Canadian Labour Market and Skills Researcher Network

Working Paper No. 7

An Analysis of Unemployment Incidence and Duration: Some New Evidence from Canada

Michele Campolieti
University of Toronto

January 2009

CLSRN is supported by Human Resources and Social Development Canada (HRSDC) and the Social Sciences and Humanities Research Council of Canada (SSHRC).
All opinions are those of the authors and do not reflect the views of HRSDC or the SSHRC.

An Analysis of Unemployment Incidence and Duration: Some New Evidence from Canada

Michele Campolieti*
Department of Management, University of Toronto at Scarborough
Centre for Industrial Relations, University of Toronto

January 2009

Abstract
This paper studies the incidence and duration of unemployment in Canada at an aggregate and a number of disaggregated levels with data from the Canadian Labour Force Survey covering 1976 to 2006. The principal empirical findings indicate that most of the changes in steady state unemployment rates during the study period can be attributed to changes in incidence rather than changes in expected duration.

JEL Classification: J64, J63, C41

Keywords: Education, Training, Youth, Labour Market Outcomes

---

* I gratefully acknowledge the financial support of the Canadian Labour Market and Skills Researcher Network (CLSRN) and helpful comments from Steve Jones and participants at the CLSRN Labour Market Adjustment Workshop. Please address correspondence to Michele Campolieti, Centre for Industrial Relations, University of Toronto, 121 St. George Street, Toronto, Ontario, M5S 2E8, Canada; email: campolie@chass.utoronto.ca.

Executive Summary

This paper examines the expected duration and incidence of unemployment spells using Canadian data from Statistics Canada's Labour Force Survey (LFS), covering the period between 1976 and 2006. These models are estimated at both the aggregate and disaggregated level (e.g., demographic groups, type of unemployment spell and province). In order to account for some changes in EI legislation and changes in the LFS that occurred in 1996, the models are also estimated for the 1976-1996 and 1997-2006 periods. The analysis produces a number of new findings about unemployment duration and incidence in Canada.

First, like previous U.S. estimates, unemployment duration is counter-cyclical in Canada during the study period, but this pattern is not as strong as that observed in the United States. Second, most of the steady state changes in unemployment rates cannot be attributed to changes in the expected duration of unemployment spells at the aggregate level. This finding is also observed when the data is disaggregated for a number of different demographic groups. Most of my estimates indicate that changes in expected duration account for about 30-40 percent of steady state increases in unemployment rates. This differs from most U.S. evidence that indicates changes in duration play a bigger role than incidence for steady state changes in unemployment rates. For example, U.S. estimates from comparable methodologies indicate about 60 percent of increases in unemployment rates can be attributed to changes in expected duration. Other more recent U.S. studies that use different methodologies also indicate that duration has a bigger effect on unemployment rates. Third, there are substantial differences in the cyclicality of unemployment duration when the data is disaggregated by province. In particular, duration plays a much larger role in the steady state increases in unemployment rates in Ontario and the Western provinces than in Quebec and the Atlantic provinces where changes in incidence are more important. Fourth, there is some cyclical variability in the incidence of unemployment for many demographic groups and types of unemployment spells. This is particularly true for young adults who are enrolled in school, who have unemployment spells that are counter-cyclical in nature. Fifth, there is a negative trend in the expected duration of unemployment in Canada between 1976 and 2006 at both the disaggregated and aggregated levels. Moreover, this trend becomes much stronger between 1997 and 2006. There is also some evidence of a negative trend in the incidence of unemployment in many of the subgroups that are examined, but this trend is not as strong as that observed in the duration regressions.

These findings provide some new insights into the characteristics and variability of unemployment in Canada. It is clear that these Canadian findings differ from many of the established results from U.S. data. One plausible explanation for these differences may lie in the regional differences in labour markets in Canada. My estimates indicate that there is a much larger role for incidence influencing changes in unemployment rates in the Quebec and the Atlantic provinces, while

duration is more important in Ontario and the Western provinces. While regional differences in labour markets in Canada are not surprising, the effect of these differences on aggregate unemployment dynamics has not been closely explored. This is an important question for future research to address.

From the perspective of policy makers, these regional differences mean that initiatives that may well suited for some regions in the Canada, may not be well suited for others. This raises the issue of what is the optimal strategy for the development of policy to deal with unemployment. In particular, should policy initiatives be more segmented and tailored to fit a particular province instead of treating all regions equally? This is also an important question for future research to address.

1 Introduction

Cyclical changes in unemployment can be an important characteristic of the labor market. These changes will depend on the flows into and out of unemployment. Understanding the nature of these changes can be quite important from the perspective of policy makers, who may be interested in the composition and characteristics of these inflows and outflows and how they contribute to unemployment. In particular, cyclical and long-term variation in aggregate unemployment rates could reflect changes in the incidence of new spells or, alternatively, changes in the average duration of unemployment. Once the nature of these changes in the flows and stock of unemployed persons are understood it may be easier to design the appropriate policies to better deal with unemployment.

A number of studies have examined these issues using U.S. data. Earlier U.S. studies, which used data from the 1950s, 1960s and 1970s and utilized estimators of expected duration based on steady state frameworks, found that changes in incidence were more important than changes in duration when looking at changes in unemployment rates. The studies by Sider (1985) and Baker (1992a,b) used non-steady state estimators of duration and found that changes in U.S. unemployment rates were mostly due to changes in duration rather than changes in the incidence of unemployment spells based on data from the 1970s and 1980s. Moreover, Sider (1985) and Baker (1992a,b) have also determined that there are biases associated with estimators based on steady state frameworks and, consequently, have advocated the use of non-steady state estimators, which are not as prone to these systematic biases.

In contrast, there is very little (if any) evidence on the cyclical nature of unemployment incidence and duration in Canada as well as the trends in the incidence and duration of unemployment spells. As has been recognized in the literature (e.g., among others, Ashenfelter and Card (1986), Card and Riddell (1993), and Baker, Corak and Heisz (1998)), there are differences in the labor market and labor market institutions between Canada and the United States that mean it might not be possible to generalize findings from the United States to Canada.

This paper studies the incidence and duration of unemployment in Canada with aggregated grouped data. The duration estimates are obtained using a non-steady state estimator based on data from the Canadian Labour Force Survey from 1976 to 2006. While steady state estimators assume an equilibrium between unemployment inflows and outflows, the non-steady state frameworks, do not rely on this assumption. The analysis focuses on a number of key issues. First, to determine whether changes in unemployment rates can be attributed to changes in duration or incidence. Second, to assess the extent of the cyclicality in Canadian unemployment spells. Third, to examine the trends in the duration and incidence of unemployment spells. These issues are examined at an aggregate level and a number of disaggregated levels (i.e., different demographic groups, types of unemployment spells and by province).

The empirical results provide a number of new findings about the incidence and duration of unemployment in Canada. First, like previous U.S. estimates, unemployment duration is found to be counter-cyclical in Canada between 1976 and 2006, but this variation is much smaller than that observed in U.S. data. Second, unlike the U.S., most of the steady state changes in unemployment rates in Canada can be attributed to changes in incidence rather than expected duration at the aggregate level. This conclusion also holds when the data is disaggregated for a number of different demographic groups. This differs from the most comparable as well as more recent U.S. evidence that indicates changes in duration play a bigger role than incidence for changes in unemployment rates. This suggests a difference in the cyclical variability of unemployment between Canada and the United States. Third, there are substantial differences in the cyclicality of unemployment duration when the data is disaggregated by province. In particular, changes in expected duration play a much larger role in the steady state increases in unemployment rates in Ontario and the Western provinces, than in Quebec and the Atlantic provinces where changes in incidence are more important. Fourth, the estimates also indicate that there is some cyclical variability in the incidence of unemployment for many demographic groups, types of unemployment spells and by province. However, there is no clear pattern in this variation: some groups have pro-cyclical incidence, while others have counter-cyclical incidence. Fifth, unlike the existing U.S. literature, the results in this paper indicate that there is a negative trend in the expected duration of unemployment at the aggregate level and for almost all of the subgroups that are considered. This trend becomes much larger in the more recent years in our study period (1997-2006). There is also some evidence of a negative trend in the incidence of unemployment in many of the subgroups that are examined, but this trend is not as strong as that observed in the duration regressions.

