HEC MONTRÉAL

The Determinants of Job Durations in Canada

by

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Summary

How long an employee would stay at his present job or how long the employer would keep the worker employed is unknown for both parties. Employer may find it beneficial to find out what types of employees are more mobile. By knowing characteristics of employee mobility, employers wishing to have stable workforce can target less mobile workers while employers desiring to fill temporary positions can target suitable workforce – more mobile workers. Likewise job searchers may find it valuable to know the characteristics of employers where workers are prone to have short or long durations.

In this paper, we investigate the determinants of job durations in Canada using linked employer-employee data. The data comes from Workplace and Employee Survey from Statistics Canada. It covers the period of 1999 to 2005. In this paper we use the survey period covering 2003 and 2004. This survey provides us with micro data on employees as well as the workplaces in which they work. Using this database we simultaneously consider the characteristics of both the firm and the employee as determinants of job durations.

We consider three different multivariate hazard models to conduct our analysis: a standard Cox model and two Mixed Proportional Hazard Models (MPH). In the standard Cox model, we look only at observable worker and firm characteristics as determinants of job durations. In the first MPH model, we take into consideration worker heterogeneity as well. In the second MPH model we consider both worker and firm heterogeneity along with observable characteristics. Among the three models, the MPH model with both heterogeneity has the best predicting power.

Our findings indicate that the Canadian labor market shares similar characteristics with those in other developed countries. The majority of Canadian workers enjoy long-term employment relationships. Among workers, the young employees are

very mobile. The probability of job termination declines with tenure. The longer the worker is employed, the lower are his chances of quitting or being fired. Among the industrial sectors, employees in primary sectors are the most mobile.

Sommaire

Comment prévoir combien de temps un employé demeurera à l'emploi qu'il occupe ou combien de temps un employeur gardera-t'il un travailleur à l'emploi? Voilà la question qui préoccupe autant les employeurs que les employés. L'employeur peut avoir l'intérêt à savoir quels types d'employés sont plus mobiles que d'autres. En sachant les caractéristiques de la mobilité, les employeurs qui souhaitent avoir la main-d'œuvre stable peut cibler les travailleurs les moins mobiles tandis que les employeurs qui désirent combler des postes temporaires peuvent cibler la main-d'œuvre appropriée - les travailleurs les plus mobiles. De même les chercheurs d'emploi peuvent trouver utile de connaître les caractéristiques des employeurs où les travailleurs sont enclins à avoir des durées courtes ou longues.

Dans le présent document nous estimons les déterminants de la durée de l'emploi en recourant à des données liées sur le rapport employeur-employé. Ces données nous sont fournies depuis l'Enquête sur le Milieu de travail et les Employés, conduite par Statistiques Canada, couvrant la période de 1999 à 2005. Nous utilisons la période d'enquête couvrant les années 2003 et 2004. Cet enquête a mis à notre disposition des micro-données autant sur les employés, que sur les milieux de travail dans lesquels ils évoluent. En utilisant cette base de données, nous sommes à même de considérer simultanément les caractéristiques d'entreprises et de leurs employés comme déterminants de la durée d'emploi.

Nous avons eu recours à trois différents modèles de hasards multivariés pour mener notre analyse: le Modèle standard de Cox, ainsi que deux autres modèles à hasards proportionnels mixtes (HPM). Suivant le modèle standard de Cox, nous ne considérons que des caractéristiques observables sur les travailleurs et les entreprises qui les emploient, en tant que déterminants sur la durée d'emploi. Ensuite, en utilisant un premier modèle HPM, nous pouvons également prendre en

considération l'hétérogénéité non observée au niveau des employés. Avec le second modèle HPM, nous sommes à même d'analyser conjointement l'hétérogénéités non observée au niveaus des employés et de l'entreprise qui les emploie en lien avec les caractéristiques observables recueillies. De ces trois modèles, ce dernier modèle HPM colligeant les deux hétérogénéités nous apparaît comme offrant le meilleur pouvoir prédictif.

Nos conclusions indiquent que le marché Canadien de l'emploi démontre des caractéristiques similaires à ceux des autres pays développés. Une majorité de travailleurs canadiens bénéficient d'une situation d'emploi stable et de longue durée. Parmi ces travailleurs, les jeunes employés sont particulièrement plus mobiles. La probabilité de cessation ou de changement d'emploi diminue avec l'ancienneté; plus longtemps le travailleur occupe un même emploi, moins il y a de chance qu'il quitte son travail ou qu'il soit congédié. Enfin, parmi les divers secteurs industriels, la main-d'œuvre des secteurs primaires d'activités demeure la plus mobile.

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Section 1: Introduction

The notion of job stability becomes peculiarly important during recessions. It was especially true in the late 2000 when a financial crisis in the United States of America triggered a global economic slowdown. Canadian economy was not spared. In Canada job losses were recurrent in all economic sectors. During such periods, the goal of most employed individuals becomes focused on keeping their jobs as long as possible since the firms facing economic downturn oftentimes reduce the workforce. Politicians in many countries, including Canada made job creations their utter priority.

