WAGE CHANGES, INDUSTRIAL MOBILITY AND DURATION OF UNEMPLOYMENT OF DISPLACED WORKERS

Evidence from Canadian Microdata

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ABSTRACT

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A major source of job displacement is economic fluctuations at the industry (sector) level. Faced with industrial change, workers are assumed to make a rational decision whether to move to another industry or to stay where they are. In this study, the decision to move or stay is endogeneously generated. This is a departure from similar studies in the area which regard moving to a new industry or staying to be a random event. Besides following the approaches suggested by human capital and search theories, we also take into account factors which are specific to the Canadian economy. These factors weaken the results found in other studies. Using the cross-sectional files of the Labour Market Activity Survey (LMAS) data from 1986 to 1990 and employing the full information two-step maximum-likelihood procedure, it is found that there is no tendency for human capital to erode with the time spent out of work. This is especially true of the movers and is generally attributed to strong unionization and a generous income safety-net system in Canada. It is also found that those who move to a new industry on average improve their wage.

In the literature, it is recognized that long-term spells of unemployment play a major part in increasing unemployment rates. It is also true that a portion of long-term unemployed workers eventually quit the labour force. Yet, studies of duration of unemployment that incorporate these facts into the design of their models are rare. In this study, these facts are incorporated into the split population duration model. In so doing, the model is able to produce individual predictions of returning to work. These predictions are potentially useful to policy makers in designing programs to improve the prospect of long-term unemployed workers. The 1986 - 1987 LMAS longitudinal file is used in this part of the thesis. Other results generally accord with those reported by Corak (1990) and Rahman-Gera (1991).

TABLE OF CONTENTS

ACKNOLEDGMENTS ii

LIST OF TABLES vi

CHAPTER

I. INTRODUCTION 1

II. THE LMAS DATA 9

III. WAGE CHANGES AND INDUSTRIAL MOBILITY OF DISPLACED WORKERS 17

Econometric Specifications 24
Empirical Results and Analysis 33
Conclusion 56

IV. PREDICTING THE PROBABILITY OF RETURNING TO WORK USING SPLIT POPULATION DURATION MODEL 61

Model Specification 64
The Validation Sample 70
Empirical Results and Analysis 71
Checking the Models' Specification and Predictive Power 87
Conclusion 96

V. SUMMARY AND CONCLUDING REMARKS 98

APPENDIX 103

REFERENCES 120

LIST OF TABLES

Table		page
2.1	Canadian Male Workers, 1986 - 1990	12
3.1	The Treatment Effects Models	34
3.2	Maximum-likelihood Ratio Test	35
3.3	Estimates of the Decision Function (Mover - Stayer Model)	35
3.4	Wage Equation Estimates for the Movers	47
3.5	Wage Equation Estimates for the Stayers	48
3.6	Simultaneous Equation Estimates of Wage Growth and Duration of Unemployment for the Movers	52
3.7	Simultaneous Equation Estimates of Wage Growth and Duration of Unemployment for the Stayers	54
4.1	Labour Force Status in 1985 of Those Unemployed 12 Months Earlier	65
4.2	Split Lognormal - Probit Model	75
4.3	Split Lognormal - Logit Model	76
4.4	Split Logistic - Probit Model	77
4.5	Split Logistic - Logit Model	79
4.6	Probit Estimates for the Probability of Returning to Work Using the Validation Sample	84
4.7	Individual Predictions of the Probability of Returning to Work Using the Validation Sample	89
4.8	Estimates of Split Lognormal - Logit Model (Whole Population)	91
4.9	Estimates of Logistic Duration Model with a Censoring Variable (Whole Population)	93

CHAPTER I

INTRODUCTION

The unemployment rate is one of the most closely watched economic indicators. Its persistence at a high level in the past two decades in many industrial countries has challenged economists to offer explanations. Among the few widely discussed theories is the sectoral shifts hypothesis (Lilien, 1983) which argues that periods of greater dispersion in the rate of unemployment growth across sectors are associated with periods of high unemployment rates. Particular events that support this theory are the decline of the US manufacturing industry due to foreign competition and the oil price shock in the 70's, coupled with a high rate of growth in the finance and service industries. An alternative hypothesis is the standard aggregate-demand-driven business cycle theory (Abraham - Katz, 1986 and Topel - Weiss, 1985) which argues that aggregate demand shocks that hit sectors which have different cyclical sensitivity will yield the same results.

Understanding the sources of industrial fluctuations is of importance for the design of macro-economic stabilization policies. At the micro level, changes in industrial composition of economic activity, whether economy-wide or sector-specific, pose a considerable challenge to workers, because changes in industrial composition also involve changes in the composition of employment among industries or sectors of the economy. The challenge for workers is not only to get a new job quickly, but also, as far as possible, not to move to a lower wage. Thus, these industrial shifts carry two possible costs to workers, namely, a spell of unemployment and a decline in wages.

Except when the demand spillover effect is high, mobility of workers is required for a smooth labour market adjustment process. The speed of the adjustment process is of special concern for policy makers. If the pace of labour reallocation from declining industries to expanding industries is fast, the industrial fluctuations mentioned above create little or no unemployment. But if the pace of adjustment is slow, unemployment will increase. The fact that industrial mobility is not automatic and often is very slow, raises the need for studies in this area. What factors induce or discourage workers to move to another industry?

Discouraging results about the long-term cost of displacement in term of wage loss are found in Ruhm (1991) and Jacobson et al. (1993). Using the Panel Study of Income Dynamics (PSID) data Ruhm found that four years after displacement, job losers continue to earn 10% to 13% less than their non-displaced counterparts; while Jacobson et al., using the Pennsylvania data, conclude that high tenure displaced workers suffer a long-term loss averaging 25% per year.

To date, there has not been any long-term wage loss study using Canadian data. The data sets used in existing surveys, including the one used here, are lacking in workers' earnings histories. However, a quick comparison between the US labour experience as shown in Ruhm (1991) and in Jacobson et al. (1993) with that of Canada indicates that a long-term assessment of the displacement effect is less urgent in the Canadian case. Looking at the short term, before and after displacement with some intervening unemployment spell, the US quarterly wage on average dropped by more than 20% (see figure 1 in Jacobson et al., 1993), while in Canada in 4 out of the 5 years of cross-sectional samples used, on average the workers experience a wage gain (see Table 1 in the next chapter). This raises the possibility that there is a greater portion of those who were displaced getting a higher wage after displacement. It may also indicate that searching while unemployed is more efficient and hence that looking at the relationship between wage growth and unemployment duration might be important.

The purpose of the first part of this thesis is to contribute to existing studies of short-term wage change. Initiated by Mincer-Javanovic (1981), previous studies in this area have focused on job mobility (inter-firm mobility) and its impact on wages. Examples in this group are: Osberg et al. (1986), Simpson (1990) and Kidd (1991). To these authors, a worker moves to a new job if he or she changes employer. The wage of those who do not leave their job (defined as 'stayers') is used as a basis for comparison. Thus, the wage gain or loss of the movers is the opportunity cost if they had never moved to a new job. This approach may suffer from sample selection bias if there are inherent differences between stayers (in the above context) and movers, e.g.: the skill level of the stayers may be higher than that of the movers, especially if they are displaced. Jacobson et al. (1993) try to correct this bias by introducing a worker-specific time trend in their least squares regression, while Abbott - Beach (1994) do this by creating a proxy for the next period movers to be.

It is also common practice to apply the Heckman two-stage method to data on workers whose jobs are terminated voluntarily (job quitters) and those whose job are terminated involuntarily (job losers). The basic idea behind the Heckman two-stage method is that we have data which are generated by individuals making choices of belonging to one group or another (i.e. by individual self selection). However, in the inter-firm (job) mobility context, this idea does not seem to fit the situation faced by the job losers, because for them there is only one choice: to leave the firm that displaced them.

By focusing on inter-industry mobility, both of the above errors can be avoided. Another important issue raised by the shifts in industrial composition briefly outlined earlier is: who would account for the major part of the increase of the unemployment rates? would it be the stayers, who having lost their job, find a new job in the same industry? Or, would it be the movers, who, having lost their job, find a new job in another industry? In our discussion about wages, we would also normally want to know: who has the higher wage loss? would it be the stayers or the movers?

On a theoretical level, there are two opposite forces which play an important role in determining the outcome of job change. First, if we assume that individuals invest in search and that job change represents a response to perceived gains from job mobility, then we would expect that such investment will yield a positive return. However, individuals who change jobs forgo the return from any accumulated job-specific human capital. In the case of employee initiated job terminations, it is rational to expect that, in general, the first force dominates. However, this study examines displaced workers; and so the outcome is still an empirical issue. A priori, without other factors involved, job change plus industry change should strengthen the second force more than job change without industry change.

So far there has not been any empirical work combining wage change or wage growth with industrial mobility using Canadian data. The closest comparison that can be made is with the Addison - Portugal (1989) work using US data. The US and Canadian economies are comparable in many ways, but two factors which are very different in Canada may weaken or perhaps overturn some results found in the Addison - Portugal work. These factors are the unionization rate and the Unemployment Insurance (UI) program. Since the mid - 1980's, the unionization rate in Canada has been twice as high as that of the US and the length of UI benefit eligibility in Canada has also been almost twice the length of that in the US. Both factors are considered to increase distortions (departure from efficiency), though both naturally reduce income inequality. We suspect that both may indirectly affect the strength of the effect of past tenure and unemployment spell on wage growth.

Briefly, the research reported in Chapter III takes industrial mobility instead of job mobility as the driving force of the models. Throughout the models used, our assumption is that, faced with industrial changes, workers make a rational decision whether to move to a new industry or stay in their previous industry. Further, besides following the approaches suggested by human capital and search theories, in designing our wage equations we also take into account factors which are specific to the Canadian economy. We suspect that these factors will weaken the results found in other studies. Thus, the questions addressed here are:

1. What factors determine whether a displaced worker will move to a new industry?

2. What factors contribute to the wage gain or loss, taking into account the possibility that the decision to move or stay and the wage gain or loss are interrelated?
3. How does the behaviour under 1. and 2. change as the economy changes?
4. Are movers the gainers or the losers?

If the decision to move or stay in an industry is endogeneous, the full information two - step maximum likelihood model that we use will produce more reliable results than separate regressions and a probit model. As has been mentioned before, duration of unemployment is potentially endogeneous and may be correlated to the wage functions that we specify. To check if this problem exists, simultaneous equations with a selectivity model are used. To answer question number 4 above, while again assuming that the decision to move or stay in an industry is endogeneous, requires a model called the treatment effects model.

Long-term unemployed workers contribute more and more to the lengthening of unemployment rates in Canada (Corak, 1990; Gera - Rahman, 1991). Yet, due to the cross-sectional nature of the data sets used in the existing studies of unemployment duration, a lot of observations on truly long - term unemployment spells are censored at the end of survey dates. To track down these really long spells, at least a two - year observation period is needed. Some of these long unemployment spells have not in fact ended, even at the end of a two - year observation period. It is possible that the workers concerned do not return to work at all simply because they become discouraged. Existing studies of unemployment duration seem to miss this potentially important fact.

Using the 1986 - 1987 LMAS longitudinal file, the last mentioned problem will be dealt with in Chapter IV. Besides looking at factors that affect the hazard rate and duration of unemployment, this part of the research also tries to determine the probability of not returning to work and the determinants of this probability.

CHAPTER II

THE LMAS DATA

The LMAS (Labour Market Activity Survey) was carried out by Statistics Canada at the request of Employment and Immigration Canada. The purpose is to collect information about the patterns of work and types of jobs held during a specified period , as a supplement to Statistics Canada's Labour Force Survey.

Statistics Canada has interviewed two groups of people. The first group was followed from 1986 to 1987, the second group was followed from 1988 to 1990. The LMAS records as many as five jobs that have been held and the activities between jobs of a representative sample of Canadian residents aged 16 to 69. Compared to the Displaced Worker Survey (DWS) used by Addison-Portugal (1989), the LMAS is equally large and nationally representative microdata set. However, the LMAS does better in term of reducing recall bias because the interview was held in the end of one-year-period instead of five-year-period as in DWS. Beside that, in the event of more than one displacement, the DWS data refer to the job with longest duration and although continuous duration data are supplied for those whose jobless spells were still in progress, but they are only up to 99 weeks.

The data set is available in both cross-sectional files for each year 1986 to 1990 and in longitudinal files from 1986 to 1987 and from 1988 to 1990. The first part of the research (Chapter III) uses the cross-sectional files from 1986 to 1990. The second part (Chapter IV) uses the 1986 to 1987 longitudinal file.

The respondents who work are divided into six classes. Among these, only paid male workers are included in the five year cross-sectional samples used in Chapter III. The analysis in Chapter IV uses both male and female paid workers. Both cover only movement from the first job to the second job. Further, the LMAS records 52 two-digit industries and 49 occupations. Table 2.1 gives a brief description of the samples used in Chapter III.

Line 2 in Table 2.1 shows that the Canadian labour market has exhibited a substantial amount of change. About a quarter of male workers left their job each year. This figure does not markedly change during the declining years of 1989 - 1990. Surprisingly from 1986 to 1990, among those who leave their jobs, the percentage of job losers is highest in 1986 (a 'normal' year). How mobile are these workers? From the total of those who find jobs after leaving their previous jobs, as well as from smaller samples used in the models, well over 60% of job changers move to an industry different from their previous industry. 1988 is an exception, only about 50% of job changers move. The ratio of the workers who move to a new industry to total male workers who have at least one job in the year of observation, expressed as a percentage, is around 9% (line 4.2). These figures are roughly comparable to those used in Murphy - Topel (1987, see their Table 11). The highest figure in Murphy - Topel is the percentage in 1974 which is 10.71%, the lowest is in 1985 which is 7.62%. From line 4.2, in the 1990 recessionary period, the percentage goes down slightly, yet it is still higher than the percentage in 1988.

Along with a marked decrease in mobility in 1988, in the same year, there is a jump in the percentage of workers who reported losing their jobs due to non-seasonal economic or business conditions and the company going out of business (line 12 and 12.1). The economy as a whole was at its peak of growth during the 1988 - 1990 period. The growth rate of GDP was 5% in 1988, declined to only 2.3% in 1989, and fell below zero in 1990. Apparently, workers' perceptions of how the economy was performing in 1988 were worse than the national picture, and it is not clear what the sharp decline in industrial mobility In 1988 has to do with this. Topel (1988) thinks that the two are correlated. His argument is that when a demand shock first hits a sector, the unemployed workers will first wait (not try to search for alternative employment in other sectors) to see if the shock is merely temporary. Then, they will actively search in new sectors, if they perceive that the shock is permanent. From 1989 onward the mobility rates move back to prior to the 1988 figure (above 60%) indicating the probability that the workers already perceived that the shock was permanent.

Table 2.1

Canadian Male Workers, 1986 - 1990

	1986	1987	1988	1989	1990
1. # Male workers	32761	38039	31315	31230	30924
2. # Leaving jobs	8507	8997	8328	8280	7502
%	25.9	23.6	26.6	26.5	24.2
3. # Job losers	4262	3784	3384	3421	3163
%	50.1	42.1	40.6	41.4	42.1
4.1 % Moving [a]	64.7	63.3	49.6	63.6	61.1
4.2 % Moving [b]	9.4	9.6	8.6	10.5	9.0
5. # Obs. used [c]	945	931	741	682	591
5.1 Mean duration	10.35	10.80	10.46	10.23	10.45
5.2 Mean Wg. growth	- 0.013	0.042	0.013	0.032	0.032
5.3 % Moving	69.3	69.8	50.7	71.1	66.0
6. Mean dur., movers	10.51	10.80	10.46	10.23	10.44
7. Mean dur., stayers	10.01	10.07	9.58	9.50	10.24
8. Mean Wg.gr., movers	- 0.031	0.039	0.018	0.020	0.033
9. Mean Wg.gr., stayers	0.027	0.047	0.007	0.061	- 0.028
10. # Wg. increase	410	444	372	355	271
10.1 Mean Wg.gr.	0.33	0.35	0.33	0.33	0.35
11. # Wg. decrease	380	331	280	269	245
11.1 Mean Wg.gr.	- 0.39	- 0.36	- 0.39	- 0.33	- 0.36
12. % Loose job due to reason 22 & 23 [d]	11.2	12.8	17.2	18.5	21.5
12.1 % from 2	26.2	32.8	55.3	55.5	63.6
12.2 Mean dur.	11.58	11.12	10.45	10.34	10.69
12.3 Mean Wg.gr.	- 0.085	0.014	0.0007	0.027	0.007
13. # Censored Obs.	4367	3960	3616	3881	3606
%	51.3	44.01	43.4	46.8	48.06

Table 2.1 (continued)

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a) Percentage from all workers who find jobs
b) Percentage from all workers who have at least 1 job
c) Number of observations used in the samples = # male, paid worker, job loser - # workers whose unemployment spells are zero - # workers whose second job started before their first job ended but recorded to have positive duration of unemployment
d) Reason 22 is 'non-seasonal economic or business conditions'; reason 23 is 'company going out of business'

\# = number of

Wg. gr. = Wage growth

There is some interest in comparing lines 6 and 7 of Table 2.1. In each of the five years, the mean unemployment duration of industry movers is always higher than the mean unemployment duration of stayers. From line 8 and 9, the mean growth rate of the wage of the movers is higher in 1988 and 1990 than in other years.

From line 10 and 11, the number of workers experiencing positive wage growth is higher than the reverse. It is surprising to see how large the wage growth or wage decrease is when the workers are grouped separately into those who experience wage growth and those who experience wage loss. The mean wage loss or wage growth is above 30%.