2 Data and Methodology

The analysis in this paper is based on the methods used by Sider (1985) and Baker (1992a), which employ non-steady state measures of unemployment continuation probabilities. Earlier U.S. work relied exclusively on estimators of expected duration that were based on steady state frameworks (e.g., Kaitz (1970)), which assumed that the number of persons leaving unemployment are equal to the number entering unemployment. Sider (1985) emphasized the benefits of using non-steady estimators in studies looking at the cyclical variation of average unemployment duration. In particular, he noted the tendency of the steady state estimators to overestimate expected duration at cyclical peaks and underestimate expected duration during recessions. Consequently, the non-steady state estimators can provide a more accurate representation of expected durations than the estimators based on steady state frameworks.

The non-steady state methodology uses synthetic cohorts that estimate the unemployment continuation probability for different groups at an aggregated level (i.e., not at the individual level). These continuation probabilities are then used to compute an estimate of the average unemployment duration for each group. The synthetic cohorts in this paper are based on data from the public release files of Statistics Canada's Labour Force Survey (LFS) from January 1976 to June 2006.[1] This period contains a great deal of changes in economic conditions in Canada. More specifically, the study period captures the recovery period following the recession of 1974-1975, the recessions of 1981-1982 and 1991-1992, the period of the economic slowdown/slow-growth that took place during the early- to mid-1990s and the economic slowdown that occurred in 2001 (Riddell (2005)).

I define $f_i(j,t)$ as the conditional probability that group i has an unemployment spell of $j-1$ months that continues into the jth month at time t. This conditional probability can be expressed as

$$f_i(j,t) = \frac{n_i\,(j,t)}{n_i\,(j-1,t-1)}, \tag{1}$$

where $n_i\,(j,t)$ is the number of (observed) individuals in group i in the population with an unemployment spell of at least j months but less than $j+1$ months in month t and $n_i\,(j-1,t-1)$ is the number of (observed) individuals in group i in the population with an unemployment spell of at least $j-1$

[1]The LFS files, which are based on the 2001 Census weights, were obtained from the data library service at the University of Toronto.

months but less than j months in month $t-1$. Equation (1) is a non-steady state estimator of the continuation probability because it is does not assume an equilibrium between the flows into and out of unemployment. Consequently, the non-steady state estimators of the unemployment continuation probabilities are based on the actual experience of unemployed persons in a particular demographic group. However, because a synthetic panel is used the individuals represented in the numerator are not the same as those in the denominator.

For each group i, (using equation (1)) I compute monthly estimates of 6 continuation probabilities based on the following ratios:

$$f_i(1,t) = \frac{\text{number unemployed } 5-8 \text{ weeks in month } t}{\text{number unemployed } < 5 \text{ weeks in month } t-1};$$

$$f_i(2,t) = \frac{\text{number unemployed } 9-12 \text{ weeks in month } t}{\text{number unemployed } 5-8 \text{ weeks in month } t-1};$$

$$f_i(3,t) = \frac{\text{number unemployed } 13-16 \text{ weeks in month } t}{\text{number unemployed } 9-12 \text{ weeks in month } t-1};$$

$$f_i(4-6,t) = \frac{\text{number unemployed } 27-39 \text{ weeks in month } t}{\text{number unemployed } 13-26 \text{ weeks in month } t-3};$$

$$f_i(7-12,t) = \frac{\text{number unemployed } 53-78 \text{ weeks in month } t}{\text{number unemployed } 27-52 \text{ weeks in month } t-6}; \text{ and,}$$

$$f_i(13-24,t) = \frac{\text{number unemployed } 99+ \text{ weeks in month } t}{\text{number unemployed } 53-98 \text{ weeks in month } t-12}.$$

The estimates for $f_i(4-6,t)$, $f_i(7-12,t)$ and $f_i(13-24,t)$ are raised to the power of 1/3, 1/6 and 1/12 (respectively) in order to convert them to monthly equivalents and make them correspond with $f_i(1,t)$, $f_i(2,t)$ and

$f_i(3,t)$. These continuation probabilities are used to compute an estimate of the expected duration of unemployment using the following relationship

$$D_i(t) = \sum_{x=1}^{N} \prod_{j=1}^{x} f_i(j,t). \tag{2}$$

Because of the lags involved with the computation of $f_i(13-24,t)$ the estimates of the unemployment durations can only be computed between January 1977 and June 2006.[2]

Baker (1992a,b) also highlighted that there could be biases in the estimates of the expected duration of unemployment because of digit preferences, which is the tendency of individuals to report the length of their current unemployment spell in integer multiples of one month.[3] In order to deal with these problems Baker (1992a,b) suggested smoothing the data prior to estimating the continuation probabilities used to compute the expected durations of unemployment spells. In particular, Baker (1992b) provides a preferred smoothing procedure for data from the U.S. Current Population Survey (CPS). However, Corak and Heisz (1996) found that this would not be the best choice for smoothing data from the Canadian LFS. Corak and Heisz (1996) found that a smoothing procedure that reallocates 50 percent of individuals at the longest duration to the second longest duration and 30 percent for the other durations to the neighboring intervals would be more appropriate for the LFS than the procedure Baker (1992b) suggested for the CPS. I have followed Corak and Heisz's suggestion when smoothing the continuation probabilities prior to computing the expected durations in this analysis.

[2]Corak (1996) also used this framework to estimate unemployment durations for Canada using LFS data from 1977 to 1992. However, Corak did not estimate the duration and incidence regressions that are examined in this paper. Consequently, his paper does not contain answers to the questions that are being examined in this paper.

[3]Similarly, there could also be calendar effects, which is the tendency of spells to begin (end) at the beginning (end) of a month (Campolieti (2000)).

These aggregate data can also be used to determine the size of a cohort entering unemployment and examine the incidence of unemployment. The estimate of group i's entrance share is

$$s_i(t) = \frac{n_i(<5,t)}{n(<5,t)}, \tag{3}$$

where $n_i(<5,t)$ is the number of individuals in demographic group i that report unemployment durations of less than 5 weeks and $n(<5,t)$ is the number of individuals in the aggregate population reporting a duration of less than 5 weeks. However, as noted by Baker (1992a), the limitation of the entrance share variable is that it combines information on incidence with information on unemployment duration. This means that an increase in the entrance share over time by a group could result from one of three factors: 1) an increase in the incidence of unemployment; 2) lower exit rates from unemployment during the first few weeks of an unemployment spell; and, 3) some combination of 1) and 2).

