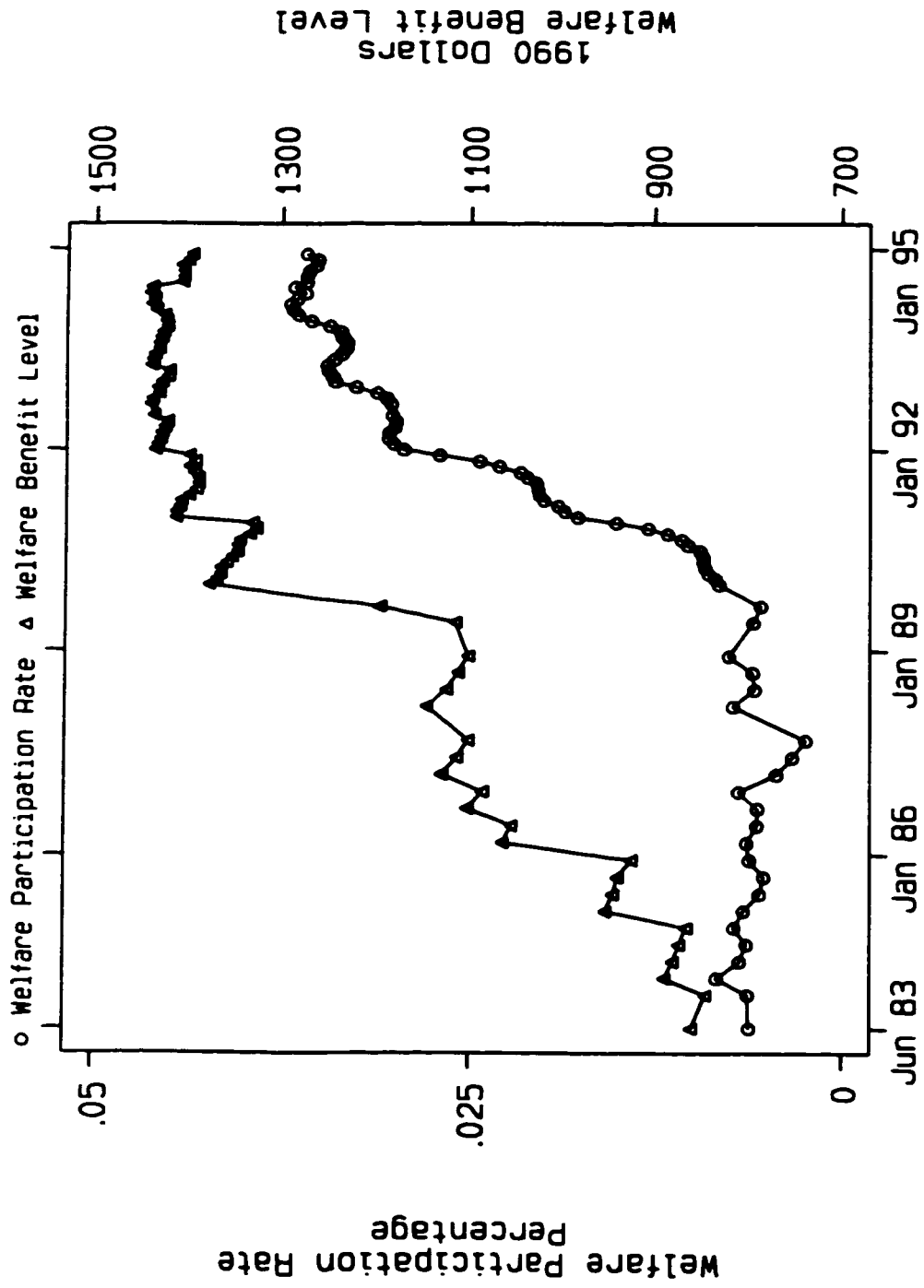


Figure 3D. Couples with Children

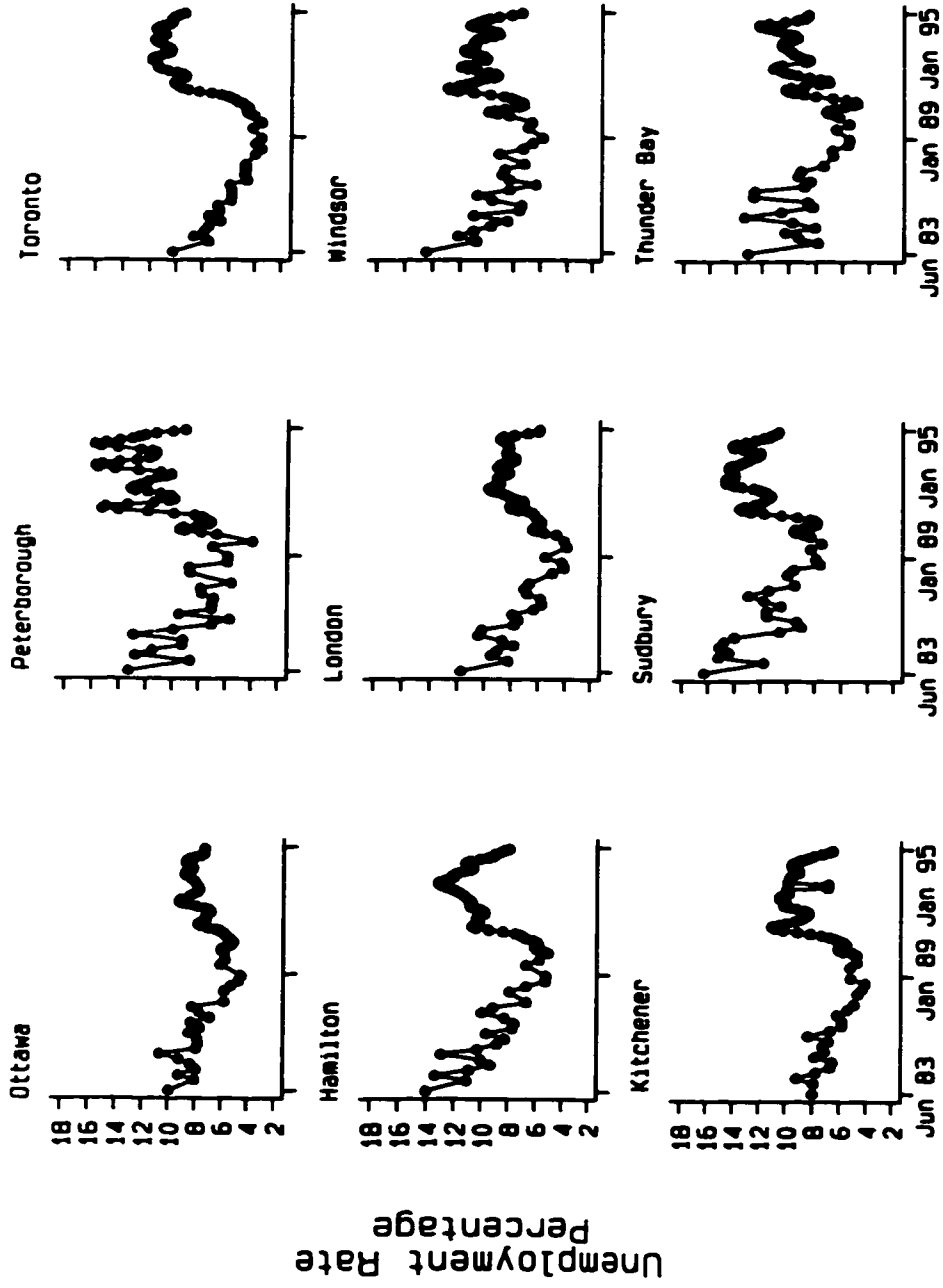


Figure 4. Unemployment Rate by Region

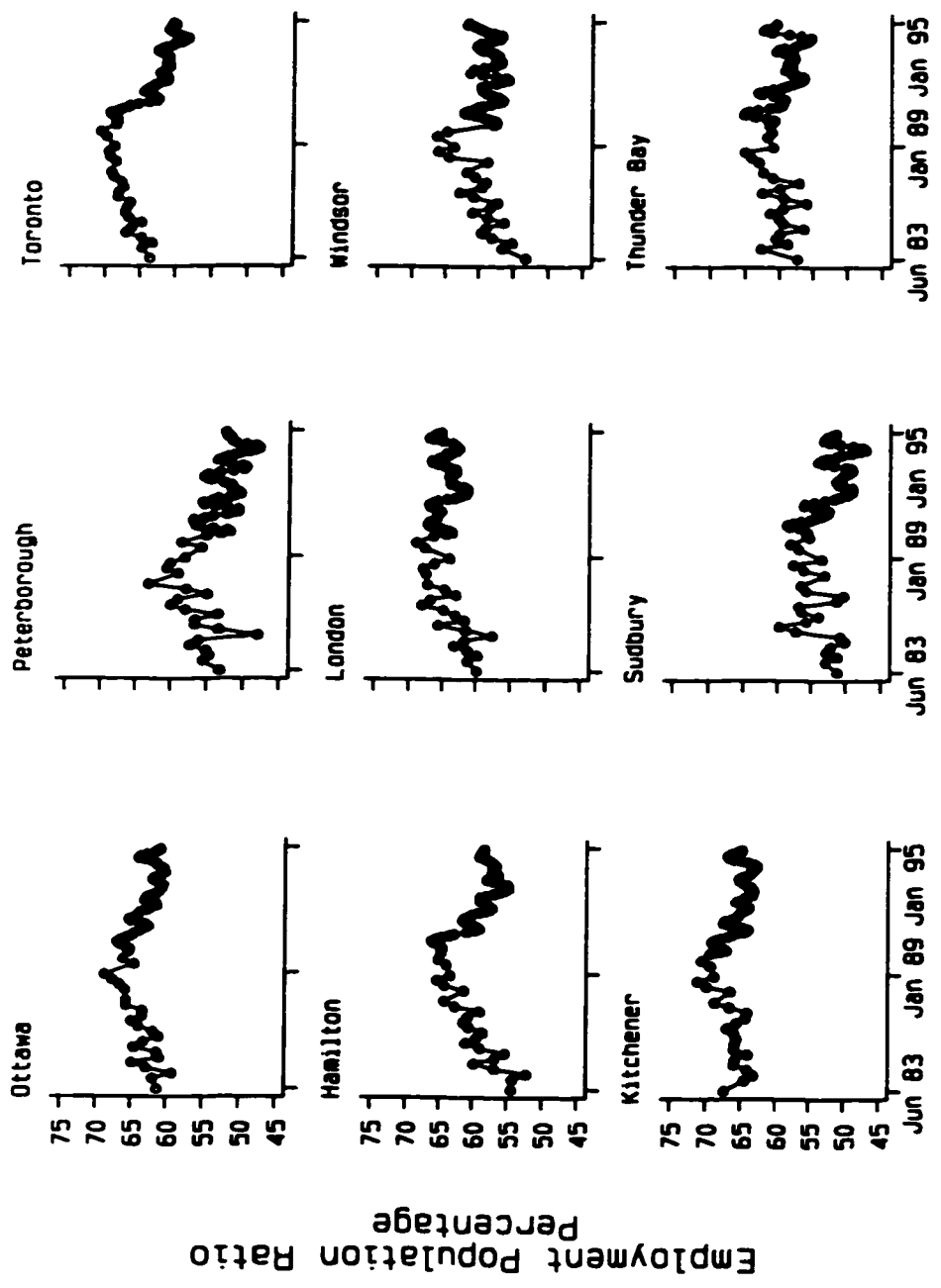


Figure 5. Employment Population Ratio by Region

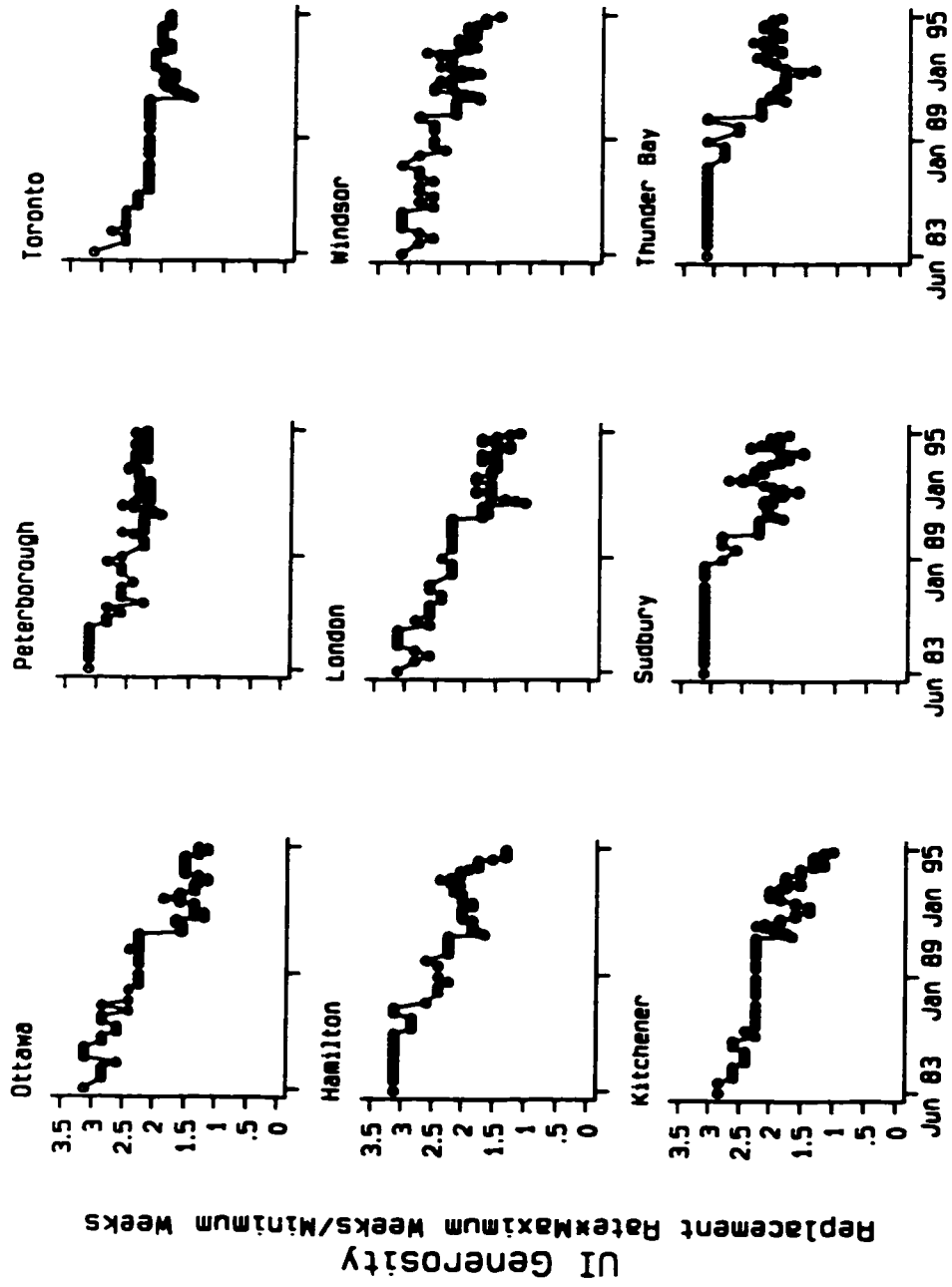


Figure 6. UI Generosity by Region

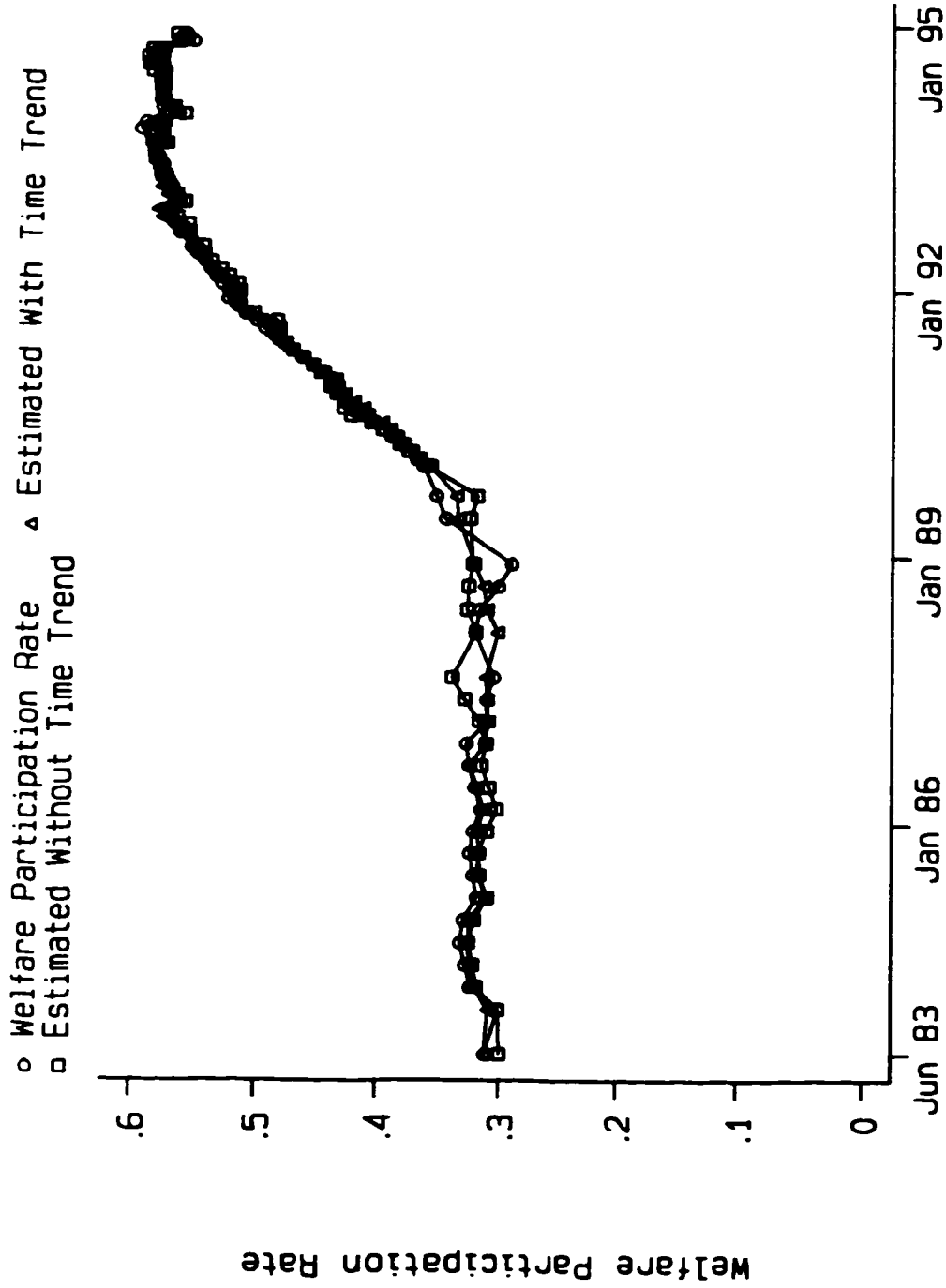


Figure 7A. Lone Mothers

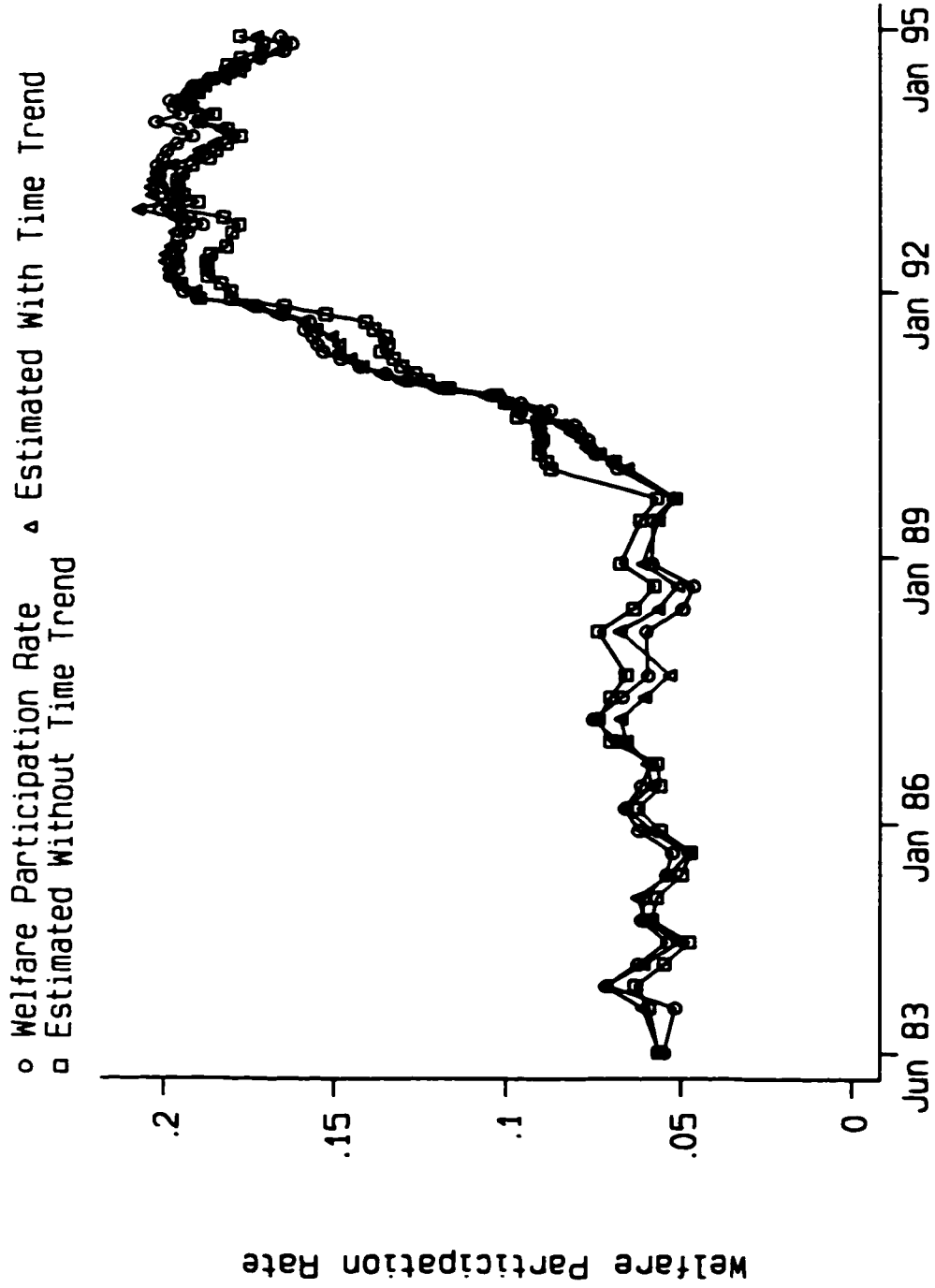


Figure 7B. Single Males

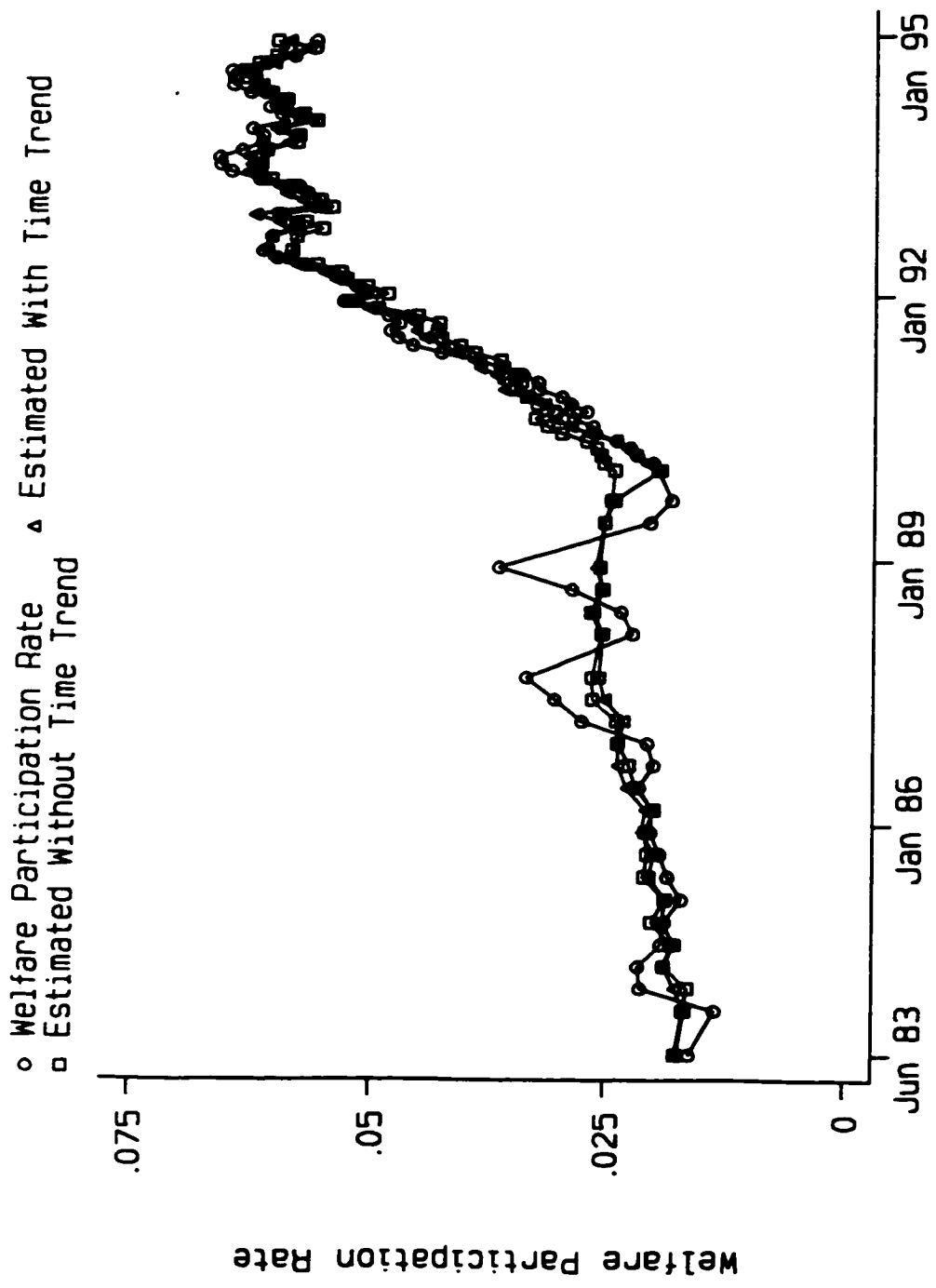


Figure 7C. Single Females

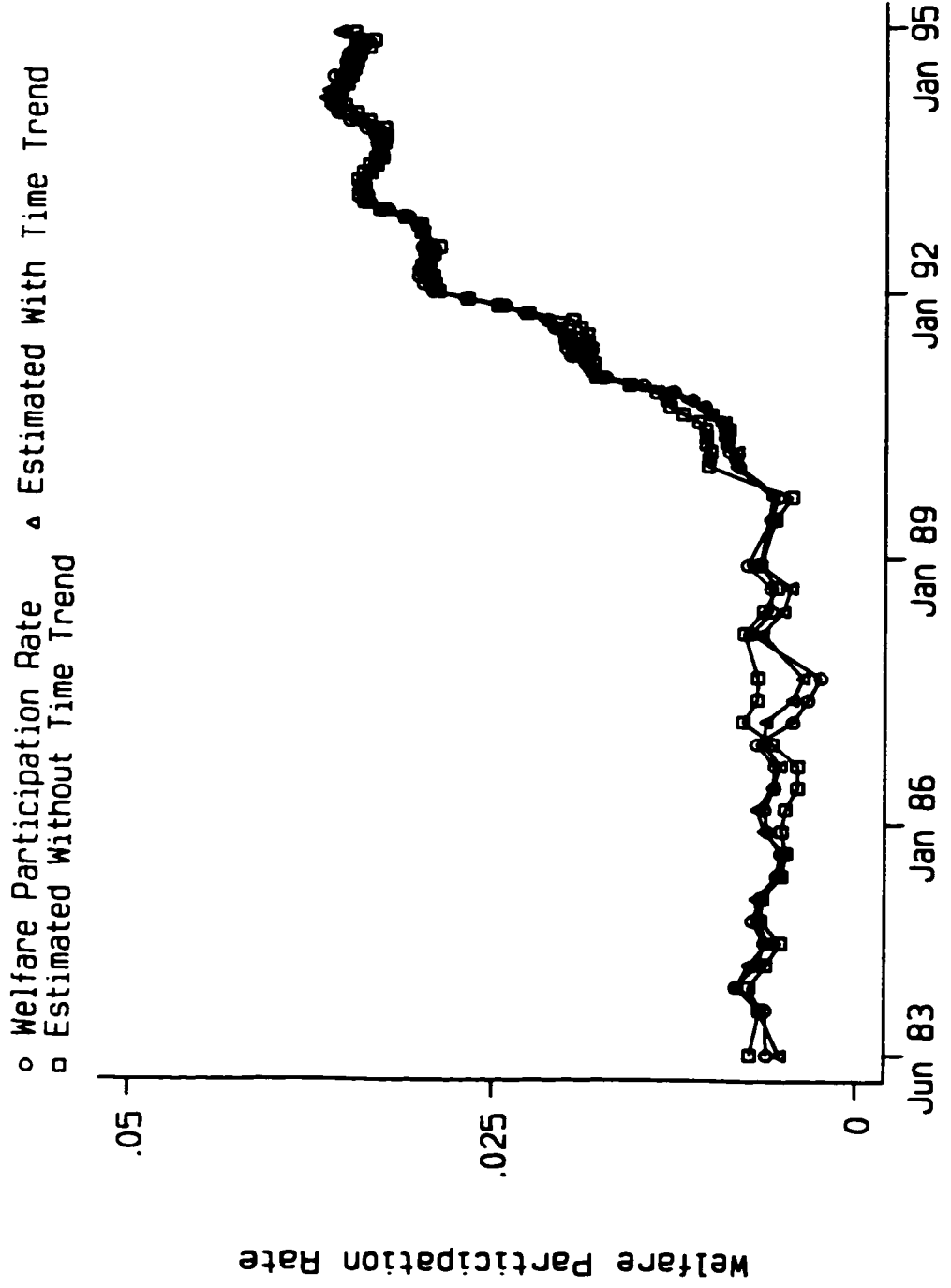


Figure 7D. Couples with Children

Table 1 Variable Definitions and Regions	
Welfare Participation Rate	Monthly Social Assistance Caseload Divided by Estimated Population Size by region.
Welfare benefits	Monthly benefits in 1990 dollars for a single person or lone parent with two children or a couple with two children. One child is assumed to be under age 13 and the other age 13 and over.