The variables used in the models are as follows:

DWG : Wage growth rate = log (post-displacement wage) - log (pre-displacement wage)

GPI1 : Average industry product growth rate in the past two years for job 1 industry

GPI2	: The same as GPI1, but for job 2 industry. GPI1 and GPI2 variables are not from the LMAS file.
DGPI	: GPI2 - GPI1
LDUR	: Log (duration); unemployment duration = absolute number of days unemployed divided by 7.
Ltenure1	: Log (tenure job 1)
Ltenure 2	: Log (tenure job 2)
DHW	: Dummy for high wage. Wage > average wage = 1, otherwise = 0
DMF	: Dummy, manufacturing sector = 1, otherwise = 0
DBlCl	: Dummy, Blue collar workers = 1, otherwise = 0
DTR	: Dummy, workers ever participate in any training program held by federal or local government = 1, otherwise = 0
DAG1	: Dummy, age group 16 - 19 = 1, otherwise = 0
DAG2	: Dummy, age group 20 - 34 = 1, otherwise = 0
DAG3	: Dummy, age group 35 - 44 = 1, otherwise = 0 Default : age group above 44
DED1	: Dummy, high school degree or less = 1, otherwise = 0
DED2	: Dummy, Post Secondary / Diploma = 1, otherwise = 0 Default : university degree
DUN1	: Dummy, Union members and those whose wages are covered by wage agreement = 1, otherwise =0
DUN2	: Dummy, the same as DUN1 but for job 2

DUNI1 : Dummy, change in union status, from union member to non union member = 1, otherwise = 0

DUNI2 : Dummy, change in union status, from non union member to union member = 1, otherwise = 0

Default : union status does not change

DFIRM1 : Dummy, firm size (20 - 99) = 1, otherwise = 0

DFIRM2 : Dummy, firm size (100 - 499) = 1, otherwise = 0

DFIRM3 : Dummy, firm size (500 and over) = 1, otherwise = 0

Default : firm size < 20

DFZ1 : Dummy, change in firm size < 100 to firm size 100 and above = 1, otherwise = 0

DFZ2 : Dummy, change in firm size 100 and over to firm size < 100 = 1, otherwise = 0

Default = firm size category does not change

DOC : Dummy, change in occupation = 1, otherwise = 0

The model in chapter IV uses data on both males and females from the 1986 - 1987 longitudinal file. The total number of observations is 63,432. From this figure, 12,888 workers leave their first job. 5,753 of these job leavers had their jobs terminated involuntarily. This figure includes 1,473 workers who found a new job in 1986 (those whose second job started before the first job ends are excluded from this figure). As mentioned before, the LMAS records up to 5 jobs in a year. Upon an examination of the data, some jobs were not recorded in sequence. Because of these problems, some observations have to be eliminated. To select the workers who found a new job in 1987 it is necessary to match the stopping date of job 1 in 1986 with the starting date of unemployment duration before job 1 in 1987. From this we have 1,042 workers who left their first job in 1986 and found a new job in 1987. Next, 744 workers who left their first job in 1986 did not have any job at all in 1987. In sum, the total number of these three categories (workers displaced in 1986 who found a new job in the same year, workers displaced in 1986 who found a new job in 1987 and workers displaced in 1986 who did not have any job until the end of 1987) is 3,259. After eliminating those who have no unemployment spell, there are 2,835 observations.

CHAPTER III

WAGE CHANGES AND INDUSTRIAL MOBILITY OF DISPLACED WORKERS

More and more studies of the effect of job displacement on earnings are based on human capital and search theories. A good example is the wage equation in Addison-Portugal (1989). Here the coefficient on tenure in the previous job is given a new interpretation.

The Addison-Portugal wage growth equation is

$$\text{Ln } W_{ij} - \text{Ln } W_{ij-1} = (\alpha_j + \beta_j)\, \text{Tenure}_{ij} - \beta_{j-1}\, \text{Tenure}_{ij-1} + \gamma_j\, \text{SLU}_{ij} + (X_{ij} - X_{ij-1})\, \Omega + (\mu_{ij} - \mu_{ij-1});$$

$i = 1, 2, \ldots\ldots\ldots N$

j refers to the number of jobs

α_j is the transferable, general training component of the return to tenure for the j'th job.

β_j is the nontransferable, specific training component for the j'th job.

SLU_{ij} is the i'th observation's completed spell length of unemployment after displacement.

μ_{ij} is a disturbance term.

X_{ij} is a vector of other exogenous variables and Ω is its corresponding vector of coefficients (see Addison-Portugal, 1989, p.287). Included in X are personal and demographic characteristics, and dummy variables for changes in industry and occupation. Variables that are common to both Ln W_{ij} and Ln W_{ij-1} will vanish if the wage equation is specified in terms of wage differences instead of wage levels.

The negative sign of the previous tenure coefficient implies a specific human capital investment loss, or as the authors put it, "tenure on the lost job raises wages on that job by more than it does on the second job" (p. 282).

In this study we will incorporate other factors into the above wage function. As will be argued later, the Addison-Portugal wage function is inadequate to account for the earnings of Canadian workers during the period 1986 - 1990. Other factors which are at least potentially a cause of a decrease or an increase in wages are:

- entry to or exit from a unionized job;
- short-term job training, representing an effort to improve human capital;
- movement to a different size of firm;
- growth in the industry in which the worker is employed.

The decision whether to move from or stay in an industry after separating from a job is often treated as exogenous in wage equations. If this decision is an outcome of a rational comparison of the worker's current position against perceived returns in an alternative position, then the decision should be treated endogenously. A displaced worker faces choices whether to search in the same industry or in other industries. Assuming that tenure in the previous job has specific human capital value, then, the longer the tenure, the more preferable is a job in the previous industry. But, as time elapses, an unemployed worker has to evaluate his position with regard to the resources that sustain him while unemployed, the scarcity of jobs in his old industry, the prospect of change and the prospective wage. Thus, a new job at some accepted wage must be the best choice for that worker. The implication of this argument is that the decision to move (or stay) is endogenously generated.

Due to this endogeneity issue, we will modify the above wage function in our econometric specifications to answer the set of questions on page 6 of Chapter I. But, as a first step, it is useful to regress the pre-displacement and the post-displacement wage on a conventional set of covariates and the additional variables mentioned earlier. We expect that the results will provide some kind of justification for the inclusion of the above-mentioned additional variables. Also, these results provide a useful comparison to the results found in previous studies, including those of Addison-Portugal (1989). The estimates of these wage equations are given in Appendix 3A.

Age, education and tenure variables form the main components of a standard wage function. All these three reflect the accumulation of skill or human capital over time, and so naturally we see positive associations between these variables and the wage.

Addison-Portugal then draw attention to the duration of unemployment. Theoretically, unemployment duration has two possible opposite effects. There is a positive effect due to a more productive search outcome and a negative effect due to a declining reservation wage, depreciation of human capital and a stigma effect. The authors conclude the negative effect is stronger and therefore we are expected to see a negative relation between duration of unemployment and the wage. With other factors that play important roles in Canadian economy, such as unionization and generous income support systems which may directly or indirectly affect wages, we are less sure whether these traditionally used key variables will maintain their strong effects.

The first interesting variable to check is tenure on the first (previous) job (LTenure1). It has a positive sign in each of the annual equations, both in the pre-displacement wage and the post-displacement wage equations. The positive sign in the post-displacement wage function implies that the effect of first-job tenure does not diminish with displacement. However, the estimates are not as strong as expected in that in only 3 out of 5 coefficients in the post-displacement wage equation, and only 2 out of 5 coefficients in the pre-displacement equations are significantly different from zero. In the wage difference (DWG) equations, 3 out of 5 coefficients have a positive sign and all 5 coefficients are not significantly different from zero. This is a surprising result. It may arise due to the crudeness of the calculations: the estimates are obtained by application of ordinary least squares which may not be appropriate. Alternatively, the positive but insignificant signs may arise because of the interplay of other factors that weaken the role of the first-job tenure.

From the age dummy variables (DAG1, DAG2 and DAG3), both equations reveal that the wage increases strongly with seniority. The younger a worker, the larger the gap from the default age bracket (age > 44).

There is a tendency for the wage to increase with respect to the level of education. However, this effect is not as strong as the effect of age.

Turning to the effect of unionization, Riddell (1993) reports that from around the mid-80's onward, workers in Canada were twice as likely to be represented by a union than their counterparts in the US. From the demand side, workers must perceive that it is worthwhile to unionize. Not surprisingly, then, the coefficients of the union dummy variables (DUN1 and DUN2) in both equations show very strong positive effect on wages. As a result, it is reasonable to expect that movement into or out of a unionized job will greatly influence wage growth.

With regard to the influence of the size of a firm on wages, there is a tendency for wages to improve with the size of the firm. It is natural, therefore, to include movement to a different size of firm, as a potential source of wage growth.

Movement to a different occupation after displacement seems to pull wages downward and all the coefficients, as recorded in Appendix 3A, are significant in all years.

Another surprising result is found in the effect of duration of unemployment on post-displacement wages. As mentioned earlier, unemployment duration is one of the key variables in Addison-Portugal (1989). Using US data they found that the effect of this variable on both the post-displacement wage and wage growth (wage difference) is strongly negative. Using Canadian data, all coefficients on log duration (LDur) in the post-displacement wage equations have a negative sign, but only one of them is significant. In the wage difference equations (DWG), one coefficient has a positive sign; this, and the rest of the coefficients, are insignificant.

Naturally, industry product growth would be expected to yield a positive influence on wages. Surprisingly, in the results in Appendix 3A for Canada, there are more negative signs and significant coefficients than positive signs. It appears that in some lower growth industries wages are higher than wages in fast growing industries. This raises the following question (which will not be discussed here): Is the reverse also true? Do industries grow faster in Canada, because they pay lower wages and have no need to negotiate with a union?

Since we formulate our models in terms of wage growth (wage difference), common variables to the pre-displacement wage equation and post-displacement wage equation are dropped. The remaining variables are: a training dummy variable (DTR), change in unionization status dummy variables (DUNI1 and DUNI2), a change in occupation dummy variable (DOC), a tenure in the first job variable (LTenure1), a tenure in the second job variable (LTenure2), change in firm size dummy variables (DFZ1 and DFZ2), a change in industry product growth variable (DGPI), and duration of unemployment (LDur). The results of the wage difference regressions are also recorded in Appendix 3A. In these regressions, we also include a change in industry dummy variable (DM) as an exogenous variable. This permits a comparison both with Addison-Portugal results and later with our own results (when we treat industry change as an endogenous variable). Addison-Portugal conclude that a change in industry following job loss is associated with a reduction in the post-displacement wage of 18.1%. From our results, 2 out of 5 coefficients are positive and only one of them is significant at the 10% level.

Econometric Specifications

We will start with a less complicated model specification, one which will be directed to answering question number 4 on page 6 of the Introduction, namely: Are movers the gainers or the losers?

Let us write the wage growth equation as:

$$DWG_i = X_i \beta + \alpha DM_i + \mu_i . \tag{1.1}$$

$DMi = 1$ if the worker moves, 0 otherwise.

If the decision to move or stay is endogenous, and the process is specified as:

$$DM_i^* = Z\gamma + \varepsilon_i \tag{1.2}$$

where $DM_i = 1$ if $DMi^* > 0$, zero otherwise,

then this equation can be estimated by a two-stage procedure as follows.

First, the vector coefficient γ in (1.2) can be estimated using the probit transformation. This yields $DM_i = F(Z_i\gamma) + \nu_i$, which can be substituted into (1.1) to get:

$$DWG_i = X_i \beta + \alpha F(Z_i\gamma) + \omega_i . \tag{1.3}$$

DWG , by definition, is wage growth, α in this sense represents the impact of a move to a new industry on wage growth.

Another solution to the endogeneity of industry change is offered by Barnow et al. (1981). They incorporate selectivity bias into the equation:

$$DWG = X\beta + \alpha DM + \delta \frac{f}{F(1-F)} + \omega \tag{1.4}$$

(subscript i is removed for convenience). F and f are the cumulative distribution function and the density respectively.

The type 1 models above are rather restrictive. A more general model can be specified as follow:

$$DWG_{mi} = X_{mi}\beta_m + \mu_{mi} \tag{2.1}$$

$$DWG_{si} = X_{si}\beta_s + \mu_{si} \tag{2.2}$$

m and s refer to move and stay respectively.

As before,

$$DM_i^* = Z_i\gamma + \varepsilon_i \tag{2.3}$$

$$DM_i = 1 \text{ if } DM_i^* > 0 \text{, zero otherwise} \tag{2.4}$$

The observed DWG is defined as:

$$DWG_i = DWG_{mi} \text{ if } DM_i = 1$$

$$DWG_i = DWG_{si} \text{ if } DM_i = 0$$

It is also assumed that:

$$(\mu_m, \mu_s, \varepsilon) \sim N(0, \Sigma)$$

$$\text{where } \Sigma = \begin{bmatrix} \sigma_{mm} & \sigma_{sm} & \sigma_{\varepsilon m} \\ \sigma_{ms} & \sigma_{ss} & \sigma_{\varepsilon s} \\ \sigma_{m\varepsilon} & \sigma_{s\varepsilon} & 1 \end{bmatrix}$$

Var(ε) can be set equal to 1 because DM* is not observable. This may be regarded as a form of normalization. Thus, the parameter γ can only be estimated up to a scale factor, using maximum likelihood (ML). To obtain efficient estimates of the model, the full information ML (FIML) procedure is used..

Let $f_m(\mu_m, \varepsilon)$ and $f_s(\mu_s, \varepsilon)$ be the joint normal distribution of (μ_m, ε) and (μ_s, ε) respectively, and write

$$f_k(\mu_k, \varepsilon) = h_k(\mu_k) \cdot g_k(\varepsilon \mid \mu_k)$$

$$k = m, s.$$

Then the likelihood function for all the parameters may be written

$$
\begin{aligned}
& L(\beta_m, \beta_s, \gamma, \sigma_m^2, \sigma_s^2, \sigma_{m\varepsilon}, \sigma_{s\varepsilon}) \\
&= \prod_{n=1}^{N} \left[\int_{-\infty}^{Z\gamma} g_m(\varepsilon \mid \mu_m) \cdot h_m(\mu_m)\, d\varepsilon \right]^{DM} \times \\
&\qquad \left[\int_{Z\gamma}^{\infty} g_s(\varepsilon \mid \mu_s) \cdot h_s(\mu_s)\, d\varepsilon \right]^{1-DM} \\
&= \prod_{n=1}^{N} \left[\int_{-\infty}^{Z\gamma} g_m(\varepsilon \mid WG_m - X_m\beta_m) \cdot h_m(WG_m - X_m\beta_m)\, d\varepsilon \right]^{DM} \times \\
&\qquad \left[\int_{Z\gamma}^{\infty} g_s(\varepsilon \mid WG_s - X_s\beta_s) \cdot h_s(WG_s - X_s\beta_s)\, d\varepsilon \right]^{1-DM} \qquad (2.5)
\end{aligned}
$$

where $h_k(WG_k - X_k\beta_k) = \dfrac{1}{\sqrt{2\pi} \cdot \sigma_k} \exp\left\{ -\dfrac{1}{2\sigma_k^2} (WG_k - X_k\beta_k)^2 \right\}$.

From the general form of the conditional normal distribution,

$$f(\,y \mid x\,) = N\left\{ \mu_y + \frac{\rho_{xy}\rho_y}{\sigma_x}\,(\,x - \mu_x\,),\ \sigma_y^2(\,1 - \rho_{xy}^2\,) \right\},$$

it is easy to derive

$$g_k\,(\,\varepsilon \mid WG_k - X_k\,\beta_k\,) = \frac{1}{\sqrt{2\pi}.\sqrt{1-\rho_{k\varepsilon}}} \quad x$$

$$\exp\left\{ -\frac{1}{2(1-\rho_{k\varepsilon}^2)}\,(\,\varepsilon - \rho_{k\varepsilon}\,\frac{1}{\sigma_k}\,(WG_k - X_k\,\beta_k\,))^2 \right\}$$

$k = m\,,\,s.$

In the last equation, $\rho_{m\varepsilon}$ and $\rho_{s\varepsilon}$ are the correlation coefficients of $(\,\mu_m\,,\,\varepsilon\,)$ and $(\,\mu_s\,,\,\varepsilon\,)$.

Maximization of (2.5) entails first and second derivatives which are highly non-linear. To estimate the parameters, iterative procedures are therefore needed. This requires good starting values which can be obtained from the estimates of the parameters using Heckman two-stage estimation procedures. First, ML is applied to obtain the estimates of γ in the decision function (2.3). With these estimates we can compute the Inverse Mills Ratio for the movers and the stayers. Let these be λ_m and λ_s . Then,

$$\lambda_{mi} = \frac{\phi(Z_i\gamma)}{\Phi(Z_i\gamma)} \quad \text{and}$$

$$\lambda_{si} = \frac{\phi(Z_i\gamma)}{1-\Phi(Z_i\gamma)}$$

Since

$$E(\mu_{mi} \mid DM_i = 1) = -\sigma_{m\varepsilon}\lambda_{mi} \text{ and}$$

$$E(\mu_{si} \mid DM = 0) = \sigma_{s\varepsilon}\lambda_{si}$$

we can get the estimates of β_m, β_s, $\sigma_{m\varepsilon}$, $\sigma_{s\varepsilon}$ by performing OLS for the two equations:

$$DWG_{mi} = X_{mi}\beta_m - \sigma_{m\varepsilon}\lambda_{mi} + \eta_{mi}$$

$$DWG_{si} = X_{si}\beta_s + \sigma_{s\varepsilon}\lambda_{si} + \eta_{si}$$

These estimates, as Lee and Trost (1978) have proved, are consistent and therefore provide good initial estimates for the Davidon, Fletcher and Powel (DFP) algorithm to maximize poorly behaved likelihood function like (2.5).