In order to examine the cyclical movements in the expected duration of each group's unemployment spells, I estimated the following regression

$$\ln D_i(t) = \alpha + \beta \ln UR(t) + Month'\Xi + \gamma t + u_i(t), \tag{4}$$

where $\ln D_i(t)$ is the log of the expected duration for group i, $\ln UR(t)$ is the log of the seasonally unadjusted unemployment rate (both sexes, persons aged 15 to 64) in Canada, $Month$ is a vector of month dummies, t is a linear time trend and $u_i(t)$ is a residual.[4]

The cyclical movements in the entrance shares are examined by estimating the following regression

$$s_i(t) = \alpha + \beta UR(t) + Month'\Xi + \gamma t + e_i(t), \tag{5}$$

[4]The seasonally unadjusted unemployment rate was obtained from Statistics Canada's CANSIM database.

where $s_i(t)$ is the entrance share for group i, the other variables are defined as above and $e_i(t)$ is a residual. The entrance share regressions were estimated using ordinary least squares.[5]

3 Empirical Findings

3.1 Duration Estimates

The estimates from the duration regressions are presented in Tables 1 and 2. Using equation (2), the expected duration for unemployment spells from the aggregate Canadian data during the period covered by this study (January 1976 and June 2006) is 2.35 months.

I plotted the expected duration of unemployment spells in Figure 1. The plot in Figure 1 illustrates the variability of the expected duration of unemployment spells. The expected durations are longest during recessions and fall during the recovery periods. Also the expected duration of spells has been declining somewhat over the study period, with the longest spells in the late-1970s and early-1980s. While there is a cyclical pattern in the 1970s and 1980s, the pattern after 1990 is different. In the 1990s there is a marked decrease in the expected duration of unemployment spells after 1996. Two factors could have contributed to this change. First, there were major changes in Employment Insurance (EI) legislation taking effect in 1997 that could have had an effect on the duration of unemployment spells as well as their incidence (Gray (2004)).[6] Second, there was a redesign of the LFS and

[5]The entrance share regressions were also estimated as a censored regression model. Unfortunately, the estimator did not converge for all of the subsamples and demographic groups that were examined. However, for those subgroups where the censored regression estimator did converge it produced estimates that were identical to the ordinary least squares estimates that are presented in Tables 3 and 4.

[6]These changes included more stringent eligibility criteria, reducing benefits for repeat

a change in the way the information was collected that also occurred at this time.[7] Consequently, the data collected before 1997 may not be comparable to the data collected after 1997. In order to account for this difference I also estimated the duration regressions using the data for 1976-1996 and 1997-2006. Note that because of the lags involved in the computation of the conditional probabilities used to create the expected durations, the first 12 months in each of these two sub-periods are used to compute the conditional probabilities in the following year. I discuss the estimates for the pooled sample first (1976 and 2006) and then discuss whether there are differences in the estimates before and after 1997.

The LFS also changed its education question in 1990, which means that it is not possible to get a definition of high school graduate that is consistent across the study period. This means that I had to present some estimates for different levels of high school education in Table 2 based on the different education questions. Table 1 does contain estimates for educational attainment based on a university degree, which is the only consistently defined education grouping that can be created between 1976 and 2006.

The pooled (aggregated) sample produced an unemployment rate elasticity for duration of 0.37 (see the first row in Table 1). This suggests that a 1 percentage point increase in the unemployment rate (or an 11.4 percent increase relative to the mean unemployment rate of 8.77 percent during the study period) would be associated with a 4.2 percent increase in unemployment duration. The elasticity estimate suggests that only about 37 percent of a steady-state increase in the unemployment rate is accounted for by changes in the duration of unemployment.[8] In contrast, Baker (1992a)

users, and stronger incentives to work longer in the qualifying period.

[7]The LFS switched from pencil and paper interviewing to CATI interviewing as well as more extensive use of telephone interviewing.

[8]The unemployment rate in a steady state can be expressed as the incidence rate

found that about 60 percent of steady state increases in unemployment rates could be attributed to changes in expected duration with U.S. data from 1979 to 1988. My estimates, like those in Baker (1992a) and others, suggest that unemployment duration in Canada is counter-cyclical, but this variation is much smaller than that observed in the U.S. data.

Since my study period overlaps Baker's, I also estimated the duration regression using data from 1979 to 1988 to get a comparable Canadian estimate. In other words, I use the same methodology and the same study period as Baker (1992a). I obtained a statistically significant elasticity of 0.35 with the Canadian data, which indicates that only 35 percent of a steady increase in unemployment rates can be attributes to changes in the expected duration of unemployment spells. This additional estimate confirms that there is a large difference between the factors driving unemployment rates in Canada and the United States.

The next set of estimates in Table 1 presents the unemployment rate elasticities for duration by the type of unemployment spell: layoffs (temporary layoff), job losers (i.e., permanent layoff), quits, new entrant to the labor market, and reentering the labor market. These estimates differ somewhat from the estimate for the aggregate sample. The estimate for the layoffs sub-sample is not statistically significant, while the elasticity for the job losers is quite small (0.11) relative to the benchmark set by the aggregate data (0.37). On the other hand, the elasticities for the quits (0.65) and new entrants (0.48) are considerably larger than the estimate from the aggregate data. The estimates for the quits and new entrants indicate that 65 and 48 percent of steady state increases in unemployment rates can be attributed to changes in expected duration for these types of unemployment spells. Only

multiplied by average duration. Taking the logarithm of this relationship leads to the interpretation of the estimates provided in the text and Baker (1992a).

the estimate for the re-entrants is similar in magnitude to the aggregate estimate.

Table 1 also presents the estimates for various demographic groups, by gender and age. The estimates for males and females are quite similar to the aggregate estimate. I also looked at different university education and gender groups. The university/no-university estimates for males are larger than the aggregate estimate, while those for women are smaller than the aggregate estimate.

The estimates that are disaggregated by gender and age also present some interesting findings. For males, the largest estimate (0.42) is for youths and young adults, while the prime age and older males have a somewhat smaller estimates. A similar pattern is also observed for females; the elasticity for youths and young adults tend to be larger than the estimates for prime age and older females.

A further analysis of the youths and young adults was also conducted by school enrollment status (enrolled versus non-enrolled). The youth subgroup is of particular interest because poor initial experiences in the labor market for this group could lead to future unemployment or poor labor market outcomes. For both males and females the elasticity for enrolled youths and young adults is larger than those for non-enrolled youths and young adults. This difference in the size of the elasticities may be the result of enrolled teenagers and young adults relying more on part-time and seasonal work, which could be impacted more severely during an economic downturn.

The remaining rows in Table 1 present the duration elasticities by province. There is a great deal of variation in the duration elasticities by province. The duration elasticities for Prince Edward Island and New Brunswick were less than 0.1, but they were not precisely estimated. Newfoundland and Nova Scotia had statistically significant duration elasticities of about 0.25.

Quebec also had a duration elasticity that was slightly smaller than the aggregate estimate. In contrast, Ontario had an elasticity of about 0.46, which is larger than the aggregate estimate. The Western provinces also tended to have larger duration elasticities. The largest estimate was for Alberta, 0.73, which clearly indicates that changes in duration matter more than changes in incidence. The estimates for the other three Western provinces were not as large, lying between 0.39 and 0.44. The estimates from the duration regressions disaggregated by province suggest that incidence plays a much larger role in the unemployment dynamics in the Atlantic provinces and Quebec, than in Ontario and the Western provinces.

The estimates for the data based before and after 1997 are presented in the remaining columns of Table 1. For the period between 1976 and 1996, the estimates are quite similar to those for the whole study period presented in the first column. However, the estimates for the period between 1997 and 2006 are somewhat different. Most of the estimates tend to be slightly smaller than those before 1997. However, most of the elasticities are not precisely estimated, so the pattern in the estimates is difficult to ascertain with confidence. The estimates of the duration elasticities for some provinces are statistically significant. Alberta and Ontario had smaller elasticities in the 1997-2006 period, relative to the 1976-1996. On the other hand, British Columbia and Manitoba had bigger elasticity estimates during the 1997-2006 period, relative to the estimates based on the 1976-1996 period..