Minimum Wage	Monthly (140 hours) value in 1990 dollars.
Unemployment Rate	Three month moving average of the monthly rate for the total civilian labour force by region.
Employment/Population Ratio	Three month moving average of the monthly rate for the entire population age 15+ by region.
UI (EI) Adequacy	Replacement Rate times the ratio of the Maximum Weeks of Benefits to the Minimum Qualifying Weeks of Work by region.
Time	Months from June 1983 (first complete data) through December 1994.
Labour Force Region	Each region is identified by its largest city and constituent census divisions (counties, regional municipalities or districts). The asterisk (*) indicates divisions for which no GWA data are available.
<p>Region One (Ottawa): Frontenac, Hastings, Lanark, Leeds-Grenville, Lennox-Addington, Ottawa-Carleton, Prescott-Russell, Prince Edward, Renfrew, Stormont-Dundas-Glengarry.</p> <p>Region Two (Peterborough): Haliburton, Muskoka, Northumberland, Peterborough*, Victoria.</p> <p>Region Three (Toronto): Durham, Halton, Peel*, Toronto, York</p> <p>Region Four (Hamilton): Brant, Haldimand-Norfolk, Hamilton-Wentworth*, Niagara.</p> <p>Region Five (London): Elgin*, Middlesex, Oxford*.</p> <p>Region Six (Windsor): Essex, Kent, Lambton.</p> <p>Region Seven (Kitchener): Bruce, *Dufferin, Grey, Huron*, Perth*, Simcoe, Waterloo, Wellington.</p> <p>Region Eight (Sudbury): Algoma, Cochrane, Manitoulin*, Nipissing, Parry Sound, Sudbury, Timiskaming.</p> <p>Region Nine (Thunder Bay): Kenora, Rainy River*, Thunder Bay.</p> <p>* Excluded from analysis because no GWA data are available.</p>	

Table 2 Descriptive Statistics											
	Welfare Participation Rates				Monthly Welfare Benefits ^a			Min Wage ^a	Unem. Rate	Emp./ Popul.	UI (EI) Adequacy ^b