The goodness of fit of this model relies on whether or not there are correlations between the two wage equations and the decision function. If $\sigma_{m\varepsilon}$ and $\sigma_{s\varepsilon}$ are zero, the estimates from the two-step ML procedure above will be reduced to probit estimates for the decision function and OLS estimates for the wage equation for the movers and the wage equation for the stayers. Therefore, investigation of whether simultaneity occurs or not needs to be carried out.

Lee and Trost (1978) suggest the use of a likelihood ratio test for this purpose. The null hypothesis is that there is no correlation between the disturbance in the mover or stayer wage equations and the decision function. In other words we may constrain $\sigma_{m\varepsilon}$ and $\sigma_{s\varepsilon}$ to equal to zero. The ML estimates of the mover or the stayer wage equations are now reduced to simple OLS estimates and the ML estimates of the decision function are Probit estimates. Denote these estimates by $\hat{\theta}_o$. The alternative hypothesis is that $\sigma_{m\varepsilon}$ and $\sigma_{s\varepsilon}$ are not equal to zero, and therefore the estimates are the two-step ML estimates above. Denote these estimates by $\hat{\theta}_I$. In this case the likelihood ratio is $\{ L(\hat{\theta}_0 / L(\hat{\theta}_I) \} = l$ and $-2 \ Ln \ l$ is distributed as the chi -square distribution with two degrees of freedom ($\chi^2_{(2)}$), centrally under the null, non-centrally otherwise.

In the second model above one of the variables included in X is unemployment duration. As has been mentioned before, the duration of unemployment is potentially endogenous; the causality between duration and wage growth may run both ways, especially when we think of unemployment search as a form of investment that responds to the perceived wage gain or loss.

To correct this, a simultaneous equations model which corrects for selectivity bias is used. This is written

$$\begin{aligned} DWG_i &= \alpha_1 X_{1i} + \beta_1 (LDur)_i + \eta_{1i} \\ (LDur)_i &= \alpha_2 X_{2i} + \beta_2 DWG_i + \eta_{2i} \end{aligned} \tag{3.1}$$

$$Dm_i^* = \gamma Z_i + \varepsilon_i \tag{3.2}$$

The structure (3.1) is observed if $DM_i^* > 0$ or if $DM_i^* < 0$. Thus, we have:

$$\left.\begin{aligned} DWG_{mi} &= \alpha_{1m} X_{1mi} + \beta_{1m} (LDur)_{mi} + \eta_{1mi} \\ (LDur)_{mi} &= \alpha_{2m} X_{2mi} + \beta_{2m} DWG_{mi} + \eta_{2mi} \end{aligned}\right\} \quad \text{if } DM_i^* > 0 \qquad (3.3)$$

$$\left.\begin{aligned} DWG_{si} &= \alpha_{1s} X_{1si} + \beta_{1s} (LDur)_{si} + \eta_{1si} \\ (LDur)_{si} &= \alpha_{2s} X_{2si} + \beta_{2s} (DWG)_{si} + \eta_{2si} \end{aligned}\right\} \quad \text{if } DM_i^* < 0 \qquad (3.4)$$

Another condition is that at least one variable in X_2 is not included in X_1, and at least one variable in X_1 is not included in X_2. The above sets of simultaneous equations can be written as follows:

$$B_1 \mathbf{Y}_{1i} = A_1 \mathbf{X}_{1i} + V_{1i} \quad \text{if } DMi^* > 0 \qquad (3.5)$$

$$B_2 \mathbf{Y}_{1i} = A_2 \mathbf{X}_{2i} + V_{2i} \quad \text{if } DM_i^* < 0 \qquad (3.6)$$

The residuals V_1, V_2 and ε are assumed to have a multivariate normal distribution with mean vector 0 and covariance matrix:

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} & \Sigma_{1\varepsilon} \\ \Sigma_{21} & \Sigma_{22} & \Sigma_{2\varepsilon} \\ \Sigma_{31} & \Sigma_{32} & 1 \end{bmatrix}$$

$\mathbf{Y}_{1i}$ and $\mathbf{Y}_{2i}$ are vectors of k endogenous variables, $\mathbf{X}_{1i}$ is a vector of $m1$ exogenous variables, $\mathbf{X}_{2i}$ is a vector of $m2$ exogenous variables, B_1 and B_2 are k x k matrices, A_1 is a k x $m1$ matrix, A_2 is a k x m_2 matrix V_{1i} and V_{2i} are k x 1 vectors of residuals. In our case, $k = 2$.

Equations (3.5) and (3.6) can be written in reduced form

$$\mathbf{Y}_{1i} = \Pi_1 \mathbf{X}_{1i} + V_{1i} \tag{3.7}$$

$$\mathbf{Y}_{2i} = \Pi_2 \mathbf{X}_{2i} + V_{2i} \tag{3.8}$$

where $\Pi_1 = - B_1^{-1} A_1$ and $\Pi_2 = -B_2^{-1} A_2$

Let y_{1i} be the first equation in (3.7) such that

$$y_{1i} = \mathbf{X}_{1i} \Pi_{11} + v_{1i} \tag{3.9}$$

where v_{1i} is the first element of V_{1i}.

Since

$E(v_{1i} \mid DM^* > 0) = - \sigma_{1\varepsilon} \dfrac{\phi_i}{\Phi_i}$, we can write (3.9) as

$$y_{1i} = \mathbf{X}_{1i} \Pi_{11} - \sigma_{1\varepsilon} \frac{\phi_i}{\Phi_i} + \upsilon_{1i} \tag{3.10}$$

where $E(\upsilon_{1i}) = 0$ and $\sigma_{1\varepsilon} = \text{cov}(v_{1i}, \varepsilon)$. $\dfrac{\phi_i}{\Phi_i}$ can be estimated after we estimate γ in (3.2) by ML using the Probit transformation. Then we estimate

$$y_{1i} = \mathbf{X}_{1i} \Pi_{1i} - \sigma_{1i} \frac{\hat{\phi}_i}{\hat{\Phi}_i} + \upsilon_{1i} \tag{3.11}$$

Lee, Maddala and Trost (1980) suggested using the fitted value of (3.11) as an instrumental variable to estimate the coefficients of the simultaneous equations (3.1). The two-stage least squares estimator of the parameters can be written as:

$$\hat{\Theta} = (W_1' W_1)^{-1} W_1' y_1 \text{, where}$$

$$\Theta' = [\beta_{12}, \beta_{13}, \ldots\ldots\beta_{1m}, \alpha_1, \sigma_{1\varepsilon}] \text{ and}$$

$$W_1 = [y_2, y_3, \ldots\ldots y_m, X_1, \frac{\hat{\phi}}{\hat{\Phi}}]$$

$$\text{Var}(\hat{\Theta}) = \sigma_1^2 (W_1' W_1)^{-1} - \sigma_{1\varepsilon}^2 (W_1' W_1)^{-1} W_1' \{A - AZ_1 (Z' \Lambda Z)^{-1} Z_1 A\} W_1$$

$$\times (W_1' W_1)^{-1}.$$

where $\text{Var}(\hat{\Theta})$ is taken to mean variance-covariance matrix. In this last equation, Z_1 corresponds to the observations on Z for $DM^* > 0$; if the total sample size equals N and N_1 equals the number of observations for which $DM^* > 0$, then Z_1 is an $N_1 \times l$ matrix. Λ is an $N \times N$ matrix, defined as

$$\Lambda = \text{diag.} [\frac{\phi_i}{\Phi_i(1-\Phi_i)}], \quad i = 1, 2, \ldots\ldots N$$

A is an $N_1 \times N_1$ matrix defined as

$$A = \text{diag.} [Z_i \gamma \frac{\phi_i}{\Phi_i} + (\frac{\phi_i}{\Phi_i})^2], \quad i = 1, 2, \ldots\ldots N_1$$

For the structural equations corresponding to the second regime where $DM^* < 0$, we use $\sigma_{2\varepsilon} \frac{\phi_i}{1-\Phi_i}$ instead of $-\sigma_{1\varepsilon} \frac{\phi_i}{\Phi_i}$.

Empirical Results and Analysis

The most important coefficients to examine in model 1.3 and model 1.4 are the coefficients of the moving dummy variable and the selectivity bias variable. The moving dummy (DM) coefficient represents the impact of the moving decision on the wage change or the difference in wage change between the movers and the stayers. The coefficient of the selectivity bias variable (lambda) reveals whether the moving decision is indeed endogenous.

Both model 1.3 and model 1.4 are used for program evaluation (e.g.: training programs). Here, selectivity bias arises because the decision of the individuals to participate in the program is related to unmeasured characteristics that themselves are related to the program outcome under study. These models are called treatment effects models. We adopt these models because of the similarity of the case they handle to ours. We expect that both models will produce close results for the coefficient of DM.

At the beginning, we include as covariates: LDur, DTR, DUNI1, DUNI2, DFZ1, DFZ2, DOC, LTN1, LTN2, DGIP. Some of these coefficients are not significantly different from zero and the more of these, the larger the difference between the results of the two models. When the variables of the coefficients with the smallest t-values are removed, the results for both models become comparable.

All coefficients of DM are significant except the 1988 coefficients which have a p value slightly above 10%. These coefficients range from 6% to 18%, and all are positive. This means that those workers who move industry have a wage growth 6% to 18% higher than those who stay in the same industry after displacement. The selectivity bias coefficients are also significant, except the 1988 and 1990 coefficients which have a p value slightly above 10%.

Table 3.1

The Treatment Effects Models

	1986	1987	1988	1989	1990
DM (model 1.3)	0.186	0.069	0.129	0.141	0.148
	(3.350)[a]	(2.358)[b]	(1.545)[d]	(2.402)[a]	(2.203)[b]
DM (model 1.4)	0.170	0.058	0.119	0.139	0.137
	(3.285)[a]	(2.194)[b]	(1.514)[d]	(2.456)[a]	(2.140)[b]
Lambda	-0.155	-0.069	-0.081	-0.129	-0.072
	(4.284)[a]	(2.894)[a]	(1.547)[d]	(3.215)[a]	(1.580)[d]

Note: t - values are given in parentheses.
a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Before analysing the estimates of the parameters in the second model, let us check the goodness of fit of this model, from the ML ratio test performed on each sample.

Table 3.2

Maximum-likelihood Ratio Tests

	1986	1987	1988	1989	1990
ML Ratio	41.52	29.50	20.81	11.77	24.44
Signif. level	1%	1%	1%	1%	1%

All ML ratios are highly significant, showing that there are indeed correlations between the moving or staying decision function and the wage growth equations. Ignoring these correlations will produce biased results. The evidence of the endogeneity of the moving or staying decision is stronger when the samples are spilt into movers and stayers than when they are not, like in model 1.3 and model 1.4.

Table 3.3

Estimates of the Decision Function (Mover / Stayer Model)

	1986	**1987**	**1988**	**1989**	**1990**
Constant	0.722	0.386	0.026	0.981	-0.061
	(2.762)[a]	(1.283)	(0.092)	(2.733)[a]	(0.188)
GPI 1	-0.007	0.016	-0.003	-0.001	0.028
	(0.746)	(1.569)[d]	(0.344)	(0,038)	(1.648)[c]
LDUR	0.010	0.124	0.061	0.060	0.069
	(0.228)	(2.323)[b]	(1.141)	(0.981)	(1.089)
LTenure1	-0.018	-0.023	0.056	-0.071	-0.080
	(0.640)	(0.725)	(1.767)[c]	(1.825)[c]	(2.091)[b]

Table 3.3 (continued)

	1986	1987	1988	1989	1990
DHW	-0.755	-0.576	-0.731	-0.582	0.315
	(7.141)[a]	(5.252)[a]	(7.118)[a]	(4.622)[a]	(2.663)[a]
DMF	0.323	0.546	0.243	0.504	0.443
	(2.003)[b]	(3.188)[a]	(2.017)[b]	(2.661)[a]	(2.936)[a]
DBlueCl	0.048	0.114	-0.242	-0.180	-0.234
	(0.540)	(1.191)	(2.633)[a]	(1.569)[d]	(2.162)[b]
DTR	0.383	-0.052	0.111	0.351	0.383
	(2.189)[b]	(0.337)	(0.689)	(1.422)	(1.822)[c]
DAG1	0.256	0.385	-0.123	0.299	0.561
	(1.431)	(2.045)[b]	(0.628)	(1.302)	(2.577)[a]
DAG2	0.044	0.038	-0.143	0.027	0.444
	(0.364)	(0.292)	(0.863)	(0.181)	(3.162)[a]
DAG3	0.093	-0.020	0.038	0.160	0.209
	(0.661)	(0.140)	(0.213)	(0.953)	(1.378)
DED1	-0.069	-0.102	-0.026	-0.108	0.203
	(0.390)	(0.496)	(0.132)	(0.422)	(0.848)
DED2	0.046	-0.046	0.044	0.007	0.201
	(0.246)	(0.208)	(0.210)	(0.030)	(0.818)
DUNI	-0.047	-0.244	0.071	-0.119	-0.180
	(0.434)	(1.920)[b]	(0.624)	(0.924)	(1.364)
DUI	-0.081	-0.069	0.033	-0.076	-0.029
	(0.842)	(0.691)	(0.337)	(0.605)	(0.262)
DMS	-0.023	-0.067	0.250	-0.032	-0.150
	(0.229)	(0.652)	(2.490)[a]	(0.267)	(1.316)
DFIRM 1	-0.066	0.098	-0.046	-0.184	0.002
	(0.549)	(0.811)	(0.442)	(1.381)	(0.018)
DFIRM 2	0.354	0.501	0.368	0.285	0.090
	(2.490)[a]	(2.918)[a]	(2.152)[b]	(1.478)[d]	(0.510)

Table 3.3 (continued)

	1986	1987	1988	1989	1990
DFIRM 3	0.327	0.283	0.099	0.319	0.285
	(2.974)[a]	(2.533)[a]	(0.905)	(1.872)[b]	(1.896)[b]

Note: t - values are given in parentheses.
a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

From the introduction to this chapter, we know that implicitly the decision to move or stay in an industry depends on the evaluation of the associated negative and positive factors faced by the workers. Sometimes these effects are hard to disentangle. We try to capture the determinants of this decision using the variables in Table 3.3. The results are discussed below.

From Table 3.3 above, the expected sign of the coefficient of industry product growth (GPI 1) is negative. We predict that those who were displaced from a declining industry will be more likely to move, while those from high-growth industries will have an easier time getting a new job without having to move industry. It turns out that the three negative signs on this variable are not significant. However, two positive coefficients are significant at 10% and slightly above 10%. These positive signs are for the 1987 and the 1990 coefficients. If it is true that high growth industries are industries that pay less for equivalent skills, and have workers that are not unionized or covered by a wage agreement, then industry product growth may send a mixed signal.

Murphy-Topel (1987), Lilien (1983) among others blame the stayers for the increase of the average spell of unemployment. This might be misleading if the probability of moving is higher the longer the unemployment spell. As assumed before, at the beginning of the spell the workers will not give up searching in the same industry except if they know earlier that the probability of getting a new job in this sector is slim. Lines 6 and 7 in Table 1 (chapter II) provide some support for this; the average unemployment spell in each of the 5-year cross-sectional samples is higher for the movers. The coefficient on LogDuration ineach year is positive, though only the 1987 coefficient is significant.

From the human capital point of view, the longer the job tenure , the more the workers try to preserve their investment by staying where they are, in the same industry. Thus, we expect that the sign of LTenure1 coefficients will be negative. This is confirmed, except for the 1988 coefficient.

As expected, the coefficients of the high wage job variable (DHW) are negative, and they are all highly significant. There is a change in sign for the 1990 coefficient. however, and it is significant. Evidently, the recessionary period encouraged workers to be less selective in choosing employment.

It has been a common view that in the past two decades the manufacturing sector in North America has been declining, largely due to foreign competition. The sign on the manufacturing dummy variable (DMF) coefficient support this view. All signs are positive and significant at the 5% level or less. Of those who move from their old industries, around 80% move to industries outside the manufacturing sector (SIC 09 - 28).

It is not clear what to expect for the sign of the blue collar dummy variable (DBlueCl). It is commonly thought that workers with high skill levels are more mobile; thus the demand for unionization is low for this type of worker. For blue collar workers, we might expect the reverse to be true. This does seem to hold in the US. In Canada, however, the unionization rate of managerial and professional occupations is only slightly lower than that of blue collar occupations (Riddell, 1993). If there is a correlation between blue collar occupation and unionization we expect the sign to be negative. Three coefficients support this, and they are significant.

The training programs of both the federal and local governments in Canada seem to target the lower end of the skill level. It is expected that improving these workers' skills will provide them with greater flexibility in searching for a job. We expect the sign of the training dummy (DTR) coefficients will be positive. The results are all positive except the 1987 coefficient.

A younger age generally implies a lower education level, lower experience, lower tenure, and less household responsibility. On the one hand, the skill level of the young constraints mobility; however, on the other hand, these workers are more trainable and more eager to learn new things than those in the older age brackets. Some firms even prefer hiring the young and the inexperience. Overall we would expect a positive effect of a younger age on the probability of moving to a new industry. The coefficients of the first age bracket that are positive are all larger than the coefficients of the older age brackets, showing that the first age bracket has a higher probability of moving. The only negative sign in this age category is in the 1988 coefficient.