Table 2 presents the duration elasticities by high school educational attainment. As noted earlier, the LFS education variable was changed in 1990. After the change it was possible to identify high school graduates, but this was not possible prior to 1990. Prior to 1990, the aggregate elasticity was 0.31. For males with grade 11 or less, the elasticity was similar to the aggregate estimate, but the elasticity for males with "more than grade

11" grouping had a larger elasticity (0.41). The estimates for women were smaller than those for men. The "grade 11 or less group" had an elasticity of 0.17, while the "more than grade 11" group had an elasticity of 0.27. For the period between 1990 and 2006 the aggregate duration elasticity was 0.19, which is much smaller than the estimate for the period prior to 1990. However, most of the duration elasticities for the high school graduate/non-graduate were not precisely estimated, most of them were not statistically significant. I also estimated regressions for the high school graduates/non-graduates for the 1997-2006 period and obtained estimates that were larger than those presented in Table 2, but none of these estimates were statistically significant.

Overall, the estimates from Table 1 indicate that the cyclical variation in the expected durations of unemployment spells in Canada is less than that observed in the U.S. At the aggregate and disaggregated level about 30-40 percent of a steady state increase in the unemployment rate is accounted for by changes in expected duration. Unlike the most comparable estimates (in terms of methodology and similar study periods) from the U.S., in Canada most of the steady state changes in unemployment rates can be attributed to changes in incidence rather than changes in the duration of unemployment spells. While most of the estimates in this paper differ from U.S. estimates like those in Baker (1992) and Sider (1985), they are not out of line with earlier U.S. studies that used data from before the 1970s. For example, Perry (1972) found that changes in incidence played a more prominent role influencing unemployment rates than changes in duration for youths relative to adults, using data from 1954 to 1972.

The evidence on the factors driving unemployment obtained with other methodologies also does not converge to a common conclusion. For example, Blanchard and Diamond (1990) examined Current Population Survey

(CPS) gross flows data from 1968 to 1986 and found that incidence contributed more to changes in unemployment rates than changes in duration. On the other hand, Abbring, van den Berg and van Ours (2001) used aggregate U.S. unemployment data from the CPS for the period covering 1968 to 1992 to study the variation in the flows into unemployment as well as the aggregate unemployment duration distribution and also found estimates that were consistent with those in Sider (1985) and Baker (1992a). More specifically, their estimates indicated that cyclical variation in unemployment durations accounted for at least 50 percent of the cyclical variation in the log of the unemployment rate.

More recently, Shimer (2005) studied job finding (i.e., the hazard rate for exiting unemployment) and separation probabilities in the United States from 1948 to 2004. Note that the job finding probability in Shimer's analysis is not directly comparable to the hazard rates computed in my analysis because they cannot be used to compute expected durations. Shimer's analysis indicates that the job finding probability in the U.S. is very pro-cyclical. Moreover, Shimer's estimates also indicated that there was not a great deal of cyclical variation in the separation probability in the U.S., particularly in the 1980s and 1990s. Shimer's findings suggest that duration plays a stronger role than incidence in influencing unemployment rates.

Elsby, Michaels and Solon (2007) replicated Shimer's analysis of the U.S. data using a log scale and added a few refinements to his methodology. The analysis of Elsby et al. (2007) confirms Shimer's findings on the job finding probability (i.e., duration plays a strong role in influencing unemployment). However, they also found using Shimer's data and methods that there was an important role for countercyclical inflows into unemployment (which differ's from Shimer's conclusion) if they are viewed in what Elsby et al. (2007) refer to as the "correct perspective".

Elsby, Micheals and Solon (2007) also look at the differences in unemployment dynamics in more recent decades compared to earlier decades. Their analysis indicates that the flows into and out of unemployment in more recent U.S. data do differ from those in earlier time periods. More specifically, the period covered by the last two U.S. recessions (i.e., the years since 1991. Moreover, they also found differences in unemployment patterns between the last two recessions and previous recessions. In addition, Elsby et al. argue that weak aggregate inflow effect that Shimer (2005) found in his preferred analysis are a feature of the last two recessions, which also differs from earlier periods. These findings suggest that unemployment dynamics in more recent U.S. data differ from those from earlier time periods. There are some parallels in this paper's analysis to the differences in the pre- and post-1991 recession differences found by Elsby, Michaels and Solon (2007). In particular, the smaller duration elasticities I find for the 1990-2006 period in Table 2 as well as some of the differences between the 1976-1996 and 1997-2006 period in Table 1.

Another important finding from the expected duration regressions presented in Tables 1 and 2 are the estimates on the time trend. The coefficient estimates on the time trend variable are all negative and statistically significant with a few exceptions. The size of the decreases in the duration of unemployment spells does depend on the sample period being considered. For the 1976-2006 and 1976-1996 the estimates on the time trend imply decreases in expected duration of less than 1 percent per annum. However, for the period between 1997 and 2006 the estimates on the time trend imply much larger decreases in the expected duration of unemployment spells. For example, for the aggregate group the time trend suggests a decrease of 1.8 percent per annum. Some of the estimates for the gender and education groups imply decreases in the duration of unemployment spells of about 2 percent per annum or more. These results differ from U.S. estimates based on data from earlier time periods, which have found a positive trend.[9] This difference could reflect an improvement in the labor market prospects in Canada during the study period relative to earlier decades. This is also consistent, as we noted earlier, with Elsby et al. (2007) who found differences in the characteristics of unemployment data before and after the 1991 recession.

There are a few explanations that could be consistent with the strong negative trend in the duration of unemployment spells during the 1997-2006 period. First, there were no major recessions during the 1997-2006 period, unlike the 1976-1996 period. Second, some of the changes in EI legislation that took effect in 1997 could have reduced the length of unemployment spells.

3.2 Incidence Estimates

The estimates for the entrance share regressions are presented in Table 3 by demographic group, type of unemployment spell and province. Table 4 contains additional estimates for educational attainment, defined by level of high school completed. Like the duration estimates, I discuss the estimates for the pooled sample period first and then discuss the estimates for the two sub-periods (i.e., 1976-1996 and 1997-2006).

There is some variation in the size of the entrance share elasticities by the type of separation. The largest unemployment rate elasticities are obtained for the quits and new entrants. These estimates indicate that the incidence of unemployment spells due to quits and new entrants to the labor market

[9] Abbring et al. (2002) also found an upward trend in the duration of unemployment spells (i.e., lower exit probabilities) in quarterly French data from 1982 to 1994.

are counter-cyclical. The estimate for job losers (i.e., permanent layoffs) is also fairly large. However, unlike the estimates for quits and new entrants, it suggests that the incidence of 'job loser' spells are pro-cyclical. The elasticity estimates for layoffs and reentrants tended to be much smaller than the others based on the type of unemployment spell. The estimate for the layoffs is not statistically significant, while those for re-entrants to the labor market are counter-cyclical and statistically significant.

The entrance share elasticity for males is positive and statistically significant, while that for females is negative and statistically significant. This indicates that unemployment incidence for males is pro-cyclical, while that for females is counter-cyclical. However, neither of these estimates suggests a particularly large effect. Disaggregating the data by gender and university degree also produces small elasticities for men, while those for women are not statistically significant.