Policy makers may help with creating jobs, however, maintaining existing jobs may not an easy task. Job separation may be an efficient outcome (McLaughlin 1991 or Parsons 1986 cited by Bergemann and Mertens (2004)). Job separation occurs when either the employee no longer wishes to stay employed or when the employer no longer wishes to have him employed. The latter may occur when the firm facing financial difficulties lays off the workforce or when management decides to fire an employee. After how long does the employment relationship come to an end is the purpose of the study of this paper. Job durations are used to infer about job stability. (Heisz (1996) and Nardone et al. (1997)). In this paper we investigate the determinants of job durations in Canada.

Employment duration refers to the length of an employment relationship between an employer and an employee. The duration of this relationship is determined either by the individual's decision to quit or the firm's decision to fire/layoff.

Participants in the labour market engage in a two sided search to form employment relationships. More specifically, individuals search for employment while employers search for employees. In the presence of information asymmetries between employers and employees, both parties scrutinize each other and form new employment relationships when the terms and conditions of both parties are satisfied. However, not all of the information is exposed in the process. Only after the relationship has developed will both parties' qualities be revealed.

Firms' retention and firing policies also affect employment duration. Firms wishing to have a longstanding workforce may invest considerably in its employees so that employees feel more attached to firm. These policies depend to a great extent on geographical location and the type of industry in which the firm operates. For instance, service industries tend to be concentrated in urban areas while locations offering natural resources attract primary sector industries. White collar workers constitute the majority of the workforce in service industries while blue collar workers are concentrated in the production, manufacturing and construction industries.

This thesis is inspired by the work of Horny et al. (2009). They analyze job durations using Portuguese linked employee-employer data. This type of data provides researches with the possibility to account for both worker and firm unobserved heterogeneity in analyzing job durations.

The studies taking into considerations worker heterogeneity are numerous (Farber, 1999, Bellmann et al. 2000, and Del Boca and Sauer, 2006 cited by Horny and al). However, the studies that account for both worker and firm heterogeneity are limited. The lack of this kind of studies can be attributed to the unavailability of matched employee-employer data (Willis (1986) p.598). When matched employee-employer data were made available, the limits of computers hindered their utilisation (Abowd, J. M. and F. Kramarz (1999a) p.2704).

Statistics Canada collected matched worker-employer data in the period of 1999 to 2005. The employer component of the Canadian dataset represents almost all Canadian businesses that had paid employees.[1] The respondents in the employee component of the survey are drawn from the workplaces that are selected in the employer component of the survey. The survey thus provides matched employee-employer that is necessary to conduct our analysis. From this dataset we obtain employee characteristics as well as the characteristics of workplaces they work for.

The plan of this thesis is the following: The next section is the literature review which consists of three subsections: In the first subsection, we look at stylized facts regarding job durations; In the second subsection, we look at a theory that explains workers' mobility and some evidence for it that would help us at choosing workers' characteristics as determinants of job durations; In the last subsection, we look at a theory where firm decides to layoff and some evidence for it. Section 3 presents the source of the data and the construction of the sample used in this paper as well as explanatory variables and descriptive statistics of the explanatory variables. Section 4 presents the model to be used in this thesis as well as how the model is estimated. The section 5 covers the estimation results. The concluding remarks are presented in last section of the thesis.

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[1] The survey excludes businesses operating in Canadian Territories and businesses operating in crop production and animal production; fishing, hunting and trapping; private households, religious organizations and public administration

Section 2: Literature review

A job exit occurs if an employee decides to quit his job or an employer decides to dismiss the worker, or it may involve the simultaneous decision of both parties. It is, thus, possible that employee mobility may be explained by characteristics of both employees and employers. Neal (1999) claims the focus of the modern theoretical work on labor mobility has been primarily on firm-specific considerations. For example, in human capital investment models, a firm-specific investment reduces the separation rates while in principal-agent models, rising benefits reduces the labor mobility. Neal argues that employee mobility pattern is more complex – the mobility arises from employee decision to move from a firm to another firm or from an industry to another industry.

In this section, we will look at some previous literatures which document observable patterns in employment durations. We will also cover bodies of literature that attempt to theoretically explain job durations followed by empirical evidence for the considered theories.

In the subsection that follows, we discuss stylized facts regarding job durations. Since this paper investigates both worker and firm determinants of job durations, in the subsequent subsections we look separately at theories where quits and layoffs are modeled.

Section 2.1: Stylized facts about job durations

Labor markets in developed countries feature some similar characteristics. The similarities have been documented by Farber (1999). He presents these similarities as stylized facts regarding job durations. Stylized fact 1 asserts that long-term employment relationships are common. In 1996 almost one third of American employees older than 35 years old have held the same occupation for more than 10 years while on the time, one fifth of employees older than 45 years old have had the same occupation for more than 20 years. Stylized fact 2 dictates that most new jobs end early. While more than half of employment relations are long lasting (more than 10 years), new jobs do not last long. More precisely, almost one fifth American employees aged 20-64 had been with the same employer for less than one year. If the job termination does not occur early (in the first year), it leads to the stylized fact no 3 which states that the probability of job ending declines with tenure. If the job exit does not occur in the first year then there is less and less chance that the termination occurs in the subsequent year so that Fact 1 holds true.