It is to be expected that the workers in the first age bracket have a low level of education, but, this statement cannot be reversed. Those who have low education are not necessarily also young. Of course there might be a correlation between age and education, but a priori this is not a clear-cut. For this reason, it is hard to guess what sign the education dummy variables might take. If the workers are older and less educated, their probability of moving is lower and the sign of the coefficients will be negative. The coefficients of both education dummies (DED1 and DED2) are all insignificant, and there are more negative signs in the first education level than in the second.

As mentioned earlier in this chapter there is a significant wage gain associated with being a union member or if the wage is covered by a collective agreement. The workers will be reluctant to leave a highly unionized industry with its perquisites, especially if the prospect of entering another unionized job in a new industry is low. From the results, except for the 1988 coefficient, all signs are negative although only the 1987 coefficient is significant.

The sign of the UI benefit dummy (DUI) is also uncertain, a priori. On one hand, the UI benefit system in Canada provides generous support to the unemployed and so they have more flexibility in searching for a preferable job (which is mostly in their old industry). But as the spell lengthens, they also search in other industries and may eventually move industry. All coefficients for the UI dummy are insignificant and four out of five have negative signs.

Married workers are perhaps less flexible and less adventurous than young and /or unmarried ones. But we cannot make a strong expectation about the sign of marital status (DMS) coefficients. The results show four negative signs and one positive sign, and only the 1988 (positive) coefficient is significant.

The set of firm size dummy variables (DFIRM1, DFIRM2 and DFIRM3) yields surprising results. Almost all coefficients for the two larger categories are significant. It is not clear why workers displaced from large firms are more likely to leave their industry. Perhaps in Canada big firms also have dominance in their industries and so a decline in those firms also implies a decline or even stagnancy in that industry.

As has been mentioned above, search and human capital theories often influence wage analysis. Without human capital depreciation or stigma effects, and without the interplay of other factors, the standard search model with a constant reservation wage predicts a higher post displacement wage due to search efficiency. The presence of such factors often justifies the inclusion of additional regressors in wage equations. The most often used additional variable is unemployment duration. This regressor alone might or might not be enough. In the Canadian case, we would suggest that this is not enough. Looking at the strength of unionization in Canada and how significantly it affects the wage, unemployment duration is at least another additional regressor that should be used. However, the more factors incorporated into the analysis, the less predictable the results will be.

From Table 3.4 and Table 3.5, the first variable, LogDuration, yields mixed results. From standard search theory a long unemployment spell may send a signal that a worker is a "lemon" in which case the arrival rate would decline. This in turn will discourage the worker and lead to a fall in the reservation wage. General human capital might also be diminished by time spent out of work. Both forces lead to the conclusion that the longer the duration of unemployment, the lower the post displacement wage or wage growth. Two other factors appear to cushion the above negative impact. These factors are the UI benefit (which prevents the dropping of reservation wage) and unionization (which prevents the post-displacement wage to drop significantly). The insignificance of many of the coefficients of LogDuration, and even the fact that we have both positive and significant results, may reflect the interplay of these forces.

The training dummy variable (DTR) is expected to produce a positive coefficient, but we have two negative signs in the mover wage equation and one negative sign in the stayer wage equation. However, these coefficients are insignificant. The effect is strong and significant only during the 1990 recessionary period for the stayers.

The most noticeable strong results are found for the coefficients of the change in union status dummies (DUNI1 and DUNI2), especially for the movers. Those who move from a unionized job to a non-unionized job suffer a decrease in wage growth of 15% to 24%, and those who move from a non-unionized job to a unionized job gain from 14% to 30% wage growth. The effect is weaker for the stayers: changing union status from unionized to non-unionized, while staying in the same industry also lowers wage growth (though only three out of five are significant). Moving from a non-unionized to a unionized job yields a positive sign (wage gain), though only two out of five are significant.

Large firms pay higher wages (see Appendix 3A). Riddell (1993) observes that there is a strong relationship between union incidence and establishment size. He argues further that this relationship could be due to a stronger desire for union representation among workers in large establishments. Perhaps these workers have a greater need for a collective voice than do workers in small establishments. This relationship could also exist because union leaders target large establishments in their organizing drives, in an attempt to maximize the number of potential new members per dollar of organizing expenditure. Moreover, large firms also benefit from returns to scale and so are generally more able to pay for fringe benefits such as pensions and health insurance. Movement from a small-sized firm to a large-sized firm should bring positive wage growth and we expect the reverse to happen for movement in the opposite direction. From the coefficient signs, all signs in the wage equation for the movers confirm this expectation. For the stayers, the 1989 sign for the second firm size dummy is positive, but it is supposed to be negative. Given the level of significance, the results of these regressors are not as strong as those of the union status change dummies. Only five out of ten coefficients in the wage equation for the movers are significant, while in the stayers part only four out of ten coefficients are significant. The amount of loss or gain from firm size change is lower than the amount of loss or gain from union status change.

Occupation change (DOC) is expected to bring a wage loss, given the associated specific human capital loss, especially for displaced workers. However, we observe more positive signs than negative signs. All coefficients in the mover part are not significant while in the stayer part only the 1990 coefficient is significant at slightly above 10% level.

The signs of the first job tenure (Ltenure1) coefficients are expected to be negative in theory. This negative sign reflects specific human capital as well as that part of general human capital that is diminished by time spent out of work. This variable and the unemployment duration variable are often claimed to be the most important variable to capture the link between human capital and search effort, and the wage. But with the strength of other factors such as unionization and the income safety-net system (especially the UI benefit system), the above expectation may not hold. From our results, in the mover equation four out of five coefficients are positive but all five are insignificant. In the stayer equation, four out of five coefficients are negative. The positive one is significant at slightly above 10% level. Apparently those who move to a new industry have a tendency not to lose their human capital investment, while those who stay tend to lose part of it.

Wages are expected to increase with the length of current job tenure (LTenure2). This appears to hold for the movers, except during the recessionary year, and when workers stay in their old industry.

Higher industry product growth is expected to increase the wage through a better wage offer. The results do not confirm this. Those who move to a higher growth industry tend to have lower wage growth though the effect is very small, less than 1% mostly. Our guess is that the higher growth industries might be industries with low rate of unionization, and they do not face a power struggle with union members, especially in terms of monetary compensation.

The correlation coefficients in both the movers and the stayers wage equations are all significant at very low p-values. This and the ML ratio test results in Table 2 signify the importance of the correlation between the decision to move or stay in an industry with the wage growth of the movers or the stayers.

Table 3.4

Wage Equation Estimates for the Movers

	1986	1987	1988	1989	1990
LDUR	-0.016	0.015	0.022	0.004	-0.045
	(0.813)	(0.716)	(0.980)	(0.194)	(1.522)[d]
DTR	0.082	0.049	-0.005	-0.041	0.020
	(1.270)	(0.731)	(0.082)	(0.454)	(0.238)
DUNI 1	-0.153	-0.172	-0.180	-0.031	-0.243
	(2.259)[b]	(2.282)[b]	(2.752)[a]	(0.406)	(2.568)[a]
DUNI 2	0.181	0.219	0.307	0.250	0.144
	(2.601)[a]	(3.828)[a]	(3.972)[a]	(3.491)[a]	(1.475)[d]
DFZ 1	0.101	0.061	0.136	0.030	0.099
	(1.916)[b]	(1.325)	(2.226)[b]	(0.518)	(1.473)[d]
DFZ 2	-0.121	-0.085	-0.025	-0.086	-0.053
	(2.477)[a]	(1.676)[c]	(0.453)	(1.353)	(0.683)
DOC	0.065	-0.027	-0.009	0.036	0.028
	(1.259)	(0.559)	(0.156)	(0.763)	(0.454)
LTenure1	0.019	0.011	0.011	0.011	-0.011
	(1.304)	(0.754)	(0.772)	(0.713)	(0.538)
LTenure2	0.034	0.051	0.063	0.025	-0.024
	(1.970)[b]	(2.945)[a]	(3.108)[a]	(1.324)	(0.918)
DGPI	-0.008	-0.007	0.006	-0.007	-0.001
	(2.563)[a]	(2.614)[a]	(1.643)[c]	(1.353)	(0.176)
σ_m	0.564	0.497	0.497	0.478	0.561
	(40.67)[a]	(30.42)[a]	(17.73)[a]	(23.70)[a]	(27.28)[a]
$\rho_{tn\varepsilon}$	-0.755	-0.631	-0.746	-0.629	0.680
	(19.74)[a]	(9.340)[a]	(9.863)[a]	(5.388)[a]	(9.931)[a]

Note: t - values are given in parentheses.

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$

b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table 3.5

Wage Equation Estimates for the Stayers

	1986	1987	1988	1989	1990
LDUR	-0.024	-0.038	-0.079	-0.050	0.073
	(0.930)	(1.273)	(2.543)[a]	(1.554)[d]	(2.030)[b]
DTR	0.052	0.055	-0.055	0.161	0.379
	(0.398)	(0.684)	(0.577)	(1.482)[d]	(3.867)[a]
DUNI 1	-0.105	-0.049	-0.228	-0.327	-0.155
	(0.864)	(0.451)	(2.510)[a]	(2.291)[b]	(1.545)[d]
DUNI 2	0.090	0.261	-0.083	0.145	0.274
	(0.779)	(2.410)[a]	(0.587)	(0.611)	(2.418)[a]
DFZ 1	0.092	0.028	0.011	0.047	0.139
	(1.249)	(0.414)	(0.171)	(0.513)	(1.559)[d]
DFZ 2	-0.183	-0.123	-0.131	0.083	-0.009
	(2.655)[a]	(1.585)[d]	(1.758)[c]	(1.072)	(0.119)
DOC	-0.056	0.061	0.057	0.084	0.106
	(0.989)	(1.113)	(0.560)	(1.273)	(1.588)[d]
LTenure1	-0.019	-0.013	-0.001	0.027	-0.002
	(1.329)	(0.733)	(0.077)	(1.450)[d]	(0.111)
LTenure2	-0.017	-0.021	-0.027	-0.030	0.067
	(0.788)	(1.030)	(1.006)	(1.059)	(2.826)[a]
σ_s	0.393	0.397	0.547	366	0.465
	(20.88)[a]	(19.83)[a]	(22.27)[a]	(17.58)[a]	(15.92)[a]
$\rho_{s\varepsilon}$	0.513	0.502	0.693	0.323	-0.844
	(5.014)[a]	(3.660)[a]	(10.29)[a]	(1.672)[c]	(15.24)[a]

Note: t - values are given in parentheses.

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$

b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table 3.6 and Table 3.7 show the estimates for the wage growth equations, corrected for the simultaneity between wage growth and unemployment duration (see model 3). There are some changes after this correction, but these changes are not very significant.

In the Mover equation, the 1990 training dummy variable (DTR) coefficient changes from positive to negative, but in both cases the coefficient is not significant. The coefficients of the union status change dummies (DUNI1 and DUNI2) do not change in sign, though they do change slightly in numerical value. The signs of estimates of both dummy variables for firm size change (DFZ1 and DFZ2) also do not change, but the 1989 estimate for the second firm size change dummy (DFZ2) is now significant. The occupation change dummy (DOC) estimates are all negative, and only the 1988 coefficient is significant. As before, all coefficients of the previous job tenure variable (LTenure1) are not significant, but there are now two negative signs instead of one. The signs of the present job tenure variable (LTenure2) coefficients do not change, though two coefficients which were formerly significant are now not significant. Both the sign and the coefficients that are significant, do not change for the industry product growth difference variable (DGPL). All coefficients for the log duration variable (LDUR) have positive signs and three of them are significant. These are the 1986, 1989 and 1990 coefficients.

For the Stayer equation (Table 3.7), the training dummy variable (DTR) coefficients do not change in sign and only the 1990 coefficient is now significant. Both the union status change dummy variables (DUNI1 and DUNI2) and firm size change dummy variables (DFZ1 and DFZ2) coefficients do not change in sign, and the coefficients which were significant remain so. These coefficients change slightly in numerical value. All coefficients of the occupation change dummy variable (DOC) also have the same sign as before, and the 1987 coefficient is now significant. There is one sign change in the previous job tenure variable (LTenure1) coefficients, the 1988 coefficient is now positive though not significant. The present tenure variable (LTenure2) coefficient do not change in sign, but the 1990 coefficient is now less significant. The sign of the 1988 coefficient for log duration (LDUR) changes from negative to positive. None of the log duration coefficients are significant. This implies that log duration is an exogeneous variable and therefore Table 3.5 gives more reliable estimates for the wage growth equation of the stayer.

From the log duration equation in Table 3.6 and Table 3.7, only the 1989 coefficient of the wage growth variable (DWG) in the mover equation is significant with a positive sign. For this particular year, the causality between wage growth and log duration for those who move to a new industry appears to run both ways. There is no degeneration of human capital from the time spent out of work. The rest of the wage growth coefficients, both in the mover and the stayer equations are not significant and the signs are mixed.

An examination of the coefficients of the other variables in the log duration equations yields some interesting results. Note that education dummy variables and provincial dummy variables are eliminated, because they are highly insignificant across the years.

The manufacturing dummy variable (DMF) coefficients in both the mover and the stayer equations all have negative signs. Six out of ten are significant. This means that those displaced from the manufacturing sector find a new job faster. Perhaps this is due to advance notice of plant closure, or because the workers realized earlier that their company or industry is in trouble. Both of these factors would lead workers to initiate a job search earlier.

The UI dummy variable (DUI) coefficients are mostly significant and have positive sign. This means that the UI recipients have longer duration of unemployment than those who do not receive UI benefit (for whatever reason). The effect of the manufacturing dummy variable and the UI dummy variable on duration of unemployment is stronger using the Heckman two-stage model applied to log duration without wage growth (see appendix 3B).

The coefficients of the previous job tenure variable (LTenure1) all have positive sign, except the 1988 coefficients in both the mover and the stayer equations, but only three out of ten coefficients are significant. This provides some evidence that higher tenure workers experience a longer spell of unemployment. The levels of significance do not change much when the Heckman two-stage model is used. All selectivity bias coefficients in the Heckman two-stage model, both for the movers and the stayers, are significant.

Table 3.6

Simultaneous Equation Estimates of Wage Growth and Unemployment Duration for the Mover

	1986	1987	1988	1989	1990
Wage Growth Equation					
DTR	0.050	0.041	-0.007	-0.035	-0.087
	(0.636)	(0.442)	(0.100)	(0.485)	(0.987)
DUNI1	-0.164	-0.161	-0.188	-0.041	-0.216
	(2.374)[b]	(1.567)[d]	(2.429)[a]	(0.595)	(2.412)[a]
DUNI2	0.170	0.215	0.310	0.219	0.150
	(2.384)[b]	(2.511)[a]	(4.163)[a]	(3.238)[a]	(1.647)[c]
DFZ1	0.060	0.049	0.116	0.030	0.109
	(1.069)	(0.735)	(1.913)[b]	(0.549)	(1.548)[d]
DFZ2	-0.181	-0.106	-0.045	-0.092	-0.097
	(3.424)[a]	(1.430)[d]	(0.691)	(1.701)[c]	(1.318)
DOC	-0.033	-0.052	-0.105	-0.018	-0.022
	(0.693)	(0.798)	(1.755)[c]	(0.379)	(0.373)
LTenure1	-0.013	0.001	0.006	-0.002	0.013
	(0.852)	(0.071)	(0.040)	(0.140)	(0.627)

Table 3.6 (continued)

	1986	1987	1988	1989	1990
LTenure2	0.011	0.040	0.025	0.006	-0.016
	(0.581)	(1.501)[d]	(1.162)	(0.353)	(0.637)
DGPI	-0.007	-0.007	0.006	-0.007	-0.001
	(2.256)[b]	(1.746)[c]	(1.562)[d]	(1.595)[d]	(0.268)
LDUR	0.106	0.052	0.038	0.077	0.120
	(2.673)[a]	(1.248)	(1.009)	(2.445)[a]	(2.268)[b]
Lambda	-0.360	-0.288	-0.098	-0.278	-0.340
	(3.364)[a]	(2.385)[b]	(1.181)	(2.766)[a]	(2.651)[a]
LogDuration Equation					
Constant	2.452	3.728	2.726	2.633	2.287
	(8.851)[a]	(2.174)[b]	(3.953)[a]	(7.469)[a]	(6.037)[a]
DMF	-0.426	-0.043	-0.062	-0.586	-0.379
	(2.282)[b]	(0.940)	(0.169)	(2.574)[a]	(2.265)[b]
DAG1	-0.259	-0.036	0.143	-0.393	-0.245
	(1.284)	(0.880)	(0.366)	(1.553)[d]	(0.993)
DAG2	-0.134	-0.554	-0.054	-0.322	-0.495
	(1.069)	(0.741)	(0.188)	(1.956)[b]	(2.751)[a]
DUI	0.256	0.374	0.600	0.517	0.558
	(2.096)[b]	(0.627)	(2.173)[b]	(3.312)[a]	(4.253)[a]
DUNI	0.165	0.545	-0.002	0.513	0.133
	(1.137)	(0.650)	(0.007)	(2.678)[a]	(1.042)
LTenure1	0.081	0.115	-0.033	0.028	0.086
	(2.364)[b]	(0.599)	(0.373)	(0.559)	(2.025)[b]
DWG	-0.072	0.176	-0.146	1.168	0.120
	(0.225)	(0.094)	(0.174)	(2.691)[a]	(0.330)