Disaggregating the data by age and gender produces some interesting patterns in the estimates from the entrance share regressions. In particular, the prime age (aged 25-44) and younger males (aged 15-24) have larger elasticities than the older males. More specifically, the prime age males have an entrance share elasticity of about 0.5 and the young adults and youths have an elasticity of -0.3, while the older males have a much smaller elasticity of -0.11. A similar pattern also emerges for females, but the magnitudes differ from those observed for males. The prime age women have an entrance share elasticity of about 0.28, but the young females have an elasticity of about -0.37. The elasticity for older women is -0.17, but not statistically significant. These estimates indicate that, for both males and females, the incidence patterns for these cohorts is counter-cyclical for the 15-24 and the 45-64 age group, but pro-cyclical for the prime age group. The oldest age group displays much less cyclical variability than the prime age and youth groups. Card and Riddell (1993), in their work looking at the difference between U.S. and Canadian unemployment rates, found that the incidence of unemployment in Canada tended to be concentrated among younger persons. The estimates in Table 3 are consistent with their finding.

The estimates for the entrance share regressions, like those from the duration regressions, indicate that the youngest age groups (15-24) are quite sensitive to changes in the unemployment rate. Like the duration regressions, I also estimated the entrance share regressions by enrollment status. These regression estimates indicate for both gender disaggregations that the entrance share elasticities are much larger for the enrolled group. They also indicate that the incidence of unemployment for the young adults, regardless of enrollment status, would be counter-cyclical.

While there is quite a bit of regional variation in the duration elasticities, the regional variation in the entrance share elasticities is much more moderated. Most provinces have relatively small entrance share elasticities for the 1976-2006 period.

Conducting the analysis by splitting the study period before and after 1997 also produces some differences in the estimates of the entrance share elasticities. For the groupings based on demographics and the type of unemployment spell the entrance share elasticities tended to be smaller in the 1997-2006 period. However, in the disaggregation by province the entrance share elasticities tended to be larger in the 1997-2006 period. There are also some changes in whether unemployment incidence is pro- or counter-cyclical between the 1976-1996 and 1997-2006 period. There are a few plausible explanations for this switch in the nature of cyclicality of the incidence of unemployment spells. First, the changes in the data collection methods in the LFS could have changed the reporting patterns in unemployment spells. Second, the changes in EI legislation could have had an impact on the incidence of unemployment spells after 1997.

The estimates for different levels of educational attainment also reveal some interesting findings. For women with lower levels of educational attainment (whether it is less than grade 11 or not graduating from high school) the entrance share elasticities tend to be larger and counter-cyclical. Also the incidence of unemployment for women disaggregated by high school educational attainment is counter-cyclical regardless of the period. On the other hand, the estimates for males depend on the period being considered. During the 1976-1989 period, males with more than a grade 11 education have a larger incidence elasticity. Also the "more than grade 11" group has pro-cyclical incidence, while the "grade 11 or less" grouping is counter-cyclical. For the 1990-2006 period the "did not graduate from high school" group did not have a statistically significant estimate, while the males who graduated from high school had statistically significant elasticity of -0.11.

While the coefficient estimates on the time trend from the duration regressions are almost all negative, the estimates on the time trend from the entrance share regressions do not have a clearly defined pattern. About half of the coefficient estimates on the time trend are negative, while the rest are positive. Unlike the duration estimates, the estimates on the time trend are quite similar across different periods (i.e., 1976-1996 and 1997-2006). The literature based on U.S. data has found an upward trend in the incidence of unemployment.[10] Consequently, these results (like the estimates on the time trend from the duration regressions) also represent a difference relative to U.S. studies because they suggest a negative trend in the incidence of unemployment at some disaggregated levels.

[10] Abbring et al. (2002) also found an upward trend in the incidence of unemployment spells based on quarterly aggregate data from France for the period between 1982 and 1994.

4 Concluding Remarks

This paper examined the expected duration and incidence of unemployment spells using Canadian data from Statistics Canada's Labour Force Survey, covering the period between 1976 and 2006. The analysis in this paper produces a number of new findings about unemployment duration and incidence in Canada.

First, like previous U.S. estimates, unemployment duration is counter-cyclical in Canada during my study period, but this pattern is not as strong as that observed in the United States. Second, most of the steady state changes in unemployment rates cannot be attributed to changes in the expected duration of unemployment spells at the aggregate level. This finding was also observed when the data was disaggregated for a number of different demographic groups. This differs from most U.S. evidence that indicates changes in duration play a bigger role than incidence for steady state changes in unemployment rates. Third, there are substantial differences in the cyclicality of unemployment duration when the data is disaggregated by province. In particular, changes in expected duration play a much larger role in the steady state increases in unemployment rates in Ontario and the Western provinces, than in Quebec and the Atlantic provinces where changes in incidence are more important. Fourth, there is some cyclical variability in the incidence of unemployment for many demographic groups and types of unemployment spells. This is particularly true for young adults who are enrolled in school, who have unemployment spells that are counter-cyclical in nature. Fifth, there is a negative trend in the expected duration of unemployment in Canada between 1976 and 2006 at both the disaggregated and aggregated levels. Moreover, this trend becomes much stronger between 1997 and 2006. There is also some evidence of a negative trend in the incidence of unemployment in many of the subgroups that are examined, but this trend is not as strong as that observed in the duration regressions.

These findings provide some new insights on the characteristics and variability of unemployment in Canada. It is clear that these Canadian findings differ from many of the established results from the U.S. data. One plausible explanation for these differences may lie in the regional differences in labor markets in Canada. My estimates indicate that there is a much larger role for incidence influencing changes in unemployment rates in the Quebec and the Atlantic provinces, while duration is more important in Ontario and the Western provinces. While regional differences in labor markets in Canada are not surprising, the effect of these differences on aggregate unemployment dynamics has not been closely explored. This is an important question for future research to address.

From the perspective of policy makers, these regional differences mean that initiatives that may well suited for some regions in the Canada, may not be well suited for others. This raises the issue of what is the optimal strategy for the development of policy to deal with unemployment. In particular, should legislation be more segmented and tailored to fit a particular province instead of treating all regions equally? This is also an important question for future research to address.

References

[1] Abbring, J.H., G.J. van den Berg and J.C. van Ours (2001), 'Business Cycles and Compositional Variation in U.S. Unemployment,' Journal of Business and Economic Statistics 19, 436-448.

[2] Abbring, J.H., G.J. van den Berg and J.C. van Ours (2002), 'The Anatomy of Unemployment Dynamics,' European Economic Review 46, 1785-1824.

[3]Ashenfelter, O. and D. Card (1986), 'Unemployment in Canada and the U.S.,' Economica 53, S171-S196.

[4]Baker, M. (1992a), 'Unemployment Duration: Compositional Effects and Cyclical Variability,' American Economic Review 82, 313-321.

[5]Baker, M. (1992b), 'Digit Preference in CPS Unemployment Data,' Economics Letters 39, 117-121.

[6]Baker, M., M. Corak and A. Heisz (1998), 'The Labour Market Dynamics of Unemployment Rates in Canada and the United States,' Canadian Public Policy 24, S72-S89.

[7]Blanchard, O.J. and P. Diamond (1990), 'The Cyclical Behavior of the Gross Flows of U.S. Workers,' Brookings Papers on Economic Activity 1990, 85-155.

[8]Campolieti, M. (2000), 'Bayesian Estimation and Smoothing of the Baseline Hazard in Discrete Time Duration Models,' Review of Economics and Statistics 82, 685-701.

[9]Card, D. and C. Riddell (1993), 'A Comparative Analysis of Unemployment in Canada and the United States,' in Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States, ed. D. Card and R. Freeman. Chicago: University of Chicago Press.

[10]Corak, M. (1996), 'Measuring the Duration of Unemployment Spells,' Canadian Journal of Economics 29, 43-49.