	Lone Mother	Single Male	Single Female	Couple W/ Children	Lone Mother	Singles	Couple				
1983	30.6	5.3	1.5	0.6	886	407	853	140 hours	10.7	58.6	3
1984	32.9	6.2	2	0.7	910	432	877	706	9.9	59.4	2.9
1985	32.2	5.7	1.9	0.6	937	458	939	697	8.9	60.3	2.9
1986	32.3	6.4	2.1	0.6	1017	485	1078	682	8.1	61.6	2.7
1987	31	6.7	3.1	0.3	1054	502	1116	695	7.5	62.3	2.7
1988	30.8	5.4	2.8	0.7	1060	506	1122	698	6	64.1	2.5
1989	35	5.5	2	0.6	1081	502	1156	679	5.7	64.5	2.4
1990	40.2	8.5	2.6	1	1236	556	1352	700	6.6	62.9	2.2
1991	48.3	15.6	4.4	2.1	1281	582	1402	721	9.7	60.5	1.9
1992	55.1	19.7	5.7	3.1	1309	603	1435	787	10.5	58.6	1.9
1993	58.2	20.1	6.2	3.4	1306	603	1432	810	10.7	58.6	1.9
1994	57.7	18.4	6.1	3.6	1309	604	1423	854	10.1	58.7	1.7

^a 1990 dollars. Lone mothers and couples are assumed to have two children, one under age 13 and other age 13 or over.