Table 3.6 (continued)

	1986	1987	1988	1989	1990
Lambda	-1.586	-3.527	-1.259	-1.756	-1.100
	(3.857)[a]	(1.340)	(1.841)[c]	(3.240)[a]	(2.451)[b]

Note: t - values are given in parentheses.
a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table 3.7

Simultaneous Equation Estimates of Wage Growth and Unemployment Duration for the Stayer

	1986	1987	1988	1989	1990
Wage Growth Equation					
DTR	0.095	0.049	-0.023	0.171	0.272
	(0.650)	(0.674)	(0.275)	(1.245)	(1.690)[c]
DUNI1	-0.085	-0.062	-0.256	-0.323	-0.148
	(0.605)	(0.556)	(2.997)[a]	(2.404)[b]	(1.084)
DUNI2	0.083	0.271	-0.082	0.134	0.295
	(0.771)	(2.705)[a]	(0.738)	(1.205)	(1.712)[c]
DFZ1	0.101	0.033	0.019	0.051	0.117
	(1.046)	(0.479)	(0.290)	(0.664)	(0.962)
DFZ2	-0.177	-0.102	-0.098	-0.088	-0.013
	(1.857)[c]	(1.448)[d]	(1.479)[d]	(0.956)	(0.142)
DOC	-0.048	0.092	0.087	0.092	0.086
	(0.732)	(1.759)[c]	(1.050)[c]	(1.271)	(0.890)
LTenure1	-0.015	-0.009	0.021	0.032	-0.010
	(0.885)	(0.607)	(1.383)	(1.664)[c]	(0.336)

Table 3.7 (continued)

	1986	1987	1988	1989	1990
LTenure2	-0.007	-0.011	-0.019	-0.024	0.053
	(0.287)	(0.505)	(0.786)	(0.960)	(1.441)[d]
LDUR	-0.042	-0.022	0.014	-0.053	0.016
	(0.727)	(0.478)	(0.222)	(0.911)	(0.170)
Lambda	-0.187	-0.116	-0.001	-0.088	0.201
	(1.848)[c]	(1.573)[d]	(0.013)	(0.911)	(1.378)
<u>LogDuration Equation</u>					
Constant	0.714	-1.112	0.561	-0.804	-0.164
	(1.030)	(1.256)	(1.880)[c]	(0.378)	(0.112)
DMF	-0.820	-1.937	-0.272	-1.377	-0.717
	(2.035)[b]	(3.226)[a]	(1.507)[d]	(1.008)	(0.897)
DAG1	-0.013	-1.341	0.402	-0.502	-0.478
	(0.033)	(2.346)[b]	(2.089)[b]	(0.398)	(0.524)
DAG2	-0.115	-0.423	0.268	-0.073	-0.552
	(0.558)	(1.589)[d]	(2.063)	(0.120)	(0.903)
DUI	0.501	0.466	0.452	0.532	0.550
	(2.297)[b]	(1.796)[c]	(3.458)[a]	(0.746)	(1.125)
DUN 1	0.389	0.466	0.212	0.377	-0.025
	(1.671)[c]	(1.529)[d]	(1.588)[d]	(0.503)	(0.053)
LTenure1	0.030	0.125	-0.015	0.092	0.186
	(0.536)	(1.584)[d]	(0.420)	(0.392)	(1.102)
DWG	0.648	0.338	-0.138	-1.562	-0.246
	(0.468)	(0.354)	(0.356)	(0.502)	(0.160)
Lambda	-0.688	-2.516	-0.145	-2.144	-1.552
	(1.146)	(3.428)[a]	(3.961)[a]	(1.227)	(1.236)

Table 3.7 (continued)
Note: t - values are given in parentheses.

a: $p \leq 1\%$	c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$	d: $10\% < p \leq 15\%$

Conclusion

The fact that unemployment in Canada remains high suggests that labour movement across industries is far from being an automatic or a smooth process. This raises a concern: do workers who move to a new industry incur significant costs? We try to answer this question while considering whether the workers' decision to move from or stay in an industry is governed by a rational evaluation, rather than by chance.

Surprisingly, our results show that displaced workers who move to a new industry on average experience higher wage growth than those who stay, after some positive unemployment spell. Our best guess is that those who move have 6% to 18% higher wage growth than those who stay. Even during the recessionary year in 1990, those who moved had around 14% higher wage growth.

Another concern is whether workers who move to a new industry incur a longer unemployment duration. Our simple mean statistics tell us they do. Our equation estimates also show that there is such a tendency, though the evidence is not very strong. This finding stand in contrast to the common belief that the stayers are the big contributors to the increase in the unemployment rate.

In general, those who move are more likely to move industry have the following characteristics: they are young, unmarried, from the manufacturing sector, have a wage lower than average, are displaced from big firm, from a non-unionized job and did not have a long tenure in the previous job.

Our next step is to uncover the determinants of wage growth, while still considering that the decision to move or stay in an industry is an endogenous process. Tenure on the previous job and unemployment duration have become key variables that link the wage with factors representing human capital and job search. Without other factors influencing the worker's decision, the conclusion would be that the longer the unemployment duration, the lower the wage. Moreover, workers can incur a specific human capital loss, and sometimes lose part of their general human capital, after being out of work for a period of time. These factors imply negative signs for both the coefficient of unemployment duration and the coefficient of tenure in the previous job.

We argue that the strength of unionization and the generous income support system in Canada could change, or at least weaken, the above results. In Canada, the unionization rate is twice the rate in the US. These factors will affect both reservation wages and wage offers to influence the results. Our findings as outlined below support this.

After the simultaneity correction, the signs of the previous job tenure (LTenure1) coefficients are mixed as before, but now one out of ten coefficients is significant and has a positive sign. Before the simultaneity correction, most coefficients of log duration (LogDur) are insignificant and have mixed positive and negative signs. After the correction, all signs in the mover part are positive and three of them are significant (the 1986, 1989 and the 1990 coefficients). In the stayer equations we see more negative signs, but all remain insignificant.

The signs of the wage growth (DWG) coefficients in the log duration equations (Table 3.6 and Table 3.7) are also mixed. Only one out of ten coefficients is significant, and this significant coefficient has a positive sign (the 1989 coefficient). Thus, in 1989 the positive causality between wages and duration of unemployment runs both ways. Wages improve with the time spent searching for a job, and at the same time the higher possibility of getting better wage offers induces workers to search longer. This positive direction of causality is exactly the opposite result of the wage-duration causality found in Addison-Portugal (1989).

Not every one of our results is completely the opposite of the results found in Addison-Portugal, but the fact that they do not support Addison-Portugal's findings raises the question whether other factors play a significant role. The longest spell in our sample is 49 weeks; this is still within the eligibility of UI benefit. Further, the mean of duration of unemployment in Addison-Portugal's sample is below 9 weeks, while ours is above 10 weeks. This means that we cover enough observations with long spells of unemployment. Evidently these long spells do not significantly reduce wage growth. We also sought to discover if the mean wage growth among those whose spells are censored at the end of the year 1986, but are completed in 1987, is positive or negative. We find a positive value. We attribute this upward trend of the wages to UI benefits and unionization.

Strong results are found in the union status change dummy variables (DUNI1 and DUNI2), especially for the movers. The signs are all negative for the change from a unionized job to a non-unionized job, and all are positive for the change from a non-unionized to a unionized job. The highest loss is 21%, the lowest loss is 16%. The highest gain is 31% and the lowest gain is 15%. The firm size change variables (DFZ1 and DFZ2) yield similar results, though the results are not as strong and the amount of loss or gain is only around 10% and lower.

We expect that cross-sectional comparisons will provide some kind of consistency check for the estimates, while keeping in mind that economy-wide changes might affect some results. For example, 1990 was a recessionary year in Canada. A few signs do change in the 1990 results, but more changes in signs occur in the 1988 results. As has been mentioned earlier, marked changes in other aspects also occur in this year such as the percentage of mobility and the percentage of workers who reported having been displaced due to plant closing and bad economic conditions. Perhaps this finding relates to workers' anticipations about the timing of the economic swings.

The fact that the recession does not show much of an effect on the wage and the decision to move leads us to believe that such effects might be more pronounced if the set of observation is extended to include those workers with unemployment spells that are longer than those examined, which are of course, presently censored. This would require a longitudinal data set.

CHAPTER IV

PREDICTING THE PROBABILITY OF RETURNING TO WORK USING A SPLIT-POPULATION DURATION MODEL

For the country as a whole it is found that the average annual unemployment rate increased significantly in the recessionary period of the early 80's. Thereafter, there was a small tendency for it to fall during the recovery. Corak (1990) found that these changes could be traced almost entirely to an increase in the number of individuals who were unemployed for more than 6 months during the year.

Corak further found that the distribution of the total time spent unemployed shifted towards males from females during the recession, but reverted to its pre-recession pattern relatively quickly during the recovery. For both genders, there was a shift in the distribution of the total time spent unemployed from the young to the old. Across the regions, the total time spent unemployed was highly concentrated among the long-term unemployed, particularly in Quebec and British Columbia during the aftermath of the recession.

Corak used the Annual Work Pattern Survey which offers information on the total time that an individual spends during the year. Unfortunately, this recorded time is not always continuous. Rahman and Gera (1991) used the data on continuous spells and found that the average reported length of ongoing periods of unemployment (duration of incomplete spells) reached 21.8 weeks in 1983. The completed spells would be approximately double these durations. The average reported length of the ongoing period of unemployment decrease somewhat to 20.3 weeks in 1986 and 1987. Rahman and Gera further reported that the incidence of long-term unemployment (unemployment which lasts 12 months or more) rose from 3.5% in 1979 to 10.1% in 1985, and subsequently declined to 6.6% in 1989.

Other findings in Rahman-Gera are that the incidence of long-term unemployment tends to rise with age and tends to decrease with education level. Older workers (aged 45 and over) are the most vulnerable. Further, individuals in the Atlantic Provinces, British Columbia and Quebec are more likely to become long-term unemployed than those in the Prairies and Ontario.

Long-term unemployment imposes considerable social and private costs. For society, an increase in the incidence of long-term unemployment means higher costs for unemployment insurance and other social programs. For individuals, it erodes human capital. Long-term unemployment also has macroeconomic implications. According to the concept of hysteresis, the NAIRU (Nonaccelerating Inflation Rate of Unemployment), the rate of unemployment accompanying a stable rate of inflation, changes in response to movements in past unemployment rates. Persistently high unemployment will therefore lead to a higher natural rate of unemployment.

Despite the importance of the above issue, most empirical work does not give it much attention. When a cross-sectional data set is used, many observations on unemployment spells are censored at the end of survey date. We miss long-term unemployemnt spells which are completed in the next survey year and the very long-term spells which may never be completed. By not including these two groups in our models, we eliminate potentially useful information. This is unfortunate since, presumably, workers in these very groups are the ones who ought to be the government's labour policy priorities.

Generally the group that we are concerned with the most is the unemployed who are job losers (those whose jobs are terminated involuntarily). Focusing on this group is also easier in that at least at the beginning of an unemployment spell, the workers still want a job. As the spell gets longer, there may be a diminishing probability of getting a job due to prospective employers' negative perceptions and the degradation of the worker's motivation to search. With the unemployed job quitter, this motivation is harder to detect. Part of the decrease in unemployment rates can be attributed to workers who leave labour force. Job quitters may exit the labour force in order to return to school or for some personal reason. For job losers, the reason they stop looking for and wanting a job is most likely because they are discouraged.

In this chapter, using the LMAS 1986-1987 longitudinal file, we apply models whose structures can accommodate the following features of unemployment. (1) The majority of workers are reemployed after spending some time out of work, though for certain workers this time is longer than for others. (2) Some workers spend a far longer time out of work, and the chances are they will not return to work due to becoming discouraged.

This raises two questions. What factors lengthen unemployment spells and what are the characteristics of those who have a greater chance of returning to work? We make separate statements about the effects of explanatory variables on these two conceptually different aspects, namely, the timing of returning to work and the probability of eventually returning or not returning to work. Another potentially useful result is our individual predictions about whether a displaced worker with certain characteristics will return or not return to work.

Model Specification

A split population duration model is a duration model applied to a special case in which the probability of eventual failure is less than one. In the usual case, it is assumed that in the end the object of observation will always eventually fail (as time gets larger the cumulative distribution function equals one). This is true for cases in biostatistics, but in other cases this assumption can lead to unreasonable and dramatic conclusions. In criminology for instance, it is unreasonable to assume that every ex-convict will always commit a crime and return to prison.

We have not heard much about the application of split population duration models in economics. The application of duration models themselves has been mostly concentrated in labour economics, and so far it is the biostatistics' type of duration model that has been used. However, the following facts should make us reconsider the eventual failure assumption behind these models. In the 1986 - 1988 period, the percentages of unemployment which is long-term in various OECD countries are as follows: US: 8.1%, Canada: 9.2%, Sweden: 8.2%, Australia: 28.2%, France: 46%, Japan: 19.2%, Belgium: 71.7%, Germany: 32.0%, Netherlands: 56%, and UK: 42.9%. The following table confirms that a portion of the long-term unemployed do quit the labour force.

Table 4.1

Labour Force Status in 1985 of Those Unemployed 12 Months Earlier

Country	**Unemployed**	**Employed**	**Not in the labour**
Belgium	69	22	9
Denmark	37	49	14
France	54	29	17

Table 4.1 (continued)

Country	Unemployed	Employed	Not in the labour
Ireland	69	18	13
Italy	61	32	7
Netherlands	62	24	14
UK	51	29	20
USA	26	49	25

Source: OECD 1987

Split population duration models have been used in the statistical literature at least since Anscombe (1961). This approach was introduced in the criminology literature by Maltz and MCCleary (1977), and further developed by Maltz (1984) and Schmidt and Witte (1988, 1989).

Except for Cox's proportional hazard model, which requires no assumption about the underlying spells distribution, other parametric duration models assume that duration follows a certain distribution. The most commonly used distributions are weibull, exponential, normal, logistic and gamma. These functional distributions are given in Appendix 4B.

The split population duration model can be expressed as follows. Let R_w be an unobservable variable which indicates whether an individual will or will not eventually fail (to return to work, in our case). Let R_w equals one for individuals who would eventually fail, and zero for individuals who would never fail. Assume that there is a finite but unknown probability that an individual will eventually return to work. Let this probability of failure be denoted by:

$$P(R_w = 1) = \omega$$

Since by assumption all others never fail, we have

$$P(R_w = 0) = 1 - \omega$$

The parameter ω is the eventual return to work rate. Further, let us assume there is some cumulative distribution function (cdf) $G(t \mid R_w = 1)$ for individuals who would ultimately fail, and $g(t \mid R_w = 1)$ is the corresponding density. Note that this distribution is defined conditional on $R_w = 1$ and is irrelevant for individuals for whom $R_w = 0$. Here t is the exposure time; it is the duration of unemployment when the spell is completed or will be completed.

Define T to be the length of the observation pericd and let d be an observable dummy variable; $d = 1$ for those who return to work prior to the end of observation period and $d = 0$ for those who do not return to work until the end of the observation period. For the returnees we observe $d = 1$ and the failure time t, and we know that $R_w = 1$. The unconditional probability density of failure at time t is:

$$g(t) = g(t \mid R_w = 0) \,.\, P(R_w = 0) + g(t \mid R_w = 1) \,.\, P(R_w = 1)$$

$$g(t) = 0 \,.\, (1 - \omega) + g(t \mid R_w = 1) \,.\, \omega$$

$$g(t) = \omega \,.\, g(t \mid R_w = 1) \tag{4.1}$$

For those who are still unemployed in the sample, we only observe $d = 0$. Therefore, the probability of no failure before time T for individuals is:

$$P(t > T) = P(d = 0) = P(R_w = 0) \,.\, P(t > T \mid R_w = 0) + P(R_w = 1) \,.\, P(t > T \mid R_w = 1),$$

that is

$$P(t > T) = (1 - \omega) + \omega\,(1 - G(t \mid R_w = 1)) \tag{4.2}$$

Thus, the likelihood function can be written as:

$$L = \Pi_{d=1}\ \omega \,.\, g(t \mid R_w = 1)\,/\sigma \,.\, \Pi_{d=0}\,(1 - \omega + \omega(1 - G(t \mid R_w = 1))) \tag{4.3}$$

in which σ = standard deviation of log(t).

Now, we have to decide which distribution to use for $g(t \mid R_w = 1)$ and its corresponding cdf. From the description of the unemployment experience in Canada in the introduction to this chapter, as well as the unemployment experience in other developed countries, it appears that the probability of leaving the state of unemployment rises at the beginning, then slowly decreases, and then decreases very fast as time gets very large. Two of the distribution functions listed previously meet this criterion, namely the lognormal distribution and the logistic distribution. The exponential distribution produces a constant hazard function, while the weibull and gamma distributions produce a monotonic hazard function; neither is likely to mimic the actual distribution of unemployment spells.