[11]Corak, M. and A. Heisz (1996), 'Alternative Measures of the Average Duration of Unemployment,' Review of Income and Wealth 42, 63-74.

[12]Elsby, M.W., R. Michaels and G. Solon (2007), 'The Ins and Outs of Cyclical Unemployment,' National Bureau of Economic Research, Working Paper #12853.

[13]Gray, D. (2004). Employment Insurance: What Reform Has Delivered. C.D. Howe Institute Backgrounder.

[14]Kaitz, H. (1970), 'Analyzing the Length of Spells of Unemployment,' Monthly Labor Review 93, 11-20.

[15]Perry, G.L. (1972), 'Unemployment Flows in the U.S. Labor Market,' Brookings Papers on Economic Activity 1972, 245-278.

[16]Riddell, W.C. (2005), 'Why is Canada's Unemployment Rate Persistently Higher than in the United States,' Canadian Public Policy/Analyse de Politiques 31, 93-100.

[17]Shimer, R. (2005), 'Reassessing the Ins and Outs of Unemployment,' Department of Economics, University of Chicago, unpublished manuscript.

[18]Sider, H. (1985), 'Unemployment Duration and Incidence: 1968-1982,' American Economic Review 75, 461-472.

Figure 1: Expected Duration of Unemployment Spells in Canada, 1977-2006

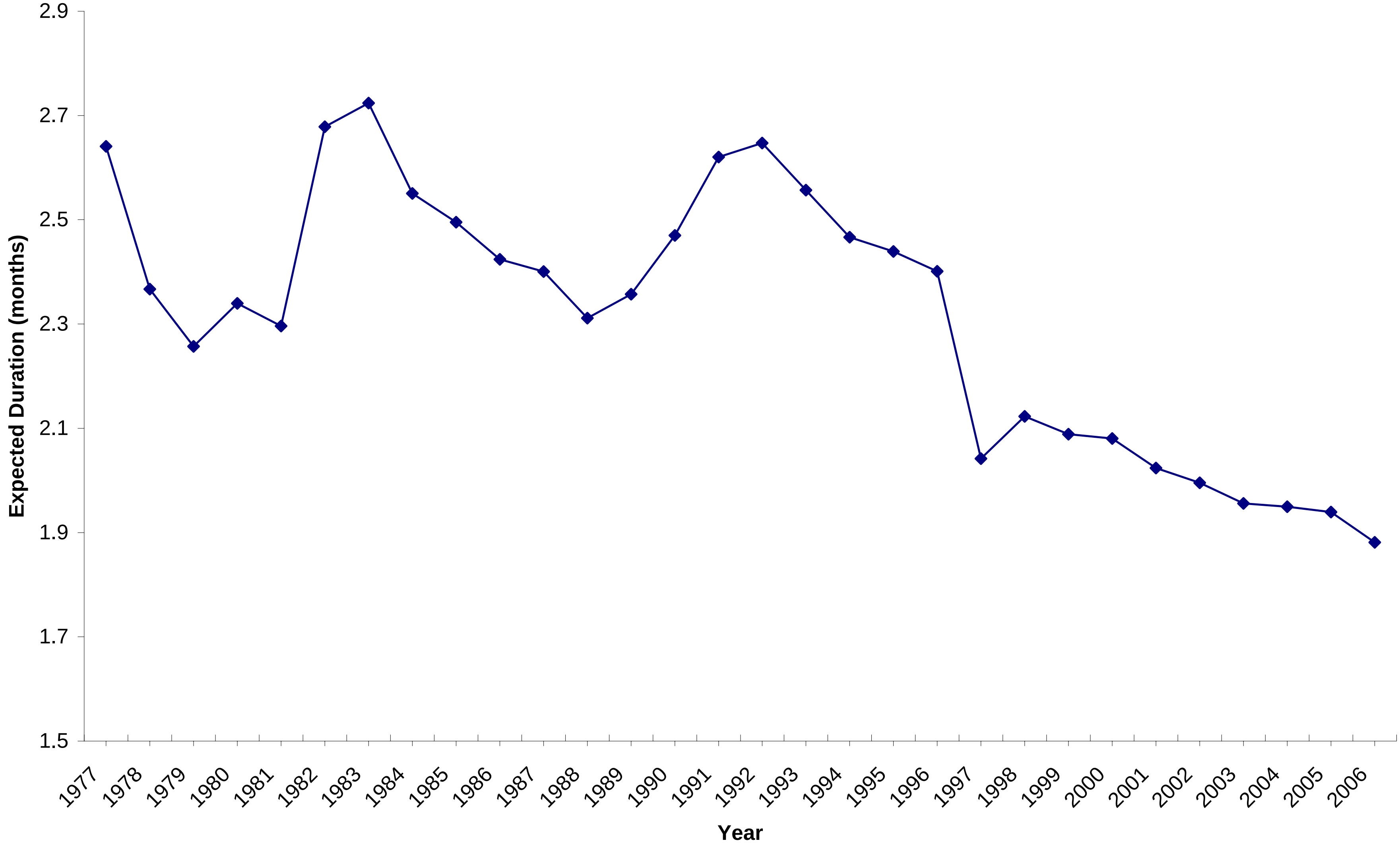

Table 1: Expected Duration Regressions

Group	1976-2006		1976-1996		1997-2006	
	$\frac{\partial \ln D_i(t)}{\partial \ln UR_i(t)}$	$\frac{\partial \ln D_i(t)}{\partial t}$	$\frac{\partial \ln D_i(t)}{\partial \ln UR_i(t)}$	$\frac{\partial \ln D_i(t)}{\partial t}$	$\frac{\partial \ln D_i(t)}{\partial \ln UR_i(t)}$	$\frac{\partial \ln D_i(t)}{\partial t}$
Aggregate	0.365***	-0.006***	0.305***	-0.002**	0.276	-0.017**
	(0.030)	(0.001)	(0.025)	(0.001)	(0.209)	(0.007)
Layoffs	0.013	0.003***	0.032	-0.003***	0.079	-0.002
	(0.033)	(0.001)	(0.035)	(0.001)	(0.224)	(0.008)
Job losers	0.107***	-0.004***	0.164***	-0.006***	0.219	-0.009
	(0.035)	(0.001)	(0.024)	(0.001)	(0.284)	(0.010)
Quits	0.651***	-0.007***	0.566***	0.001	0.522	-0.026**
	(0.051)	(0.001)	(0.050)	(0.001)	(0.312)	(0.011)
New entrants	0.481**	-0.006***	0.350***	-0.000	0.156	-0.027***
	(0.043)	(0.001)	(0.058)	(0.001)	(0.141)	(0.005)
Reentrants	0.333***	-0.005***	0.247***	0.000	0.107	-0.015***
	(0.025)	(0.001)	(0.003)	(0.001)	(0.109)	(0.004)
Males	0.389***	-0.006***	0.348***	-0.003***	0.310	-0.017**
	(0.034)	(0.001)	(0.030)	(0.001)	(0.244)	(0.008)
Females	0.330***	-0.006***	0.240***	-0.000	0.233	-0.017***
	(0.028)	(0.001)	(0.025)	(0.001)	(0.169)	(0.006)
Males, no university degree	0.414***	-0.005***	0.373***	-0.002**	0.343	-0.016**
	(0.034)	(0.001)	(0.028)	(0.001)	(0.244)	(0.008)
Males, university degree	0.407***	-0.003***	0.406***	-0.001	0.138	-0.018**
	(0.057)	(0.001)	(0.077)	(0.002)	(0.265)	(0.009)