^b Maximum weeks of benefits divided by the minimum qualifying weeks of work.

Table 3				
GLS Regression				
Dependent Variable: Welfare Participation Rate for Lone Mothers*				
	Lag Structure			
Independent Variable	Separate**	12	Separate**	12
Benefit Levels (\$100) (12 lags)	-2.114 (1.887)	-1.772 (1.810)	-2.168 (2.302)	-1.906 (2.250)
Minimum Wage (\$100) (12 lags)	-3.104 (1.882)	-2.665 (1.848)	-2.798 (2.025)	-1.898 (1.514)
Unemployment rate(%) (6 lags)	0.075 (1.920)	0.179 (2.784)	0.050 (1.391)	0.069 (1.105)
UI Generosity ((Max/Min)*RR) (7 lags)	0.037 (0.180)	0.601 (1.620)	---	---
Maximum Weeks Of Benefits (7 lags)	---	--	0.025 (1.133)	-0.063 (1.366)
Required Minimum Weeks of Work (7 lags)	---	---	-0.017 (0.399)	-0.216 (2.688)
Change in Replacement Rate (April 1993)	---	---	1.630 (3.397)	1.528 (3.497)
LM Heteroscedasticity	23.046	17.602	39.124	27.16
LM Correlation	1324.8	1102.337	1125.171	921.975
Autocorrelation Coefficient	0.658	0.6503	0.5838	0.5628
Buse R-squared	0.992	0.993	0.994	0.995
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>				

Table 4						
GLS Regression						
Dependent Variable: Welfare Participation Rate for Single Males*						
	Lag Structure					
Independent Variable	Sep.**	11	12	Sep.**	11	12
Benefit Levels (\$100) (9 lags)	1.507 (1.65)	1.613 (1.53)	1.959 (1.83)	2.226 (2.63)	2.394 (2.54)	2.694 (2.86)
Minimum Wage (\$100) (10 lags)	-1.930 (2.66)	-1.771 (2.27)	-1.736 (2.14)	-1.872 (2.72)	-1.788 (2.54)	-1.698 (2.35)
Unemployment rate(%) (10 lags)	0.090 (1.48)	0.061 (0.93)	0.053 (0.77)	0.051 (0.89)	-0.008 (0.14)	-0.054 (0.88)
UI Generosity ((Max/Min)*RR) (10 lags)	1.916 (5.62)	1.961 (5.39)	2.055 (5.34)	---	---	---
Maximum Weeks Of Benefits (10 lags)	---	---	--	-0.179 (4.39)	-0.213 (4.72)	-0.228 (4.72)
Required Minimum Weeks of Work (10 lags)	---	---	---	-0.417 (5.95)	-0.465 (6.27)	-0.527 (6.73)
Change in Replacement Rate (April 1993)	---	---	---	0.634 (2.39)	0.630 (2.45)	0.671 (2.56)
LM Heteroscedasticity	261.4	260.2	244.6	327.8	320.3	302.3
LM Correlation	322.4	291.6	305.8	270.4	247	256.9
Autocorrelation Coefficient	0.746	0.746	0.737	0.712	0.715	0.701
Buse R-squared	0.926	0.929	0.931	0.944	0.948	0.952
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>						

Table 5				
GLS Regression				
Dependent Variable: Welfare Participation Rate for Single Females*				
	Lag Structure			
Independent Variable	Separate**	12	Separate**	12
Benefit Levels (\$100) (10 lags)	0.951 (1.890)	1.773 (3.083)	0.966 (2.008)	1.735 (3.293)
Minimum Wage (\$100) (0 lags)	0.203 (1.815)	0.037 (0.086)	0.200 (1.844)	0.056 (0.141)
Unemployment rate(%) (2 lags)	-0.019 (1.766)	-0.046 (1.509)	-0.020 (1.883)	-0.082 (2.795)
UI Generosity ((Max/Min)*RR)(12 lags)	0.685 (5.258)	0.786 (4.872)	---	---
Maximum Weeks Of Benefits (12 lags)	---	--	-0.017 (0.958)	-0.052 (2.269)
Required Minimum Weeks of Work (12 lags)	---	---	-0.134 (4.920)	-0.196 (5.591)
Change in Replacement Rate (April 1993)	---	---	0.081 (0.601)	0.129 (0.883)
LM Heteroscedasticity	224.594	229.909	267.731	262.139
LM Correlation	674.383	461.398	656.528	385.338
Autocorrelation Coefficient	0.7637	0.7375	0.7675	0.7336
Buse R-squared	0.853	0.863	0.853	0.88
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>				

Table 6				
GLS Regression				
Dependent Variable: Welfare Participation Rate for Couples with Children*				
	Lag Structure			
Independent Variable	Separate**	12	Separate**	12
Benefit Levels (\$100) (8 lags)	-0.149 (4.843)	-0.154 (4.734)	-0.158 (5.757)	-0.172 (5.681)
Minimum Wage (\$100) (12 lags)	-0.265 (2.613)	-0.249 (2.431)	-0.235 (2.606)	-0.204 (2.182)
Unemployment rate(%) (7 lags)	-0.009 (1.183)	-0.005 (0.490)	-0.006 (0.833)	-0.005 (0.526)
UI Generosity ((Max/Min)*RR)(11 lags)	0.050 (0.894)	0.050 (0.841)	---	---
Maximum Weeks Of Benefits (11 lags)	---	--	-0.015 (2.043)	-0.015 (1.894)
Required Minimum Weeks of Work (11 lags)	---	---	-0.012 (0.994)	-0.014 (1.007)
Change in Replacement Rate (April 1993)	---	---	0.121 (3.143)	0.133 (3.423)
LM Heteroscedasticity	98.091	98.474	96.212	92.294
LM Correlation	275.403	274.908	242.435	236.277
Autocorrelation Coefficient	0.648	0.6453	0.6118	0.6016
Buse R-squared	0.981	0.981	0.987	0.987
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>				

Table 7				
Seemingly Unrelated Regression				
Dependent Variable: Welfare Participation Rate*				
All independent variables lagged 12 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-0.508 (0.944)	2.049 (2.192)	0.476 (0.802)	-0.179 (6.331)
Minimum Wage Earnings (\$100)	-2.317 (2.546)	-0.308 (0.686)	0.137 (0.536)	-0.238 (2.950)
Unemployment Rate	0.211 (5.146)	0.087 (1.938)	0.016 (0.825)	0.024 (3.370)
UI Generosity	1.823 (7.682)	0.322 (1.354)	-0.154 (1.569)	-0.036 (0.860)
Buse R-squared: 0.998				
Autocorrelation Coefficient: 0.6211				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Table 8 Seemingly Unrelated Regression Dependent Variable: Welfare Participation Rate* All independent variables lagged 11 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-1.532 (3.544)	1.584 (2.003)	0.266 (0.458)	-0.180 (6.559)
Minimum Wage Earnings (\$100)	-2.787 (3.071)	-0.845 (1.996)	0.096 (0.402)	-0.342 (4.335)
Unemployment Rate	0.134 (3.284)	0.086 (2.149)	0.011 (0.636)	0.029 (4.138)
UI Generosity	2.242 (10.141)	0.620 (3.105)	-0.205 (2.448)	0.047 (1.192)
Buse R-squared: 0.998				
Autocorrelation Coefficient: 0.62460				
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.</p>				