Applying the lognormal distribution to (4.3) produces the likelihood function:

$$\text{Ln L} = \sum_{i=1}^{N} \left[\, d_i \left(\ln \omega_i \;-\; 1/2 \ln(2\pi) - 1/2 \ln \sigma^2 - (\ln t_i \;-\; X_i \beta)^2 \right) + \right.$$

$$\left. (1 - d_i) \ln H_i \,\right] \qquad (4.4)$$

where $H_i = 1 - \omega_i + \omega_i \,.\, \Phi \{ (X_i \beta - \ln t_i) / \sigma \}$

For the logistic distribution we have:

$$\text{Ln L} = \sum_{i=1}^{N} \left[\, d_i \left(\ln \omega_i + (\ln t_i - X_i \beta) / \sigma + 2 \ln (1 - \exp (\ln t_i - X_i \beta) / \sigma) \right) \right.$$

$$\left. + (1 - d_i) \ln H_i \,\right] \qquad (4.5)$$

where $H_i = 1 - \omega_i + \omega_i \{ 1 / (1 + \exp(\ln t_i - X_i \beta) / \sigma) \}$

We shall note that unlike the proportional hazard model, in which positive coefficients in β imply a positive effect on the hazard rate and a negative effect on survival time, in both of the above models a positive coefficient indicates that the corresponding variable has a positive effect on time until the return to work. In other words, it makes returning to work either less likely or take a longer time.

In the above model, ω is defined as the probability of eventual failure. We will allow a row vector of explanatory variables Z, to affect this probability.

Specifically, let us assume that ω is amenable to either the probit or logit transformations. For the logit transformation, we have:

$$\omega = 1 / (1 + \exp(Z\alpha)) \tag{4.6}$$

where α is a column vector of coefficients with the same number of elements as Z has columns.

For the probit transformation we have:

$$\omega = 1 - \Phi(Z\alpha) \tag{4.7}$$

Thus, we have four combinations: split lognormal-probit, split lognormal-logit, split logistic-probit and split logistic-logit.

Special care has to be taken in interpreting the coefficients of Z. In the probit as well as the logit model, the explanatory variables have direct effect on the probability of success (the program produces output based on the definition of the dummy variable $d = 1$ for success and $d = 0$ for failure); while what we define above is the probability of failure, ω, and we have $d = 1$ for failure and $d = 0$ for success. Therefore, the variables in Z have the opposite effect on ω , i.e. a positive sign means a negative effect on the probability of eventual failure.

The Validation Sample

In the absence of censoring, residual analysis is often recommended to check the model specification (Kalbfleisch - Prentice, 1980 and Kiefer, 1988).

Since the split population duration models entail censoring, this method is not applicable. Another technique to validate a model is to divide the population under study. Each member of the subject population is randomly assigned to one of two groups. The first group (the estimation sample) is used to develop the model, that is to determine which independent variables are significantly associated with the outcome variable. The model thus developed is then applied to the other group (validation sample). If the specification is correct the estimated parameters should agree. Maltz (1984) criticized this practice, arguing that this method does not validate a model; at best, what it validates is the equivalence of the two groups, the estimation sample and the validation sample. The validity of the model is untested, because it has only been tested against a sample almost identical to the one that produced it, not against competing models.

The strategy used here is to split the population into an estimation sample and a validation sample as suggested above, but the primary use of the validation sample here is to check the predictive power of the models developed using the estimation sample. The estimation procedure is repeated using the whole population to see if the estimates from the estimation sample reflect the behavior of the whole population.

Empirical Results and Analysis

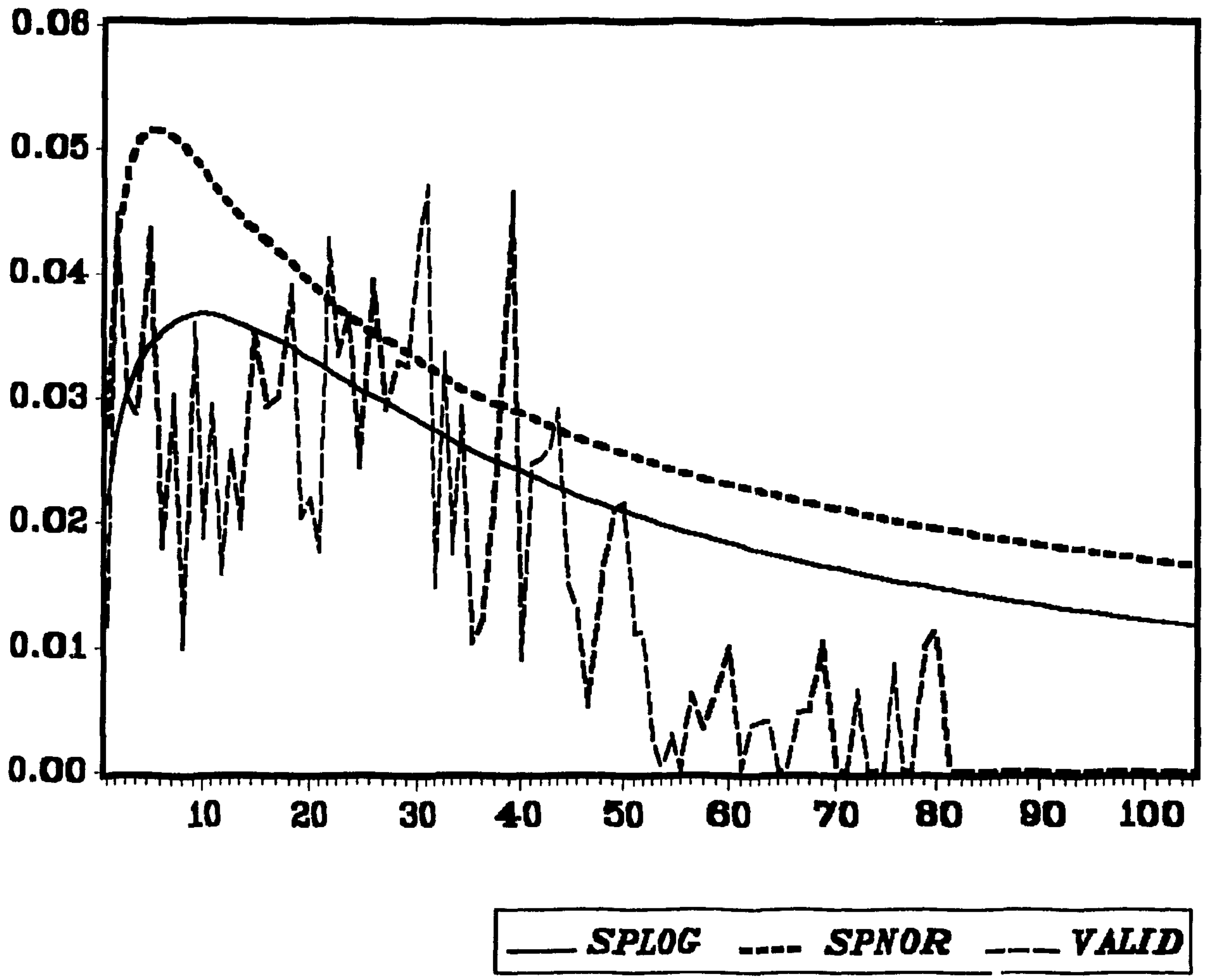
The total population under study is 2835. We select randomly 1450 observations for the estimation sample, and the rest 1385 observations for the validation sample. Then, we apply our models to the estimation sample.

First, let us drop all explanatory variables in X and Z and only put a constant in each of them. In other words, we regard all workers as being homogeneous. The purpose is to get a general picture about the trend of the probability to leave unemployment, and the average probability of returning to work. We use both split lognormal and split logistic models. From these models we get predicted individual hazard rates. We plot these hazard rates and compare these plots with the plot of the actual hazard rates from the validation sample to see if the models we choose approach the actual hazard rates (we get these actual hazard rates from a life table calculated from our data). Figure 1 describes this comparison.

Both the split lognormal and the split logistic models produce similar results. The split logistic model is slightly better in that it has a higher log-likelihood. The log-likelihood for the split lognormal model is -2270.47 while it is -2266.67 for the split logistic model. The average probability of returning to work for the split lognormal model is 0.872, and for the split logistic model it is 0.857.

From Figure 1, the plot of the actual hazard rates from the validation sample reflects our guess about the trend of the probability to leave unemployment, in general. It rises at the beginning, slowly decreases thereafter,

Figure 1.



and then decreases rapidly, especially after the end of the UI benefit eligibility (week 50). After week 80 none exit from unemployment. How good are the models we chose in reflecting this trend? Both models do pretty well in mirroring this trend, though the split lognormal model over-predicts the hazard rates close to the beginning of the spell and in the tail area. The split logistic model is slightly better in term of log-likelihood result as mentioned before and it is also slightly better in reflecting the actual trend. The exponential, weibull and gamma models would be far from being able to mimic this trend, because this trend is nonmonotonic. This nonmonotonic feature is not common in biological data, but in other cases such as in the applications involving recidivism, this feature is close to the real facts.

The next step is to incorporate explanatory variables both in the probability distribution of time spent unemployed, and in the probability of returning to work. Except for LogTenure (on the previous job), which is a continuous variable, all other variables are first tested to see if they are indeed not homogenous with regard to their effect on the hazard rate, e.g.: the UI recipients' hazard rates show a different trend than those not receiving UI benefit. Log-rank and Generalized Wilcoxon statistics are given in this tests, and all variables are significant at the 5% level or lower (the Log-rank and Wilcoxon tests are given in Appendix 4A). The following Table 4.1 to Table 4.4 present the estimates of the four models.

Table 4.2

Split Lognormal - Probit Model

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
Constant	2.075	8.918[a]	-0.462	1.773[c]
DAG2	-0.279	1.876[b]	0.195	1.109
DAG3	-0.191	1.113	-0.071	0.316
DAG4	0.037	0.212	0.563	2.948[a]
DED1	0.462	2.589[a]	0.252	1.171
DED2	0.121	0.630	0.299	1.299
DUI	0.225	2.423[b]	-0.784	5.937[a]
DUNI	0.192	1.986[b]	-0.323	1.786[c]
DSX	-0.328	3.457[a]	-0.553	4.660[a]
DMS	0.191	2.055[b]	-0.149	1.168
DTR	-0.435	2.842[a]	-0.327	1.568[d]
LTenure	0.086	3.444[a]		
DP1	0.406	3.456[a]		
DP2	0.069	0.515		
DP4	-0.108	0.680		
DP5	0.081	0.[illegible]26		
DP6	-0.750	2.094[b]		
σ	1.107	30.347[a]		

Table 4.2 (continued)

$\omega = 0.799$ (confidence int.: 0.755 - 0.844)
L = -2143.781

Survival time distribution :	0.95	0.75	0.50	0.25
t :	2.72	7.96	16.80	35.45

a: $p \leq 1\%$
b: $1\% < p \leq 5\%$
c: $5\% < p \leq 10\%$
d: $10\% < p \leq 15\%$

Table 4.3

Split Lognormal - Logit Model

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
Constant	2.078	8.966[a]	- 0.792	1.789[c]
DAG2	-0.281	1.898[b]	0.335	1.131
DAG3	-0.203	1.192	-0.108	0.281
DAG4	0.035	0.202	0.957	2.986[a]
DED1	0.466	2.622[a]	0.439	1.193
DED2	0.129	0.670	0.505	1.287
DUI	0.223	2.415[b]	-1.341	5.740[a]
DUNI	0.189	1.964[b]	-0.565	1.785[c]
DSX	-0.341	3.610[a]	-0.898	4.452[a]
DMS	0.194	2.090[b]	-0.248	1.147
DTR	-0.431	2.836[a]	-0.603	1.619[c]
LTenure	0.086	3.467[a]		
DP1	0.409	3.488[a]		

Table 4.3 (continued)

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
DP2	0.068	0.512		
DP4	-0.116	0.734		
DP5	0.077	0.593		
DP6	-0.769	2.087[b]		
σ	1.105	30.393[a]		

ω = 0.798 (confidence int. : 0.789 - 0.806)
L = -2145.523

Survival time distribution :	0.95	0.75	0.50	0.25
t :	2.72	7.96	16.76	35.31

a: $p \leq 1\%$
b: $1\% < p \leq 5\%$
c: $5\% < p \leq 10\%$
d: $10\% < p \leq 15\%$

Table 4.4

Split Logistic - Probit Model

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
Constant	2.102	9.802	-0.455	1.767[c]
DAG2	-0.206	1.506[d]	0.173	0.974
DAG3	0.111	0.690	-0.106	0.468
DAG4	0.042	0.261	0.590	3.107[a]

Table 4.4 (continued)

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
DED1	0.572	3.559[a]	0.227	1.074
DED2	0.192	1.112	0.280	1.240
DUI	0.177	2.013[b]	-0.747	5.936[a]
DUNI	0.141	1.523[d]	-0.260	1.552[d]
DSX	-0.320	3.567[a]	-0.580	4.889[a]
DMS	0.175	1.981[b]	-0.133	1.051
DTR	-0.452	3.290[a]	-0.322	1.534[d]
LTenure	0.070	2.807[a]		
DP1	0.389	3.453[a]		
DP2	0.034	0.269		
DP4	-0.202	1.347		
DP5	0.049	0.398		
DP6	-0.775	2.368[b]		
σ	0.624	28.354[a]		

ω = 0.799 (confidence int. : 0.758 - 0.840)
L = -2133.758

Survival time distribution :	0.95	0.75	0.50	0.25
t :	2.82	8.92	17.70	35.15

a: $p \leq 1\%$
b: $1\% < p \leq 5\%$
c: $5\% < p \leq 10\%$
d: $10\% < p \leq 15\%$

Table 4.5

Split Logistic - Logit Model

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
Constant	2.107	9.860[a]	-0.787	1.792[c]
DAG2	-0.209	1.538[d]	0.308	1.023
DAG3	-0.122	0.761	-0.164	0.420
DAG4	0.039	0.242	1.013	3.161[a]
DED1	0.575	3.591[a]	0.397	1.099
DED2	0.196	1.142	0.479	1.240
DUI	0.174	1.985[b]	-1.269	5.751[a]
DUNI	0.141	1.519[d]	-0.462	1.568[d]
DSX	-0.329	3.681[a]	-0.954	4.705[a]
DMS	0.177	2.013[b]	-0.224	1.043
DTR	-0.449	3.284[a]	-0.585	1.569[d]
LTenure	0.070	2.816[a]		
DP1	0.392	3.487[a]		
DP2	0.034	0.273		
DP4	-0.209	1.395		
DP5	0.046	0.372		
DP6	-0.785	2.371[b]		
σ	0.622	28.389[a]		

Table 4.5 (continued)

ω = 0.797 (confidence int. : 0.790 - 0.805)
L = -2135.577

Survival time distribution :	0.95	0.75	0.50	0.25
t :	2.82	8.92	17.68	35.04

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

All four models produce the same signs for all estimates, though some have different level of significance. The average predicted failure probabilities are all around 0.79. The split logistic - logit model has the smallest confidence interval. Comparing the log-likelihood results, the spilt logistic-Probit has the highest result.

Let us look at the estimates of the equation for duration first. In the set of age dummy variables used, we change the default from the oldest age bracket (45 years and over) to the youngest age bracket (19 years and lower). This is done to make comparison with other findings easier. Both Corak and Rahman-Gera found that older workers are more vulnerable; they are more prone to experience long-term unemployment. The difference between their study and ours is that in this part of the model, we observe only those who have found a new job (have returned to work), while in their sample the unemployment spells might be completed or not. Our results show the second age bracket (age 20 - 34) has the shortest unemployment spell. The sign of each of the coefficients of the second and the third age brackets is negative. The sign turns positive for the fourth age bracket. Comparing all four, then, we can conclude that, on average, workers that belong to the oldest age bracket have the longest unemployment duration. The youngest workers have the second longest unemployment duration.

In the Heckman two-stage estimates using cross-sectional data presented in Chapter III, it was found that the education dummy variables do not have a significant effect on unemployment duration. In this chapter, on the contrary, all coefficients of the first education dummy (high school and lower) are significant at the 1% level, and the signs are positive. This indicates that workers with the lowest education levels have longer durations than those workers who are university graduates; in fact the former have the longest average duration among the three groups. This confirms the findings mentioned earlier in this chapter.

Search theory predicts that an increase in UI benefits will raise reservation wages. This implies more wage offer rejections and longer unemployment durations, and so a lower hazard rate. The UI benefit dummy coefficients in the models all show positive signs and are significant at the 5% level or lower. This means that UI recipients have a longer unemployment duration than those not receiving UI benefits.

The union dummy variable coefficients all have positive signs though in the split logistic-probit and split logistic-logit models the p values are above 10% (around 12%). Having enjoyed the benefit of unionization in the previous job, we guess that the workers will take their time to search for a job which enables them to get that benefit again (another unionized job).

Female workers are more prone to experience a longer unemployment duration. All coefficients of sex dummy variables have negative signs and are significant at the 1% level. These results confirm Corak's finding.

Married workers maybe under greater pressure to get a job fast if they are the sole income earner in the family, but not if they have a working spouse. All coefficients of DMS have positive signs and are significant at the 5% level or lower.

Training programs are expected to improve workers competitiveness in finding new jobs. Apparently the training programs in Canada have brought some success in term of the speed of finding a job. Those who joined the programs find a job faster than those who did not. All signs of training dummy coefficients are negative and significant at the 1% level..

Long tenure means more accumulation of specific human capital. At the highest skill level, this accumulation of human capital is often highly valued by the market, i.e.: workers with this skill get a job easier. At the other end of the skill level, the displaced workers generally spend a longer time to find a similar job that still enables them to benefit from their human capital accumulation. The signs of the log tenure coefficients are all positive as expected, and they are all significant at the 1% level.

Among the provincial dummy variables, the coefficients of DP1 (Newfoundland, PEI, Nova Scotia and New Brunswick) consistently have high t-values, followed by the coefficients of DP6 (Ontario), though those two groups have opposite signs of coefficients. The default is DP3 (Manitoba and Saskatchewan). These confirm what has been talked about, namely that the Atlantic Provinces suffer the most economically and Ontario is the fastest growing province.