Females, no university degree	0.346***	-0.005***	0.253***	0.000	0.206	-0.019***
	(0.029)	(0.001)	(0.026)	(0.000)	(0.173)	(0.006)
Females, university degree	0.303***	-0.001	0.315***	0.001	0.419	-0.007
	(0.054)	(0.001)	(0.074)	(0.002)	(0.207)	(0.007)
Males, age 15-24	0.422***	-0.009***	0.365***	-0.006***	0.255	-0.022***
	(0.031)	(0.001)	(0.031)	(0.001)	(0.203)	(0.007)
Males, age 25-44	0.356***	-0.005***	0.341***	-0.003***	0.271	-0.015*
	(0.038)	(0.001)	(0.035)	(0.001)	(0.267)	(0.009)
Males, age 45-64	0.325***	-0.006***	0.328***	-0.005**	0.449	-0.009
	(0.048)	(0.001)	(0.053)	(0.002)	(0.307)	(0.010)
Females, age 15-24	0.377***	-0.011***	0.312***	-0.007***	0.199*	-0.019***
	(0.024)	(0.001)	(0.030)	(0.001)	(0.112)	(0.004)
Females, age 25-44	0.290***	-0.004***	0.188***	-0.002**	0.268	-0.015**
	(0.033)	(0.001)	(0.028)	(0.001)	(0.211)	(0.007)
Females, age 45-64	0.279***	-0.005***	0.254***	-0.001	0.196	-0.018**
	(0.042)	(0.001)	(0.047)	(0.001)	(0.246)	(0.008)
Males, 15-24, non-enrolled	0.413***	-0.008***	0.377***	-0.005***	0.172	-0.022***
	(0.032)	(0.001)	(0.038)	(0.001)	(0.191)	(0.006)
Males, 15-24 enrolled	0.529***	-0.007***	0.473***	-0.001	-0.039	-0.047***
	(0.088)	(0.002)	(0.103)	(0.003)	(0.515)	(0.017)
Females, 15-24, non-enrolled	0.376***	-0.009***	0.504***	-0.007***	0.129	-0.020***
	(0.028)	(0.001)	(0.055)	(0.002)	(0.117)	(0.004)
Females, 15-24, enrolled	0.431***	-0.008***	0.412***	-0.005*	0.366	-0.022**
	(0.069)	(0.003)	(0.093)	(0.003)	(0.302)	(0.011)
Newfoundland	0.246***	-0.007***	0.235***	-0.006***	0.162	-0.013
	(0.047)	(0.001)	(0.061)	(0.002)	(0.227)	(0.008)

Prince Edward Island	0.086	0.005***	0.077	-0.005***	0.219	-0.012
	(0.059)	(0.001)	(0.058)	(0.001)	(0.439)	(0.015)
Nova Scotia	0.257***	-0.009***	0.106	-0.003***	0.040	-0.017**
	(0.041)	(0.001)	(0.048)	(0.001)	(0.244)	(0.008)
New Brunswick	0.051	-0.013	0.113	-0.015***	0.038	-0.018**
	(0.040)	(0.001)	(0.047)	(0.001)	(0.223)	(0.008)
Quebec	0.307***	-0.007***	0.234	-0.002**	0.191	-0.018**
	(0.038)	(0.001)	(0.040)	(0.001)	(0.220)	(0.007)
Ontario	0.458***	-0.003***	0.376	-0.003***	0.319*	-0.013**
	(0.035)	(0.001)	(0.041)	(0.001)	(0.190)	(0.006)
Manitoba	0.441***	-0.007***	0.341	-0.002	0.530*	-0.009
	(0.049)	(0.001)	(0.060)	(0.002)	(0.280)	(0.009)
Saskatchewan	0.393***	-0.007***	0.306	-0.002	0.181	-0.019*
	(0.053)	(0.001)	(0.066)	(0.002)	(0.303)	(0.010)
Alberta	0.729***	-0.002**	0.654	0.005***	0.466**	-0.020**
	(0.043)	(0.001)	(0.048)	(0.001)	(0.234)	(0.008)
British Columbia	0.420***	-0.006***	0.416	-0.004***	0.609**	-0.024***
	(0.042)	(0.001)	(0.042)	(0.001)	(0.270)	(0.010)

Notes: The dependent variable in the regressions is $\ln D_i(t)$, where $D_i(t)$ denotes the expected duration of unemployment. $UR_i(t)$ denotes the seasonally unadjusted unemployment rate. Entries in the table are the coefficient estimates on the log of the seasonally unadjusted unemployment rate from equation (4) for each of the subgroups listed in the rows. The coefficient estimate $\frac{\partial \ln D_i(t)}{\partial \ln UR_i(t)}$ is an elasticity. Triple asterisk denotes statistical significance at 1 percent level. Double asterisk denotes statistical significance at the 5 percent level. Single asterisk denotes statistical significance at the 10 percent level.

Table 2: Expected Duration Regressions, Education Variables

	$\frac{\partial \ln D_i(t)}{\partial \ln UR_i(t)}$	$\frac{\partial \ln D_i(t)}{\partial t}$
1976-1989		
Aggregate	0.311***	-0.003***
	(0.029)	(0.001)
Males, grade 11 or less	0.314***	-0.006***
	(0.042)	(0.002)
Males, more than grade 11	0.406***	-0.003***
	(0.032)	(0.001)
Females, grade 11 or less	0.170***	-0.001
	(0.038)	(0.002)
Females, more than grade 11	0.273***	-0.001
	(0.028)	(0.001)
1990-2006		
Aggregate	0.190**	-0.017***
	(0.073)	(0.003)
Males, did not graduate high school	0.145	-0.024***
	(0.128)	(0.005)
Males, graduated from high school	0.117	-0.017***
	(0.120)	(0.005)
Females, did not graduate high school	0.229**	-0.020***
	(0.093)	(0.004)
Females, graduated from high school	0.062	-0.019***
	(0.100)	(0.004)

Notes: The dependent variable in the regressions is $\ln D_i(t)$, where $D_i(t)$ denotes the expected duration of unemployment. $UR_i(t)$ denotes the seasonally unadjusted unemployment rate. Entries in the table are the coefficient estimates on the log of the seasonally unadjusted unemployment rate from equation (4) for each of the subgroups listed in the rows. The coefficient estimate $\frac{\partial \ln D_i(t)}{\partial \ln UR_i(t)}$ is an elasticity. Triple asterisk denotes statistical significance at 1 percent level. Double asterisk denotes statistical significance at the 5 percent level. Single Asterisk denotes statistical significance at the 1 percent level.