Table 9				
Seemingly Unrelated Regression				
Dependent Variable: Welfare Participation Rate*				
All independent variables lagged 12 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-1.519 (3.171)	0.753 (0.891)	0.429 (0.753)	-0.176 (6.573)
Minimum Wage Earnings(\$100)	-2.124 (2.796)	-0.250 (0.677)	0.088 (0.375)	-0.209 (2.857)
Unemployment Rate	0.063 (1.555)	0.019 (0.452)	-0.006 (0.274)	0.023 (3.056)
Maximum Weeks of Benefits	-0.107 (3.290)	-0.056 (1.953)	0.017 (1.264)	-0.017 (3.265)
Required Minimum Weeks of Work	-0.468 (8.681)	-0.069 (0.452)	0.040 (1.586)	0.007 (0.677)
Change in Replacement Rate (April 1993)	1.424 (4.947)	1.277 (8.364)	0.368 (3.822)	0.168 (6.498)
Buse R-squared: 0.999				
Autocorrelation Coefficient: 0.5605				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Table 10				
Seemingly Unrelated Regression				
Dependent Variable: Welfare Participation Rate*				
All independent variables lagged 11 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-2.203 (5.300)	1.065 (1.336)	0.803 (1.400)	-0.181 (6.590)
Minimum Wage Earnings(\$100)	-2.540 (3.387)	-0.803 (2.199)	-0.075 (0.333)	-0.297 (3.983)
Unemployment Rate	0.046 (1.131)	0.043 (1.116)	-0.001 (0.043)	0.031 (4.250)
Maximum Weeks of Benefits	-0.068 (2.264)	-0.090 (3.726)	0.012 (1.165)	-0.016 (3.243)
Required Minimum Weeks of Work	-0.416 (8.231)	-0.105 (2.294)	0.069 (3.176)	-0.001 (0.134)
Change in Replacement Rate (April 1993)	1.453 (4.829)	1.256 (8.096)	0.413 (4.266)	0.157 (5.825)
Buse R-squared: 0.998				
Autocorrelation Coefficient:0.5518				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Table 11			
Abolishment of Man in the House Rule			
Dependent Variable: Difference in Welfare Participation Rates*			
Experimental Group: Lone Mothers Control Group: Single Males			
Independent Variable	Same Impact	Different Impact	
Benefits for Singles (\$100)	-14.693 (4.905)	-20.287 (4.020)	-19.652 (4.039)
Benefits for Lone Mothers (\$100)	1.850 (1.573)	4.546 (2.364)	4.176 (2.248)
UI Generosity**	---	-0.776 (2.745)	---
Maximum Weeks of Benefits **	---	---	0.127 (3.517)
Required Minimum Weeks of Work**	---	---	0.167 (2.791)
Change in Replacement Rate (April 1993)**	---	---	0.425 (1.297)
Unemployment Rate**	---	0.160 (3.083)	0.180 (3.541)
Minimum Wage Earnings**	---	1.301 (0.782)	1.293 (0.812)
Policy Change	1.316 (2.659)	0.719 (1.423)	0.608 (1.265)
Buse R-squared	0.961	0.964	0.968
LM Heteroscedasticity	102.613	90.259	95.871
LM Correlation	603.742	422.086	431.653
Autocorrelation Coefficient	0.8047	0.7939	0.7903
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable except for the policy change. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>**Reported coefficients are the difference in the impact of the independent variable on the welfare participation rate of each family type.</p>			

Table 12			
Abolishment of Man in the House Rule			
Dependent Variable: Difference in Welfare Participation Rates*			
Experimental Group: Lone Mothers Control Group: Single Females			
Independent Variable	Same Impact	Different Impact	
Benefits for Singles (\$100)	-14.408 (3.346)	-12.595 (1.507)	-14.734 (1.935)
Benefits for Lone Mothers (\$100)	0.501 (0.301)	0.867 (0.269)	1.581 (0.537)
UI Generosity**	---	-0.729 (3.291)	---
Maximum Weeks of Benefits**	---	---	0.065 (2.075)
Required Minimum Weeks of Work**	---	---	0.127 (2.657)
Change in Replacement Rate (April 1993)**	---	---	1.432 (2.780)
Unemployment Rate**	---	0.226 (5.030)	0.180 (3.985)
Minimum Wage Earnings**	---	-2.172 (0.803)	-1.135 (0.461)
Policy Change	-0.320 (0.446)	-0.829 (1.090)	-0.911 (1.340)
Buse R-squared	0.988	0.99	0.992
LM Heteroscedasticity	40.32	40.738	49.659
LM Correlation	1238.207	839.42	721.106
Autocorrelation Coefficient	0.7031	0.6445	0.6276
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable except for the policy change. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>**Reported coefficients are the difference in the impact of the independent variable on the welfare participation rate of each family type.</p>			

Table 13			
October 1991 Change in Definition of Earned Income			
Dependent Variable: Difference in Welfare Participation Rates*			
Experimental Group: Lone Mothers Control Group: Single Males			
Independent Variable	Same Impact	Different Impact	
Benefits for Singles (\$100)	-10.879 (2.761)	-23.994 (3.338)	-24.191 (3.507)
Benefits for Lone Mothers (\$100)	1.084 (0.975)	5.032 (2.125)	4.773 (2.096)
UI Generosity**	---	0.256 (0.987)	---
Maximum Weeks of Benefits **	---	---	0.079 (2.734)
Required Minimum Weeks of Work**	---	---	-0.010 (0.188)
Change in Replacement Rate (April 1993)**	---	---	0.516 (1.357)
Unemployment Rate**	---	0.099 (1.998)	0.119 (2.374)
Minimum Wage Earnings**	---	3.107 (1.708)	3.181 (1.814)
Policy Change	-0.412 (0.875)	-0.3151 (0.597)	-0.279 (0.545)
Buse R-squared	0.983	0.987	0.988
LM Heteroscedasticity	75.271	95.083	98.783
LM Correlation	483.951	338.722	292.046
Autocorrelation Coefficient	0.6811	0.6629	0.6463
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable except for the policy change. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>**Reported coefficients are the difference in the impact of the independent variable on the welfare participation rate of each family type.</p>			

Table 14 October 1991 Change in Definition of Earned Income Dependent Variable: Difference in Welfare Participation Rates* Experimental Group: Lone Mothers Control Group: Single Females			
Independent Variable	Same Impact	Different Impact	
Benefits for Singles (\$100)	-7.952 (1.434)	-10.480 (1.005)	-14.429 (1.497)
Benefits for Lone Mothers (\$100)	0.680 (0.438)	-0.131 (0.038)	1.200 (0.377)
UI Generosity**	---	0.153 (0.719)	---
Maximum Weeks of Benefits**	---	---	0.061 (2.550)
Required Minimum Weeks of Work**	---	---	0.019 (0.425)
Change in Replacement Rate (April 1993)**	---	---	1.421 (2.718)
Unemployment Rate**	---	0.047 (1.109)	0.057 (1.293)
Minimum Wage Earnings**	---	-1.963 (0.745)	-0.526 (0.215)
Policy Change	0.150 (0.224)	-0.109 (0.142)	-0.056 (0.078)
Buse R-squared	0.989	0.991	0.992
LM Heteroscedasticity	63.533	106.763	105.909
LM Correlation	1266.439	906.73	737.85
Autocorrelation Coefficient	0.6653	0.6138	0.5746
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable except for the policy change. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>**Reported coefficients are the difference in the impact of the independent variable on the welfare participation rate of each family type.</p>			

Table 15			
October 1991 Change in Definition of Earned Income			
Dependent Variable: Difference in Welfare Participation Rates*			
Experimental Group: Couples with Children Control Group: Single Males			
Independent Variable	Same Impact	Different Impact	
Benefits for Singles (\$100)	-3.798 (2.262)	-7.985 (4.384)	-9.167 (5.165)
Benefits for Lone Mothers (\$100)	0.128 (0.294)	1.238 (2.562)	1.382 (2.938)
UI Generosity**	---	-0.967 (3.704)	---
Maximum Weeks of Benefits**	---	---	0.121 (2.326)
Required Minimum Weeks of Work**	---	---	0.045 (1.463)
Change in Replacement Rate (April 1993)**	---	---	-0.545 (2.135)
Unemployment Rate**	---	-0.003 (0.068)	-0.025 (0.611)
Minimum Wage Earnings**	---	2.949 (3.466)	3.128 (3.704)
Policy Change	0.163 (0.564)	0.040 (0.143)	0.097 (0.344)
Buse R-squared	0.791	0.889	0.899
LM Heteroscedasticity	260.624	226.426	265.093
LM Correlation	521.614	322.261	347.826
Autocorrelation Coefficient	0.6881	0.7684	0.7596
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable except for the policy change. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>**Reported coefficients are the difference in the impact of the independent variable on the welfare participation rate of each family type.</p>			

Table 16			
October 1991 Change in Definition of Earned Income			
Dependent Variable: Difference in Welfare Participation Rates*			
Experimental Group: Couples with Children Control Group: Single Females			
Independent Variable	Same Impact	Different Impact	
Benefits for Singles (\$100)	-1.579 (2.013)	-1.528 (1.471)	1.768 (1.654)
Benefits for Lone Mothers (\$100)	0.072 (0.358)	-0.066 (0.244)	-0.025 (0.091)
UI Generosity**	---	0.225 (1.949)	---
Maximum Weeks of Benefits **	---	---	0.038 (1.638)
Required Minimum Weeks of Work**	---	---	0.005 (0.426)
Change in Replacement Rate (April 1993)**	---	---	-0.138 (0.658)
Unemployment Rate**	---	0.004 (0.243)	0.004 (0.211)
Minimum Wage Earnings**	---	-0.044 (0.091)	0.030 (0.059)
Policy Change	-0.008 (0.057)	0.091 (0.550)	0.075 (0.435)
Buse R-squared	0.735	0.741	0.741
LM Heteroscedasticity	262.788	214.201	246.028
LM Correlation	698.151	532.207	581.47
Autocorrelation Coefficient	0.7427	0.7137	0.7178
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable except for the policy change. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>**Reported coefficients are the difference in the impact of the independent variable on the welfare participation rate of each family type.</p>			