All of the variables above except log tenure and provincial dummy variables are included in the set of variables that determine the probability of returning or not returning to work. Before we examine the estimates of these variables, we shall make a brief comparison between the estimates from the split models with the probit model estimates assuming that returning to work is a success (those who return to work = 1).

Table 4.6

Probit Model Estimates for the Probability of Returning to Work

Using the Estimation Sample

	Coefficient	t - statistics
Constant	0.402	1.966[b]
DAG2	-0.106	0.733
DAG3	0.046	0.287
DAG4	-0.538	3.669
DED1	-0.326	1.904[b]
DED2	-0.248	1.337
DUI	0.524	6.344[a]
DUNI	0.097	1.027
DSX	0.536	6.837[a]
DMS	0.056	0.644
DTR	0.354	2.190[b]

a: $p \leq 1\%$　　c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$　　d: $10\% < p \leq 15\%$

The signs of the above estimates are, as expected, exactly the opposite of the signs of estimates of the equation for P(never fail) in Table 4.2 to Table 4.5. One may question if the estimates from the split population duration models are any better than the estimates of two separate models: the Probit model and the duration model with a censoring variable. To answer this, we can run a likelihood ratio test similar to the one on page 28 on page 28 in Chapter III. Using the whole population under study we get a very high ratio: 1582.49. This is an obvious result since the log-likelihood of any of the four split models that we have discussed is already higher than the log-likelihood of the same model without split (with censoring instead). So, based on this test, we conclude that the result from the split models are better than the results from a separate probit model and duration model with a censoring variable.

From the set of age dummy variables in the equation for P(never fail), the oldest age bracket (DAG4) estimates all have positive signs and are significant at the 1% level. The evidence that older displaced workers suffer the most is much stronger here than the evidence from the equation for duration given eventual failure. Older workers who manage to find a new job after being displaced , on average, suffer a little longer duration of unemployment than others. Also, compared with the younger groups, older workers are much more likely to withdraw from the labour force after experiencing a long unemployment spell.

In the equation for duration given eventual failure, the first education bracket dummy variable strongly and positively affects the length of unemployment spell. In the equation for P(never fail), the signs are positive, but their level of significance is above 20%. Apparently, there is a little more variation in terms of level of education in the group of workers who are prone to withdraw from the labour force.

Those who are likely not to return to work tend to be non UI benefits recipients. This is rather surprising. Our guess is that it is related to the fact that though the log tenure coefficient has a positive sign, it is highly insignificant (it is omitted from the equation). In Canada workers are only required to have 10 - 14 weeks of employment to be eligible for UI benefit. Apparently a larger portion of them did not have a stable job prior to the last displacement. It could well be that they have been in and out of several short term jobs after their last stable job.

The majority of those who do not return to work are non union members. This is in line with the above results regarding UI benefits and tenure. Normally, union members have a stronger attachment to their job.

Another characteristic of those who are likely not to return to work is that they are predominantly female. Thus, female displaced workers tend to both withdraw from the labour force, and if they indeed return to work, have longer unemployment spells. This supports Corak's finding mentioned earlier in this chapter.

The marital status dummy variable used here divides workers into married and others (single, widow, etc.). The tendency of not returning to work leans more towards those belonging to the "others" category. The signs of the marital status coefficients are negative, though their level of significance is above 20%.

Training programs seem to work both in reducing unemployment spells and in helping unemployed workers to return to work. The signs of the training dummy variable coefficients are all negative, but from their level of significance, their effects are not as strong as those in the equation for duration given eventual failure.

The provincial dummy variables are dropped from the equation for P(never fail) because they are insignificant. Among them DP1 (the Atlantic Provinces) has the highest p value, but it is still above 10%. Though the evidence is weak, this means the Atlantic provinces have a higher rate of workers dropping from the labour force.

Checking the Models' Specification and Predictive Power

In criminology, individual predictions of failure on parole or recidivism are important, particularly for determining the kind of treatment needed for the offenders, and for the safety of society as a whole. The inclusion of explanatory variables in both the equation for duration given eventual failure and in the equation for P(never fail) is very important in that they help to describe the characteristics of those two different groups as well as to show the relative strength of the effects of those variables. The same individual predictions are also useful in the unemployment case that we have been discussing.

A policy is also easier to design and to apply if the policy makers have some assurance about the correctness of the predictions. As was said earlier in this chapter, a sample of observations similar to the estimation sample used to develop the model is expected to produce the same results. Repeating the same model will be more worthwhile if a larger sample is used, i.e.: by pooling the estimation sample and validation sample in our case. In this way we can check if the estimates of the model using the estimation sample are stable or not.

We suggest a better way of using the validation sample in the context of the split population models above. This sample can be used to check how well the models predict the probability of returning or not returning to work. This can be done by reconstructing ω (which is a Probit or Logit function) using the estimates from P(never fail) and the same set of variables used in the models obtained from the validation sample. In this way, the individual probability of returning to work is obtained. We sort these into descending order, and report the results in Table 4.7.

In the first group for example, there are 369 individuals who have a probability of returning to work $0.9795 \geq \omega \geq 0.9154$ and among these 369 people, 333 (90.2%) individuals actually return to work. So, from this first 10% highest probability group we only miss less than 10% of the prediction. Thus, we have high assurance that individuals in this group will return to work. The second highest probability group successfully predict 84.5% of the return of the workers in this group. The model seems to work well in prediction for those in the top 20% highest predicted probability groups. The percentage of correct predictions gets lower for the lower probability groups. This is as expected, we should see workers with higher probability actually return to work compared to those with a lower probability. Thus, from this we can say that our models have some predictive power. Unfortunately, closer to the bottom, the percentage does not go low enough so that we have around 50% chance to be wrong when we say that workers with this low level of probability will not return to work. So, we are actually much more successful in predicting individuals who will fail (return to work) than predicting those who will never fail.

Table 4.7

Individual Predictions of Probability of returning to Work

Using the Validation Sample

Probability	**# Observation**	**# Return**	**%**
0.9795 - 0.9154	369	333	90.2
0.9153 - 0.8512	297	251	84.5

Table 4.7 (continued)

Probability	# Observation	# Return	%
0.8511 - 0.7870	239	166	69.4
0.7869 - 0.7228	165	124	75.1
0.7227 - 0.6586	108	68	62.9
0.6585 - 0.5944	48	23	47.9
0.5943 - 0.5302	76	41	53.9
0.5301 - 0.4661	40	23	57.5
0.4660 - 0.4019	35	13	37.1
0.4018 - 0.3377	7	4	57.1

Our next step is to test if our estimates are stable: whether with more information from additional observations the estimates do not significantly change. We do this by pooling the estimation sample with the validation sample and applying our models to this larger sample. Since the four split models produce quite close results we only use one of them, the split lognormal - logit model. The results are as shown on Table 4.8.

Compared with the results from the same model using the estimation sample, there are only 2 sign changes, one in the equation for duration given eventual failure (the provincial dummy for Ontario), and one in the equation for P(never fail) (the third age bracket dummy variable). The provincial dummy variable for Ontario changes from negative to positive, but it is not significant and the coefficient is close to zero. The third age bracket dummy variable changes from negative to positive, but both are insignificant.

Table 4.8

Estimates of the Split Lognormal - Logit Model

(Whole Population)

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
Constant	2.044	13.078[a]	-1.315	3.500[a]
DAG2	-0.163	1.601[c]	0.289	1.269
DAG3	-0.176	1.517[d]	0.126	0.434
DAG4	0.133	1.099	1.370	5.391[a]
DED1	0.428	3.768[a]	0.719	2.228[b]
DED2	0.129	1.040	0.739	2.145
DUI	0.276	4.342[a]	-1.652	7.977[a]
DUNI	0.080	1.288	-0.411	1.833[b]
DSX	-0.402	7.190[a]	-0.799	5.288[a]
DMS	0.037	0.607	-0.216	1.273
DTR	-0.358	3.549[a]	-0.218	0.818
LTenure	0.108	6.522[a]		
DP1	0.493	6.924[a]		
DP2	0.178	2.200		
DP4	-0.033	0.343		
DP5	0.155	1.521		

Table 4.8 (continued)

	Equation for Duration given eventual failure		Equation for P(never return to work)	
	Coefficient	t - stat.	Coefficient	t - stat
DP6	0.00006	1.084		
σ	1.077	43.727[a]		

ω = 0.797 (confidence int. : 0.8169 - 0.8288)
L = -4133.826

Survival time distribution :	0.95	0.75	0.50	0.25
t :	2.95	8.41	17.38	35.95

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

The t-values of the coefficients of some variables become markedly higher and for these variables the coefficients also increase slightly. This shows a greater effect on the duration or on P(never fail). In the equation for duration given eventual failure, these variables are: UI benefit dummy variable, sex dummy variable, logTenure, provincial dummy variable for Atlantic provinces, provincial dummy variable for Quebec and provincial dummy variable for British Columbia. In the equation for P(never fail), these variables are: the fourth age bracket dummy variable, the first and second education dummy variables and the UI benefit dummy variable. Another change is in the average predicted failure probability. It increases to 0.822, but its lower bound of the confidence interval is pretty close to the upper bound of the confidence interval of the average predicted failure probability in the split lognormal - logit using the estimation sample. Overall, the increase in the number of observations barely changes the direction of the effects of the explanatory variables. This increase in the number of observations even strengthens the effects of a good number of variables. these make us fairly confident of the results from the models using the estimation sample.

Our last step is to check if split models are better than non split models. We wish to know if differentiating the probability of eventual return from the timing of return gives more useful information than when these factors are not parameterized separately. To do this checking, we run a logistic duration model with a censoring variable and compare the results with the results from our split models

Table 4.9

Estimates of Logistic Duration Model with a Censoring Variable

(Whole Population)

	Coefficient	**t - Statistics**
Constant	2.659	17.502[a]
DAG2	0.050	0.537
DAG3	0.008	0.075
DAG4	0.640	6.110[a]
DED1	0.693	6.174[a]

Table 4.9 (continued)

	Coefficient	t - Statistics
DED2	0.399	3.295[a]
DUI	-0.342	5.950[a]
DUNI	-0.037	0.552
DSX	-0.608	11.591[a]
DMS	-0.023	0.387
DTR	-0.425	4.265[a]
LogTenure	0.085	4.937[a]
DP1	0.417	5.783[a]
DP2	0.271	3.338[a]
DP4	-0.036	0.338
DP5	0.147	1.439
DP6	0.0001	2.034[b]
σ	0.770	52.962[a]

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

A major change that we observe is in the UI benefit coefficient. This coefficient changes from positive significant to negative highly significant. The negative sign simply means that compared with the non UI recipients, the UI recipients bring down the mean of log duration by as much as the amount of the coefficient's estimate. This result is the opposite of the result of the same variable found in the equation for duration given eventual failure. The question is: which model can we trust?

As was said before, in split models we separate the timing of return and the probability of eventual return, while in the logistic model with censoring we only see the timing of return. We could expect different results if the effect if the effect of the variable on the average duration of those who eventually fail is different from the effect of the same variable on the average duration of the whole sample. A simple mean statistics using the UI dummy variable shows this. The mean duration of completed unemployment spells for UI recipients is 21.55, while for non UI recipients, the mean is 17.225. We observe a positive sign in the coefficient of the UI benefit dummy variable in the equation for duration in our split models. The mean duration of UI recipients of the whole sample is 31.49, while the mean for non UI recipients is 37.64. We observe a negative sign in the coefficient of the UI benefit dummy variable in the logistic model with a censoring variable.

From the above simple exercise, we can conclude that the split population duration models give more accurate results than an ordinary duration model with a censoring variable.

Conclusion

In economics we recognize that some unemployed workers never return to employment; they never "fail" in duration model terminology. We label these unemployed workers as discouraged workers. Our purpose is to set out and estimate a duration model which takes this into account. A split population duration model, as in Schmidt and Witte (1989) meets this need. There are three main differences between our methodology and theirs. First, besides the distribution functions that we use, in their split model without covariates they also use the LaGuerre distribution (a combination of exponential and polynomial functions). They found that this distribution fits slightly better than the logistic distribution. But Schmidt and Witte only use split lognormal-logit to develop their model using a set of covariates. The second difference is that they only use logit model for the probability of eventual failure, while we use both probit and logit models. The third and final difference is in the way we check our model specification. Due to the criticism of Maltz, we do not repeat the model estimation using the validation sample. Instead, we use the validation sample to check the predictive power of the models, and use the pooled estimation and validation samples to check the stability of our estimates.

Our results show that on average around 20% of unemployed displaced workers (job losers) will not return to work. Rahman-Gera report that in 1987 long-term unemployed accounted for 4.2% of the labour force, which is about

23.1% of the unemployed (quitters and job losers). Our results makes sense if, nationally, the majority of those who will not return to work are job losers. Further, we found that among the displaced workers who eventually return to work, those with the following characteristics tend to experience longer unemployment spells: those aged 45 and over, those with only a high school degree or less, those who receive UI benefits, females, those with high tenure, those who never joined any training program, those living in Atlantic provinces and Quebec. The following characteristics describe the displaced workers who have little probability of returning to work: those aged 45 and over, those with lower education than a university degree, non UI recipients, non union members and females.

From our predictive power checking, we conclude that our models are more successful in predicting the probability of returning to work than the opposite. This leaves the door open to those who are interested in improving the technique used in cases like ours. The results from the pooled samples show there are no results from the estimation sample that are significantly overturned. This means that our estimates are fairly stable. Compared to duration models with no split, our split models give more accurate estimates.

CHAPTER V

SUMMARY AND CONCLUDING REMARKS

The purpose of this thesis has been to discuss three important aspects of job displacement in Canada. These are: wages, industrial mobility and the duration of unemployment. Using the LMAS cross-sectional files from 1986 to 1990, the first part of this thesis has concentrated on short-term wage changes. The second part uses the 1986 - 1987 LMAS longitudinal file and focuses on the duration of unemployment.

In the first part, the analysis recognizes explicitly the importance of non-random sampling in the context of inter-industry mobility. This emphasis on inter-industry job mobility, instead of inter-firm job mobility, is a novel aspect of the study. Following Addison-Portugal (1989), Topel (1986) and Abraham-Farber (1987), the approach of this thesis is based on human capital and search theories. In addition, considerable attention is placed on factors which are specific to the Canadian economy. The analysis sets out to determine the answers to the following questions: what factors determine whether a displaced worker will move to a new industry? In term of wage, are movers the gainers or the losers? What factors contribute to the wage gain or loss? How do these behaviours change as the economy changes?

The main findings of the thesis are as follows:

1. On average, those who move to a new industry experience a wage gain ranging from 6% to 18%. On the other hand, there is also a tendency for these workers to have a longer duration of unemployment than the stayers.

2. Those who have a high probability to move to a new industry have the following characteristics: young, unmarried, from the manufacturing sector, with a wage lower than average, displaced from a non-unionized job and with a short tenure in the previous job.

3. There is a tendency for the movers to experience no loss of human capital investment after displacement. At the same time, the length of time spent unemployed does not bring down the wage for this group. After correction for simultaneity, a positive and significant causality between wage growth and duration of unemployment is found in one of the five samples used. For the stayers, the results are less positive. These results are contrary to similar findings using US data. On the other hand, our results show that moving from a non-unionized job to a unionized job strongly increases wages (and vice-versa for the movement to the opposite direction). In the Heckman two-stage model, the UI benefit positively and significantly affects duration of unemployment. It is argued that unionization and UI benefits work to weaken the effect of tenure on the previous job and duration of unemployment on the wage.

4. Surprisingly, only a few sign changes are observed in the 1990 recessionary year estimates, though more are observed in the 1988 estimates. In 1988, we also

notice that there is a significant drop in the mobility rate and a jump in the percentage of workers who reported losing their jobs because of poor economic conditions and the company going out of business.

Related to result 3 above, a question that naturally arises is: if lenient regulations concerning the formation of a union and the generous UI benefit system in Canada generally work in favour of the employed and the reemployed, who bears the costs of these system? Could it be, for example, that the persistently high unemployment rates in Canada (compared e.g. to the US) are caused by these systems? In 1985 the transfer program expenditures (UI benefit, family allowance etc.) in Canada amounted to 5.1% of its GNP, while in the US it was only 1.9% of its GNP (Blank-Hanranty, 1993). A larger portion of these expenditures in Canada is used to support the UI benefit system. If an American type of program were adopted in Canada, a large amount of money could be saved. Moreover, a streamlined program would limit the potential for misuse of the system.

So far, our results show that in general Canadian unemployed workers search longer and on average have a positive wage growth compared to their American counterparts. However, little can be said whether Canada has a better transfer program policy than the US. In Canada, this policy has been carried out at the expense of tax payers' money, government deficit and higher unemployment rates.

There are some possible causes of the different results that we get from the results of other studies using the US data that we have not explored. These are: (I) we have not taken into account geographical mobility which due to the different nature of the two countries (Canada, more spread out, less big cities, the US has more big and medium sized cities) might have different impacts on wages. (ii) we have not included variables that could measure "hardship" conditions of the workers which would partly explain the different wage growth that the workers experience.

In the second part of the thesis, split duration models were applied. These are flexible enough to admit that not every unemployed worker will eventually return to work. The aims, in this part of the thesis, are (I) to predict the probability of returning to work and to determine what factors affect this probability, and (ii) to determine those factors that affect the length of the duration of unemployment.