Table 3: Entrance Share Regressions

	1976-2006			1976-1996			1997-2007		
Group	Coefficient Estimate on $UR_i(t)$	Elasticity for $UR_i(t)$	Coefficient Estimate on Time Trend	Coefficient Estimate on $UR_i(t)$	Elasticity for $UR_i(t)$	Coefficient Estimate on Time Trend	Coefficient Estimate on $UR_i(t)$	Elasticity for $UR_i(t)$	Coefficient Estimate on Time Trend
Layoffs	-0.000 (0.001)	-0.012	0.000 (0.000)	-0.001 (0.001)	-0.053	0.000 (0.000)	-0.007** (0.003)	-0.373	-0.005*** (0.001)
Job losers	0.026*** (0.001)	0.650	-0.002*** (0.000)	0.017*** (0.001)	0.406	0.002*** (0.000)	-0.011*** (0.003)	-0.296	-0.007*** (0.001)
Quits	-0.010*** (0.000)	-0.702	-0.002*** (0.000)	-0.011*** (0.001)	-0.777	-0.002*** (0.000)	-0.000 (0.003)	-0.002	0.001 (0.001)
New entrants	-0.006*** (0.001)	-0.724	0.001*** (0.000)	-0.000 (0.000)	-0.069	-0.001** (0.000)	-0.013*** (0.002)	-0.965	-0.005*** (0.001)
Reentrants	-0.010*** (0.001)	-0.288	0.003*** (0.000)	-0.004*** (0.001)	-0.145	0.000 (0.000)	0.009*** (0.003)	-0.195	0.016*** (0.001)
Males	0.003*** (0.001)	0.044	0.000*** (0.000)	0.006*** (0.001)	0.110	-0.001** (0.000)	0.000 (0.002)	0.006	0.000 (0.001)
Females	-0.003*** (0.001)	-0.053	-0.000*** (0.000)	-0.006*** (0.001)	-0.130	0.001** (0.000)	-0.000 (0.001)	-0.007	-0.000 (0.001)
Males, no university degree	0.006*** (0.000)	0.114	-0.003*** (0.000)	0.007*** (0.001)	0.154	0.000 (0.002)	0.000 (0.02)	0.001	0.001 (0.001)
Males, university degree	-0.000*** (0.000)	-0.015	0.001*** (0.000)	0.000*** (0.000)	0.168	0.001** (0.000)	0.000 (0.001)	0.071	0.001 (0.000)
Females, no university degree	-0.001 (0.001)	-0.02	-0.001*** (0.000)	-0.005*** (0.000)	-0.120	0.002*** (0.000)	-0.001 (0.001)	-0.027	-0.001** (0.000)
Females, university degree	0.000 (0.000)	0.005	0.001*** (0.000)	-0.000* (0.000)	-0.110	0.001** (0.000)	0.001 (0.001)	0.149	0.002*** (0.000)

Males, age 15-24	-0.008***	-0.304	0.003	0.000	0.012	-0.006***	-0.005**	-0.155	0.002***
	(0.001)		(0.000)	(0.000)		(0.000)	(0.002)		(0.000)
Males, age 25-44	0.012***	0.496	-0.001***	0.005***	0.233	0.004***	0.004**	0.158	-0.004***
	(0.001)		(0.000)	(0.000)		(0.000)	(0.002)		(0.000)
Males, age 45-64	-0.001***	-0.114	0.003***	0.001	0.067	0.001**	0.001	0.059	0.002***
	(0.000)		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)
Females, age 15-24	-0.008***	-0.371	-0.002	-0.003***	-0.140	-0.004***	-0.003***	-0.134	0.001**
	(0.006)		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)
Females, age 25-44	0.006***	0.276	0.001***	-0.002***	-0.107	0.004***	0.002*	-0.090	-0.005***
	(0.001)		(0.000)	(0.000)		(0.000)	(0.001)		(0.001)
Females, age 45-64	-0.001***	-0.167	0.002	-0.001**	-0.180	0.002**	0.000	0.032	0.003***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.011)		(0.000)
Males, 15-24, non-enrolled	-0.005***	-0.261	-0.005***	0.001	0.037	-0.007***	-0.001	-0.032	0.001**
	(0.001)		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)
Males, 15-24 enrolled	-0.003***	-0.423	0.002***	-0.000	-0.097	0.001**	-0.004***	-0.372	0.001**
	(0.000)		(0.000)	(0.000)		(0.000)	(0.001)		(0.000)
Females, 15-24, non-enrolled	-0.005***	-0.327	-0.004***	-0.002***	-0.120	-0.005***	-0.000	-0.005	-0.001
	(0.001)		(0.000)	(0.000)		(0.000)	(0.000)		(0.001)
Females, 15-24, enrolled	-0.003***	-0.472	0.002***	-0.001***	-0.170	0.001**	-0.003***	-0.268	0.002***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.001)		(0.000)
Newfoundland	-0.000	-0.044	-0.001**	-0.001	-0.083	-0.001	0.000	0.021	0.000
	(0.000)		(0.000)	(0.001)		(0.001)	(0.001)		(0.000)
Prince Edward Island	0.001***	0.164	0.000***	-0.001	-0.345	-0.001	-0.002**	-0.328	-0.001**
	(0.000)		(0.000)	(0.001)		(0.001)	(0.001)		(0.000)
Nova Scotia	0.001**	0.108	-0.000	-0.000	-0.008	-0.000	-0.002*	-0.207	-0.003***
	(0.000)		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)
New Brunswick	0.000	0.047	-0.001**	-0.001*	-0.090	-0.000**	0.003***	0.355	-0.001**
	(0.000)		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)

Quebec	-0.002***	-0.099	0.001**	-0.001	-0.083	-0.000	0.005**	0.177	-0.000
	(0.000)		(0.000)	(0.001)		(0.000)	(0.002)		(0.000)
Ontario	-0.000	-0.000	0.003***	0.001	0.069	-0.003***	0.000	0.015	0.004***
	(0.000)		(0.000)	(0.001)		(0.000)	(0.003)		(0.001)
Manitoba	-0.000	-0.099	-0.000***	-0.000	-0.083	-0.000***	0.000	0.177	0.000
	(0.000)		(0.000)	(0.000)		(0.000)	(0.003)		(0.000)
Saskatchewan	0.000	0.072	-0.000***	0.001*	0.137	-0.000**	-0.003***	-0.415	-0.001**
	(0.000)		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)
Alberta	0.002**	0.143	-0.001**	0.002***	0.132	-0.001**	0.002	0.179	0.002***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.002)		(0.000)
British Columbia	-0.001	-0.114	-0.001**	0.000	0.027	-0.002***	-0.004***	-0.277	0.000
	(0.000)		(0.000)	(0.000)		(0.000)	(0.001)		(0.000)

Notes: The dependent variable in the regression is $s_i(t)$, the entrance share of group *i*. $UR_i(t)$ denotes seasonally unadjusted unemployment rate. The entries in the tables are coefficient estimates for the seasonally unadjusted unemployment rate from equation (5) for each of the groups that are listed in the table rows. Elasticities are computed at the mean. Triple asterisk denotes statistical significance at the 1 percent level. Double asterisk denotes statistical significance at the 5 percent level. Single asterisk denotes statistical significance at the 10 percent level.

Table 4: Entrance Share Regressions, Education Variables

	Coefficient Estimate on $UR_i(t)$	Elasticity for $UR_i(t)$	Coefficient Estimate on Time Trend
1976-1989			
Males, grade 11 or less	-0.002***	-0.082	-0.007***
	(0.000)		(0.000)
Males, more than grade 11	0.009***	0.291	0.004***
	(0.000)		(0.000)
Females, grade 11 or less	-0.004***	-0.240	-0.003***
	(0.000)		(0.000)
Females, more than grade 11	-0.002***	-0.070	0.005***
	(0.000)		(0.001)
1990-2006			
Males, did not graduate high school	-0.006	-0.220	-0.005***
	(0.005)		(0.002)
Males, graduated from high school	-0.004*	-0.108	0.004***
	(0.002)		(0.001)
Females, did not graduate high school	-0.008***	-0.442	-0.004***
	(0.002)		(0.001)
Females, graduated from high school	0.004*	-0.105	0.002***
	(0.002)		(0.000)

Notes: The dependent variable in the regression is $s_i(t)$, the entrance share of group *i*. $UR_i(t)$ denotes seasonally unadjusted unemployment rate. The entries in the tables are coefficient estimates on the seasonally unadjusted unemployment rate from equation (5) for each of the groups that are listed in the table rows. The elasticities are computed at the mean. Triple asterisk denotes statistical significance at the 1 percent level. Double asterisk denotes statistical significance at the 5 percent level. Single asterisk denotes statistical significance at the 10 percent level.