Appendix A: Definition of Demographic Categories in the MCSS Data

There is no one variable which identifies all lone mothers in the MCSS data. We classified as a lone mother any woman who met the criteria provided by either demographic characteristics or case classification. Our demographic criteria for lone motherhood is that the client be unmarried (registered or common-law) and have one or more dependents under the age of 22. The case classification criteria for lone motherhood are different for FBA and GWA. An FBA client is classified as a lone mother if she is classified as “single parent”. A GWA client is classified as a lone mother if her classification is “lack of principal family provider” and she has one or more dependents under age 22. (NB The MCSS data only tell us the number of dependents under the age of 22.) One must have a dependent under age 22 to be classified as an FBA “sole support parent”. Such is not the case with a GWA client who “lacks a principal family provider” and, hence, we added the criterion of “has one or more dependents under age 22” to the latter.

The above two sets of criteria for lone motherhood were used because each has a drawback. The drawback of the demographic criteria is that some women who are effectively lone parents may also still be legally married as is found in other data sources, such as the Survey of Consumer Finances. The shortcoming of case classification criteria is that some GWA lone mothers may be listed under classifications other than “lack of principal family provider”, e.g, “unable to find

employment”. For this reason, we classified as a lone mother any client who met either criteria (demographic or case classification) during any month of the spell.

Demographic criteria alone were used to define singles and couples with children because, unlike single parents, there is no case classification for these family types. A single female or male is defined as any client who is unmarried and has no dependents under the age of 22. Couples with children are married, either registered or common-law, and have at least one dependent under the age of 22. Not that we also excluded from our sample all persons who were either “nonemployable” (due to disability, poor health or old age) or in a special category (supplementary aid, special assistance or handicapped or foster children).

We used census data in order to construct the welfare participation rates as discussed in Section III. Unlike our MCSS definition, the census definition of a lone mother family and a couple with children does not require that there be children under age 22, i.e., the presence of a never married child of any age qualifies the family as “lone parent” or “couple with children”. The census category used in the welfare participation rate for single men and women was the total number of non-family persons by sex.

Appendix B : Tables with Employment Population Ratio

Table 1b				
GLS Regression				
Dependent Variable: Welfare Participation Rate for Lone Mothers*				
	Lag Structure			
Independent Variable	Separate**	12	Separate**	12
Benefit Levels (\$100) (12 lags)	-2.009 (1.902)	-1.868 (1.870)	-2.103 (2.285)	-1.867 (2.183)
Minimum Wage (\$100) (12 lags)	-2.990 (1.867)	-2.494 (1.716)	-2.785 (2.084)	-1.951 (1.589)
Employment Population Ratio(%) (12 lags)	-0.134 (3.123)	-0.075 (1.607)	-0.125 (3.249)	-0.074 (1.718)
UI Generosity ((Max/Min)*RR) (7 lags)	-0.023 (0.103)	0.634 (1.704)	---	---
Maximum Weeks Of Benefits (7 lags)	---	--	0.005 (0.185)	-0.074 (1.604)
Required Minimum Weeks of Work (7 lags)	---	---	-0.025 (0.542)	-0.189 (2.359)
Change in Replacement Rate (April 1993)	---	---	1.721 (3.659)	1.616 (3.689)
LM Heteroscedasticity	20.141	15.357	37.161	26.782
LM Correlation	1242.274	1093.44	1064.736	902.711
Autocorrelation Coefficient	0.6434	0.6369	0.5693	0.547
Buse R-squared	0.992	0.993	0.994	0.995
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>				

Table 2b						
GLS Regression						
Dependent Variable: Welfare Participation Rate for Single Males*						
	Lag Structure					
Independent Variable	Sep**	11	12	Sep**	11	12
Benefit Levels (\$100) (9 lags)	0.811 (0.83)	1.243 (1.18)	1.821 (1.69)	1.654 (2.91)	2.208 (2.33)	2.593 (2.74)
Minimum Wage (\$100) (8 lags)	-0.946 (1.41)	-1.382 (1.79)	-1.313 (1.63)	-0.780 (1.22)	-1.388 (1.89)	-1.136 (1.57)
Employment Population Ratio(%) (8 lags)	0.067 (1.87)	0.076 (1.74)	0.096 (2.11)	0.094 (2.95)	0.121 (3.15)	0.158 (4.02)
UI Generosity ((Max/Min)*RR) (10 lags)	2.027 (6.21)	1.987 (5.60)	2.125 (5.63)	---	---	---
Maximum Weeks Of Benefits (10 lags)	---	---	--	-0.192 (5.10)	-0.230 (5.22)	-0.221 (4.64)
Required Minimum Weeks of Work (10lags)	---	---	---	-0.437 (6.80)	-0.486 (6.98)	-0.530 (7.23)
Change in Replacement Rate (April 1993)	---	---	---	0.706 (2.44)	0.578 (2.28)	0.630 (2.38)
LM Heteroscedasticity	238	238.7	218.9	318.9	311.4	282.6
LM Correlation	339.2	275.7	284.3	297.2	236.9	240.6
Autocorrelation Coefficient	0.741	0.745	0.727	0.714	0.724	0.695
Buse R-squared	0.928	0.936	0.939	0.946	0.954	0.959
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>						

Table 3b				
GLS Regression				
Dependent Variable: Welfare Participation Rate for Single Females*				
	Lag Structure			
Independent Variable	Separate**	12	Separate**	12
Benefit Levels (\$100) (Lags 3)	0.325 (1.081)	1.654 (2.908)	0.417 (1.394)	1.701 (3.266)
Minimum Wage (\$100) (Lags 0)	0.307 (2.911)	0.282 (0.658)	0.296 (2.738)	0.344 (0.875)
Employment Population Ratio(%) (10 lags)	0.062 (3.984)	0.071 (3.832)	0.057 (3.792)	0.078 (4.257)
UI Generosity ((Max/Min)*RR) (12 lags)	0.758 (5.285)	0.739 (4.735)	---	---
Maximum Weeks Of Benefits (12 lags)	---	--	-0.021 (1.051)	-0.044 (1.867)
Required Minimum Weeks of Work (12 lags)	---	---	-0.129 (4.232)	-0.163 (4.930)
Change in Replacement Rate (April 1993)	---	---	0.132 (0.967)	0.179 (1.226)
LM Heteroscedasticity	234.305	266.974	279.427	319.059
LM Correlation	673.775	427.883	624.933	379.736
Autocorrelation Coefficient	0.7539	0.7158	0.7353	0.7181
Buse R-squared	0.886	0.887	0.887	0.902
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>				

Table 4b
GLS Regression
Dependent Variable: Welfare Participation Rate
for Couples with Children*

Independent Variable	Lag Structure			
	Separate**	12	Separate**	12
Benefit Levels (\$100) (8 lags)	-0.159 (5.264)	-0.159 (4.916)	-0.168 (6.239)	-0.178 (6.042)
Minimum Wage (\$100) (12 lags)	-0.252 (2.511)	-0.215 (2.117)	-0.216 (2.454)	-0.180 (1.993)
Employment Population Ratio(%) (11 lags)	0.012 (1.876)	0.012 (1.887)	0.015 (2.371)	0.016 (2.523)
UI Generosity ((Max/Min)*RR) (11 lags)	0.062 (1.102)	0.059 (0.996)	---	---
Maximum Weeks Of Benefits (11 lags)	---	--	-0.012 (1.517)	-0.012 (1.461)
Required Minimum Weeks of Work (11 lags)	---	---	-0.010 (0.778)	-0.012 (0.869)
Change in Replacement Rate (April 1993)	---	---	0.107 (2.905)	0.119 (3.192)
LM Heteroscedasticity	108.616	107.756	106.283	102.801
LM Correlation	277.854	277.452	241.746	239.293
Autocorrelation Coefficient	0.6569	0.6515	0.6215	0.6098
Buse R-squared	0.98	0.981	0.987	0.988
<p>*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 738.</p> <p>** Each independent variable has its own number of lags in this lag structure. The number of lags for each independent variable is in brackets by the variable name.</p>				

Table 5b.
Seemingly Unrelated Regression
Dependent Variable: Welfare Participation Rate*
All independent variables lagged 12 months