Close to 20% of unemployed displaced workers eventually quit the labour force. In this group are: female workers, older workers (aged 45 and over), workers with a low level of education, non-UI recipients and non-union members.

Those with the following characteristics tend to experience longer spells of unemployment: aged 45 and over, female, having a low level of education, UI benefit recipients, having long tenure on the previous job, having never joined any training program and from the Atlantic provinces or Quebec.

Older workers and female workers are often mentioned as vulnerable to unemployment. With the aging of the labour force in Canada, it will become increasingly important that older workers be integrated into the working world. The same holds for females. This will involve a greater emphasis on training to redirect these unused but potentially productive resources.

Appendix 3A

Table A1

Log Wage Regressions, 1986

	Log WG1	Log WG2	DWG
Constant	6.843	7.022	
	(75.510)[a]	(68.430)[a]	
LTenure1	0.037	0.028	-0.001
	(3.930)[a]	(2.996)[a]	(0.164)
LTenure2		0.012	0.016
		(0.874)	(1.230)
LDur		-0.008	-0.015
		(0.533)	(1.149)
DAG1	-0.690	-0.513	
	(12.450)[a]	(8.963)[a]	
DAG2	-0.284	-0.196	
	(6.441)[a]	(4.389)[a]	
DAG3	-0.098	-0.049	
	(1.880)[c]	(0.948)	
DED1	-0.073	-0.119	
	(1.003)	(1.621)	
DED2	-0.015	-0.024	
	(0.195)	(0.315)	
DUN 1	0.395		
	(11.090)[a]		
DUN 2		0.304	
		(8.631)[a]	
DFIRM1	0.055	0.015	
	(1.328)	(0.382)	

Table A1 (continued)

	Log WG1	Log WG2	DWG
DFIRM2	-0.031	0.020	
	(0.580)	(0.394)	
DFIRM3	0.085	0.043	
	(2.372)[b]	(1.259)	
GPI1	-0.014		
	(4.332)[a]		
GPI2		-0.011	
		(3.132)[a]	
DTR		-0.145	0.133
		(2.603)[a]	(2.304)[b]
DOC		-0.201	0.016
		(5.713)[a]	(0.480)
DM		-0.085	-0.033
		(2.359)[b]	(0.898)
DUNI1			-0.183
			(3.369)[a]
DUNI2			0.168
			(3.082)[a]
DFZ1			0.072
			(1.641)[c]
DFZ2			-0.119
			(2.996)[a]
DGPI			-0.007
			(2.412)[b]
R^2	0.341	0.335	0.066

Note: t-values are given in parentheses

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$

b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table A2

Log Wage Regressions, 1987

	Log WG1	Log WG2	DWG
Constant	6.972	7.019	
	(85.860)[a]	(80.320)[a]	
LTenure1	0.018	0.022	-0.008
	(1.835)[c]	(2.474)[b]	(0.920)
LTenure2		0.168	0.026
		(1.275)	(1.992)[b]
LDur		-0.001	0.007
		(0.057)	(0.507)
DAG1	-0.645	-0.520	
	(12.020)[a]	(10.600)[a]	
DAG2	-0.297	-0.269	
	(6.669)[a]	(6.651)[a]	
DAG3	-0.082	-0.074	
	(1.566)[d]	(1.575)[d]	
DED1	-0.140	-0.118	
	(2.325)[b]	(2.177)[b]	
DED2	-0.127	0.087	
	(1.908)[b]	(1.471)	
DUN 1	0.416		
	(10.720)[a]		
DUN 2		0.356	
		(11.320)[a]	

Table A2 (continued)

	Log WG1	Log WG2	DWG
DFIRM1	0.029	0.038	
	(0.710)	(1.040)	
DFIRM2	-0.013	0.039	
	(0.253)	(0.819)	
DFIRM3	0.085	0.056	
	(2.388)[b]	(1.817)[c]	
GPI1	-0.014		
	(4.332)[a]		
GPI2		-0.006	
		(2.270)[b]	
DTR		0.056	0.039
		(1.309)	(0.828)
DOC		-0.164	0.371
		(5.185)[a]	(1.069)
DM		-0.016	-0.057
		(0.502)	(1.630)[c]
DUNI1			-0.197
			(3.457)[a]
DUNI2			0.230
			(4.663)[a]
DFZ1			0.047
			(1.274)
DFZ2			-0.069
			(1.725)[c]
DGPI			-0.008
			(2.963)[a]
R^2	0.341	0.364	0.085

Table A2 (continued)

Note: t-values are given in parentheses
a: $p \le 1\%$ c: $5\% < p \le 10\%$
b: $1\% < p \le 5\%$ d: $10\% < p \le 15\%$

Table A3

Log Wage Regressions, 1988

	Log WG1	Log WG2	DWG
Constant	6.754	6.849	
	(71.720)[a]	(65.140)[a]	
LTenure1	0.037	0.025	0.015
	(0.589)	(2.552)[b]	(1.504)[d]
LTenure2		0.026	0.056
		(1.838)[c]	(0.405)
LDur		-0.015	-0.015
		(0.887)	(0.962)
DAG1	-0.573	-0.530	
	(9.559)[a]	(8.936)[a]	
DAG2	-0.232	-0.247	
	(4.538)[a]	(4.938)[a]	
DAG3	-0.007	-0.067	
	(1.338)	(1.165)	
DED1	0.040	-0.065	
	(0.547)	(0.902)	
DED2	0.114	0.036	
	(1.466)	(0.470)	
DUN 1	0.339		
	(9.193)[a]		

Table A3 (continued)

	Log WG1	Log WG2	DWG
DUN 2		0.355	
		(9.895)[a]	
DFIRM1	0.013	-0.025	
	(0.331)	(0.631)	
DFIRM2	0.036	0.056	
	(0.596)	(0.928)	
DFIRM3	0.096	0.030	
	(2.512)[b]	(0.838)	
GPI1	-0.005		
	(3.418)[a]		
GPI2		0.016	
		(3.966)[a]	
DTR		-0.057	-0.006
		(1.137)	(0.116)
DOC		-0.114	-0.026
		(2.635)[a]	(0.541)
DM		-0.003	0.011
		(0.071)	(0.230)
DUNI1			-0.226
			(4.159)[a]
DUNI2			0.192
			(3.149)[a]
DFZ1			0.068
			(1.552)[d]
DFZ2			-0.071
			(1.579)[d]
DGPI			0.005
			(1.436)[d]

Table A3 (continued)

	Log WG1	Log WG2	DWG
R^2	0.312	0.333	0.065

Note: t-values are given in parentheses
a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table A4

Log Wage Regressions, 1989

	Log WG1	Log WG2	DWG
Constant	7.087	7.207	
	(68.570)[a]	(64.270)[a]	
LTenure1	0.011	0.014	0.006
	(0.958)	(1.285)	(0.596)
LTenure2		0.013	0.006
		(0.921)	(0.459)
LDur		-0.044	-0.006
		(2.560)[b]	(0.414)
DAG1	-0.627	-0.427	
	(10.640)[a]	(7.395)[a]	
DAG2	-0.296	-0.189	
	(6.097)[a]	(4.046)[a]	
DAG3	-0.069	0.003	
	(1.227)	(0.069)	

Table A4 (continued)

	Log WG1	Log WG2	DWG
DED1	-0.134	-0.237	
	(1.642)[c]	(3.041)[a]	
DED2	-0.130	-0.176	
	(1.560)[d]	(2.209)[b]	
DUN 1	0.306		
	(7.805)[a]		
DUN 2		0.402	
		(10.920)[a]	
DFIRM1	0.035	0.039	
	(0.848)	(0.982)	
DFIRM2	0.020	0.070	
	(0.346)	(1.274)	
DFIRM3	0.035	0.076	
	(0.689)	(1.578)[d]	
GPI1	-0.001		
	(0.130)		
GPI2		0.001	
		(0.221)	
DTR		-0.002	0.036
		(0.033)	(0.626)
DOC		-0.094	0.058
		(2.413)[b]	(1.441)
DM		-0.066	-0.061
		(1.622)[c]	(1.464)
DUNI1			-0.096
			(1.693)[c]
DUNI2			0.215
			(3.814)[a]

Table A4 (continued)

	Log WG1	Log WG2	DWG
DFZ1			0.030
			(0.692)
DFZ2			-0.033
			(0.738)
DGPI			-0.007
			(1.679)[c]
R^2	0.294	0.363	0.048

Note: t-values are given in parentheses
a: $p \leq 1\%$ c: $5\% < p \leq 10\%$
b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table A5

Log Wage Regressions, 1990

	Log WG1	Log WG2	DWG
Constant	7.093	7.210	
	(63.470)[a]	(65.470)[a]	
LTenure1	0.004	0.011	0.004
	(0.340)	(0.980)	(0.297)
LTenure2		0.009	0.004
		(0.565)	(0.275)
LDur		-0.008	-0.025
		(0.505)	(1.370)

Table A 5 (continued)

	Log WG1	Log WG2	DWG
DAG1	-0.627	-0.569	
	(8.676)[a]	(9.170)[a]	
DAG2	-0.306	-0.266	
	(5.361)[a]	(5.352)[a]	
DAG3	-0.026	-0.108	
	(0.399)	(1.951)[b]	
DED1	-0.132	-0.166	
	(1.479)[d]	(2.181)[b]	
DED2	-0.016	-0.044	
	(0.176)	(0.566)	
DUN 1	0.389		
	(8.879)[a]		
DUN 2		0.409	
		(10.860)[a]	
DFIRM1	0.016	-0.009	
	(0.323)	(0.327)	
DFIRM2	0.067	0.041	
	(0.975)	(0.720)	
DFIRM3	0.084	0.033	
	(2.033)[b]	(0.726)	
GPI1	-0.001		
	(0.914)		
GPI2		-0.010	
		(2.121)[b]	
DTR		-0.011	0.013
		(0.217)	(0.206)
DOC		-0.139	0.203
		(3.578)[a]	(0.451)

Table A 5 (continued)

	Log WG1	Log WG2	DWG
DM		-0.007	0.034
		(0.199)	(0.748)
DUNI1			-0.207
			(3.111)[a]
DUNI2			0.162
			(2.247)[b]
DFZ1			0.122
			(2.235)[b]
DFZ2			-0.034
			(0.677)
DGPI			0.000
			(0.001)
R^2	0.353	0.438	0.059

Note: t-values are given in parentheses

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$

b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Appendix 3B

Table B1

Heckman Two-Stage Model for LogDuration (Movers)

	1986	1987	1988	1989	1990
Constant	2.441	3.798	2.709	2.921	2.360
	(9.481)[a]	(5.965)[a]	(8.777)[a]	(7.265)[a]	(7.480)[a]
DMF	-0.415	-1.085	-0.038	-0.743	-0.397
	(2.329)[b]	(2.570)[a]	(0.238)	(2.833)[a]	(2.449)[b]
DAG1	-0.252	-1.067	0.140	-0.468	-0.282
	(1.283)	(2.284)[b]	(0.772)	(1.562)[d]	(1.254)
DAG2	-0.132	-0.578	-0.063	-0.263	-0.519
	(1.072)	(1.993)[b]	(0.480)	(1.347)	(3.110)[a]
DUI	0.258	0.384	0.587	0.452	0.545
	(2.148)[b]	(1.572)[d]	(4.737)[a]	(2.453)[b]	(4.266)[a]
DUNI	0.170	0.519	0.018	0.590	0.124
	(1.205)	(1.580)[d]	(0.128)	(2.586)[a]	(0.974)
LTenure1	0.082	0.120	-0.034	0.336	0.088
	(2.421)[b]	(1.542)[d]	(0.850)	(0.547)	(2.072)[b]
Lambda	-1.552	-3.639	-1.232	-2.269	-1.178
	(4.132)[a]	(3.767)[a]	(4.135)[a]	(3.739)[a]	(3.033)[a]

Note: t-values are given in parentheses

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$

b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Table B2

Heckman Two-Stage Model for LogDuration (Stayers)

	1986	1987	1988	1989	1990
Constant	0.465	-1.182	0.568	-0.403	-0.104
	(1.198)	(1.329)	(1.916)[b]	(0.640)	(0.182)
DMF	-0.892	-1.937	-0.260	-1.032	-0.687
	(3.500)[a]	(3.137)[a]	(1.468)[d]	(2.866)[a]	(2.271)[b]
DAG1	-0.047	-1.353	0.404	-0.355	-0.451
	(0.178)	(2.306)[b]	(2.110)[b]	(0.933)	(1.250)
DAG2	-0.132	-0.423	0.276	0.001	-0.538
	(0.998)	(1.547)[d]	(2.155)[b]	(0.004)	(2.153)[b]
DUI	0.529	0.478	0.457	0.670	0.540
	(3.697)[a]	(1.808)[c]	(3.352)[a]	(3.198)[a]	(2.682)[a]
DUNI	0.407	0.453	0.207	0.325	0.004
	(2.618)[a]	(1.457)[d]	(1.563)[d]	(1.377)	(0.026)
LTenure1	0.028	0.125	-0.016	0.036	0.177
	(0.749)	(1.541)[d]	(0.459)	(0.540)	(2.673)[a]
Lambda	-0.933	-2.597	-1.129	-1.673	-1.511
	(3.009)[a]	(3.600)[a]	(3.968)[a]	(3.606)[a]	(3.068)[a]

Note: t-values are given in parentheses

a: $p \leq 1\%$ c: $5\% < p \leq 10\%$

b: $1\% < p \leq 5\%$ d: $10\% < p \leq 15\%$

Appendix 4.A

Homogeneity Test*

The Log-rank and Generalized Wilcoxon are both used for testing the hypothesis of homogeneity of the strata (e.g.: we have 4 strata in the age variable). They are computed as follows:

Let K = the number of strata, denoted $k = 1, ...K$

N = the number of distinct exit times

T_i = the exit time at time "i"

n_{ik} = the number of individuals in stratum k with exit time $t_{ik} \geq T_i$

$n_i = \Sigma_k n_{ik}$ = number of individuals in the sample with $t_{ik} \geq T_i$

x_{ik} = number of individuals who exit stratum k at time T_i

$x_i = \Sigma_k n_{ik}$ = number of individuals in the sample who exit at time T_i

$\mathbf{x}_i = [x_{i1} , x_{i2} .... x_{ik}]$

Under the assumption of homogeneity, conditioned on the sums n_{ik} and x_i, the vector $\mathbf{x}_i$ has a (k - 1) dimentional hypergeometric distribution with mean vector:

$$E [x_{ik}] = n_{ik} \ x_i / n_i \ , k = 1,.........K,$$

and covariances:

$$Cov [x_{ik} , x_{il}] = n_{ij} (\delta_{kl} - n_{il}/n_i) x_i (n_i - x_i) / \{ n_i (n_i - 1)\}$$

where $\delta_{kl} = 1$ if $k = l$,

$= 0$ otherwise

Adding terms, let $\mathbf{x} = \Sigma_i \mathbf{x}_i$

$$E = \Sigma_i E[\mathbf{x}_i]$$

$$V = \Sigma_i \mathrm{Var}[\mathbf{x}_i]$$

The Log Rank statistics is $LR = (\mathbf{x} - E)^{-1} (\mathbf{x} - E)$

This is a limiting chi-squared distribution with K-1 degrees of freedom.

The Generalized Wilcoxon statistics is a slight modification.

Let $W_{ik} = n_i (x_{i\cdot} - x_i n_{ik} / n_i)$

$$W_k = \Sigma_i W_{ik}$$

$$\mathbf{W} = [w_1, w_2, \ldots\ldots\ldots. w_k]$$

This vector has mean 0 and covariance matrix

$$\mathbf{Q} = \Sigma_i n_i^2 \mathrm{var}[\mathbf{x}_i]$$

The statistics is: $GW = \mathbf{W}'\mathbf{Q}^{-1}\mathbf{W}$

*) Source: LIMDEP manual (1991), page 698

Appendix 4B

The commonly used parametric distribution functions in duration models are:

Weibull	: $g(v) = \exp(v - \exp(v))$
Exponential	: $g(v) = \exp(-\exp(v))$
Normal	: $g(v) = (2\pi)^{-1/2} \exp(-v^2/ 2)$
Logistic	: $g(v) = \exp(v) . (1 + \exp(v))^{-2}$
Gamma	: $g(v) = \exp(\theta v - \exp(v) - \ln\theta)$
where	: $v = (\log t - \mathbf{x}\beta) / \sigma$

Appendix 4C

Descriptive statistics

	Whole Sample		Estimation Sample	
	Mean	SD	Mean	SD
DAG2	0.47160	0.49928	0.44759	0.49742
DAG3	0.18307	0.38679	0.18483	0.38829
DAG4	0.24198	0.42835	0.25793	0.43765
DED1	0.78377	0.41174	0.77941	0.41485
DED2	0.17037	0.37602	0.16897	0.37485
DUI	0.64339	0.47908	0.62138	0.48521
DUNI	0.21764	0.41271	0.21241	0.40916
DSX	0.55720	0.49679	0.58000	0.49373
DMS	0.61446	0.48681	0.61517	0.48672
DTR	0.06349	0.24389	0.06414	0.24508
LTenure	3.03810	1.42680	2.96050	1.43910
DP1	0.42892	0.49501	0.43241	0.49558
DP2	0.15097	0.35808	0.14138	0.34853
DP4	0.10899	0.31169	0.10069	0.30102
DP5	0.08818	0.28361	0.17241	0.37787
DP6	0.24761	0.39956	0.01103	0.10450
# Observation	2835		1450	

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