Independent Variable	Family Type			
	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-0.039 (0.076)	1.721 (1.789)	-0.038 (0.068)	-0.160 (5.398)
Minimum Wage Earnings (\$100)	-1.995 (2.316)	-0.419 (0.912)	0.129 (0.535)	-0.289 (3.495)
Employment Population Ratio	-0.145 (5.124)	0.094 (3.048)	0.080 (5.961)	-0.005 (0.782)
UI Generosity	1.752 (7.521)	0.830 (3.780)	0.122 (1.289)	0.011 (0.261)
Buse R-squared:0.998				
Autocorrelation Coefficient:0.6135				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Table 6b.				
Seemingly Unrelated Regression				
Dependent Variable: Welfare Participation Rate*				
All independent variables lagged 11 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-1.307 (2.802)	1.939 (2.269)	0.141 (0.255)	-0.169 (5.741)
Minimum Wage Earnings (\$100)	-2.784 (3.112)	-1.164 (2.663)	-0.001 (0.004)	-0.366 (4.479)
Employment Population Ratio	-0.079 (2.951)	0.065 (2.294)	0.060 (4.849)	-0.005 (0.921)
UI Generosity	2.147 (9.681)	0.924 (4.754)	-0.036 (0.423)	0.080 (2.017)
Buse R-squared:0.997				
Autocorrelation Coefficient:0.6141				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Table 7b.				
Seemingly Unrelated Regression				
Dependent Variable: Welfare Participation Rate*				
All independent variables lagged 12 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-0.830 (1.754)	1.200 (1.385)	-0.073 (0.133)	-0.142 (5.361)
Minimum Wage Earnings(\$100)	-1.782 (2.336)	-0.209 (0.547)	0.213 (0.948)	-0.248 (3.451)
Employment Population Ratio	-0.109 (3.972)	0.133 (4.585)	0.086 (6.477)	-0.008 (1.279)
Maximum Weeks of Benefits	-0.119 (3.754)	-0.059 (2.122)	0.012 (0.949)	-0.020 (3.764)
Required Minimum Weeks of Work	-0.431 (8.262)	-0.123 (2.448)	0.018 (0.799)	-0.007 (0.733)
Change in Replacement Rate (April 1993)	1.471 (5.134)	1.201 (7.681)	0.356 (4.166)	0.148 (5.697)
Buse R-Squared:0.998				
Autocorrelation Coefficient:0.5546				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Table 8b.				
Seemingly Unrelated Regression				
Dependent Variable: Welfare Participation Rate*				
All independent variables lagged 11 months				
	Family Type			
Independent Variable	Lone Mothers	Single Males	Single Females	Couples with Children
Benefit Level (\$100)	-2.112 (4.640)	1.730 (2.046)	0.576 (1.013)	-0.154 (5.385)
Minimum Wage Earnings(\$100)	-2.469 (3.114)	-0.887 (2.365)	-0.027 (0.123)	-0.315 (4.112)
Employment Population Ratio	-0.047 (1.724)	0.096 (3.658)	0.071 (5.899)	-0.010 (1.648)
Maximum Weeks of Benefits	-0.079 (2.563)	-0.092 (3.718)	0.008 (0.7442)	-0.016 (3.100)
Required Minimum Weeks of Work	-0.380 (7.551)	-0.149 (3.317)	0.044 (2.136)	-0.009 (0.946)
Change in Replacement Rate (April 1993)	1.604 (5.174)	1.196 (7.432)	0.386 (4.106)	0.147 (5.252)
Buse R-squared:0.998				
Autocorrelation Coefficient:0.5453				
*Reported coefficients are the sums of the current and lagged coefficients of each independent variable. Reported t-statistics, in brackets, are for the reported coefficient. Sample size is 2952.				

Chapter 5

Conclusion

The first essay in this thesis examined the impact of health status on the duration of unemployment spells. Past research has examined the impact of unemployment of health status by comparing the mortality rates between individuals who were unemployed at a point in time to those who were employed. These studies could suffer from a type of selection bias if individuals who are unemployed at a point in time are also more likely to have impaired health. If this selection bias were present then we would expect the unemployed to have a higher mortality rate than the employed even if employment status does not have an impact on health status. One reason for the stock of the unemployed to be composed of more individuals with impaired health than the stock of the employed is if individuals with impaired health status have longer unemployment spells. It is this possible reason that we explored in the first essay.

After controlling for various personal characteristics, the results show that individuals with impaired health have a significantly lower probability of leaving unemployment and, therefore, significantly longer unemployment spells than

individuals without impaired health. These longer unemployment spells in turn imply that individuals with impaired health will comprise a larger proportion of the stock of the unemployed than they do of the stock of employed. The results from this paper indicate that estimates of the impact of unemployment on health status are overestimates and future research has to be aware of this selection problem.

The second essay in this thesis examines the use of the social assistance system by lone mothers in Ontario from 1990 to 1994. We are interested in both how long lone mothers remain on welfare and, if they do leave welfare, how long until they return. We examined the distribution of the spells and the relationship between personal characteristics and program parameters and the length of these spells. We are also interested in determining if there is a “welfare trap” or in other words do we observe negative duration dependence. Do lone mothers find it more difficult to leave welfare the longer they have been receiving benefits? We estimate the baseline hazard in order to determine if the probability of leaving welfare decreases as the spell length increases. Complicating the issue of negative duration dependence is the possibility of unobserved heterogeneity. If we do observe a decreasing hazard after controlling for the observed covariates then the decreasing hazard may only be due to covariates we do not observe. In order to account for the presence of unobserved heterogeneity we attempt to take explicit account of it in our estimation.

Our examination reveals considerable variation in the length of both welfare and off-welfare spells. A significant portion of the sample has very short welfare spells and may be repeat users, yet another portion is composed of long-term continuous users. We estimate the impact of personal characteristics and policy parameters on the duration of welfare and off-welfare spells. Our results are generally as expected. Younger, never married lone mothers with children are more likely to remain on welfare and more likely to return. We also found the expected results for policy parameters and labour market conditions. Higher benefit levels and unemployment rates are associated with a lower probability of leaving welfare and a higher probability of returning to welfare. Higher minimum wages are associated with a higher probability of leaving welfare and a lower probability of returning to welfare.

Our estimated baseline hazards indicate that negative duration dependence is present in our sample for both types of spells. For welfare spells, however, the estimated baseline hazard becomes flatter as we control for unobserved heterogeneity and include information on education levels. Future studies with more complete information on individuals may find that in fact the baseline hazard is flat and negative duration dependence is not a problem for welfare spells. Our results indicate that there may be identifiable groups of long-term users towards whom policies could be directed. Also, we have strong evidence that once an individual is off welfare there

is a decreasing probability of returning.

The third essay examines the welfare participation rate for four family types in Ontario from 1983 to 1994. During this period, Ontario had a dramatic increase in both the caseload and benefit levels, which together led to a quadrupling of expenditures on social assistance. We are interested in examining the impact of benefit levels, minimum wage levels, the unemployment rate, and the UI system on the welfare participation rates. We have divided our data into nine regions and used cross-sectional time-series analysis to estimate the impact of the independent variables.

Our first conclusion is that the family types react differently to changes in the independent variables. Single males and females have the predicted positive coefficients on benefit levels indicating that increases in benefit levels result in an increase in welfare participation rate. In contrast, lone mothers and couples with children have negative coefficients. Lone mothers and single males have the expected positive coefficient for the unemployment rate while single females and couples with children have a negative coefficient, although not statistically significant. The impact of the minimum wage is more consistent between the family types. Except for single females, the minimum wage has a negative coefficient.

The impact of the UI system was more complicated than the other variables.

There are several aspects of the UI system that could have an impact on the welfare participation rate. We looked at the minimum required weeks of work to be eligible for UI, the maximum weeks of UI benefits, and the replacement rate. We find that the decrease in the replacement rate in April 1993 is associated with an increase in the welfare participation rate for all family types, although not statistically significant for single females. An increase in the weeks of benefits is associated with lower welfare participation rates for all family types, although not always statistically significant. The minimum required weeks of work is also associated with a decrease in the welfare participation rate for all family types. Generally, we would expect that as the required minimum weeks increased fewer individuals would be eligible for UI and then would need to use welfare.

Our second conclusion is that the policy changes we examined in the quasi-natural experiment approach did not have differential impacts on the family types. We looked at the abolishment of the man in the house rule, which we would expect to only have an impact on lone mothers. We also looked at the October 1991 change in the definition of earned income. Childcare costs could now be deducted in full from earned income and so we would expect that families with children would respond differently to this change than singles. In each case we do not find strong evidence to support our expectations.

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