This pattern of stylized facts is observed in Canada as well. Christofides et al. (1993) analyze Canadian labor market using the Labor Market Activity Survey of 1986 and 1987. In this observation window most new jobs end in less than 2 years. The matches that survive early years are likely to last long so that probability of job termination weakens as duration increases. Christofides et al. explain this occurrence by employees' age. Young employees arguably have low attachment to the labor market because they face "fewer constraints such as loss of significant pension rights, loss of firm specific human capital, and so on."

Farber, on the other hand, looks at determinants of firm, specific capital and heterogeneity across workers to explain the stylized facts. However, he falls short in explaining the observed patterns. He cites the need for "more and better data on mobility histories along with models that combine specific capital considerations with carefully specified models of heterogeneity …" to explain the observed patterns.

Horny et al. (2009) propose a model that takes into account both workplace specific and employee specific heterogeneity in explaining the stylized facts. They argue that by using matched employer-employee data, one finds answers to the concerns posed by Farber. The proposed model is a multivariate hazard model which takes into account worker-specific and firm-specific unobserved characteristics.

The data that Horny et al. use to estimate their model is Quadros de Pessoal - longitudinally matched, employer-employee data gathered by the Portuguese Ministry of Employment. They find that only half of variations in job durations are explained by observable employee and workplace characteristics. The other half is explained by unobservable characteristics (28% by firm unobservable effects and 12% by worker unobservable effects.

Stylized fact number 2 dictates that most new jobs end early. Thus, the beginning of a relationship is the most uncertain period. It is at this stage when both parties realize whether there is a match or a mismatch. In Canada, this phenomenon is particularly true for young males and uneducated employees at small workplaces (Picot (1997)). Arguably, knowledge of determinants of employment durations can help save costs resulting from mismatches. We look at determinants of job durations in Canada given that there is matched employer-employee data in Canada and that a new estimation method is available.

In the next two subsections we look at theoretical models which explain the role of employees and the role of firms in determining job durations. We also present empirical findings to support the theories in both blocks.

Section 2.2: Employee’s role in job durations

Most job separations are initiated by the employees. Christofides et al.’s (1993) estimates show that almost three quarters of mismatches are due to quits.

Section 2.2.1: Job Shopping

Johnson (1978) pioneers the model to explain observed high mobility among young workers. The model is called “job shopping.” In this model, the author provides a theory for the individual’s mobility and the reasons for this mobility. Mobility decisions require the individual to withdraw from the current job and move to the new one. This change takes place in order to maximize his lifetime wealth.

In this model a risk neutral individual lives in two periods: the early and later stage of the individual’s career. For a population composed of many identical individuals, the two periods represent young and older workers. The individual’s income depends on the earnings he receives for his job-specific abilities and general abilities. General abilities are rewarded equally in all jobs contrary to job-specific abilities which reward only for an individual’s productivity.

Prior to starting a job, the individual does not yet know in what area his abilities will be applied. He can only ascertain how specific abilities are rewarded by observing his peers in the labour market. The only way that he can learn about his own abilities is through his working experience. Finally, firms that offer jobs also differ in the way that they reward an individual’s productivity.

Once the agent enters the workforce, he accumulates knowledge about his general and job-specific abilities and therefore is able to calculate his lifetime wealth. The worker decides to change jobs for any one of the two following reasons. Firstly, if the current job does not meet his ambitions (job-specific abilities), he then quits and searches for a preferable job, ideally, a job that compensates him properly for his specific abilities. Secondly, he quits if the current job does not reward him appropriately for his input (general abilities), given that he learns about the worth of his abilities.

In the early stages of their careers, Johnson (1978) argues that people prefer jobs with "the greatest overall earning variance." Later on, they change to safer jobs only if the riskier job pays less on average. In other words, job turnover is due to what Johnson (1978) calls "workers' sequential decision". If mobility costs (the costs of changing jobs), are high enough, the individual may reconsider the quest for mobility. Losing seniority at the old job or the costs of searching for a new job can hinder the individual's mobility.

Education, in this model, may play two roles in mobility decisions. Firstly, it may diminish the mobility rate. Educated individuals learn about their general and job-specific abilities through education. As a consequence, they choose a job that rewards their abilities appropriately. For example, a recently graduated economist does not start off his career as a nurse. Secondly, education may not affect the mobility rates. Here, educated people earn on average more than uneducated ones however, their quest for a job that appropriately rewards abilities continues. For example, a graduate economist starts his career at a commercial bank then switches to a preferable job after becoming familiar with where his skills as an economist could be best applied.

Section 2.2.2: Empirical evidence for Johnson's theory

There are numerous examples that corroborate Johnson's (1978) theory. Topel and Ward (1992) observe that most job changeovers occur in the early stages of a career. In fact, they estimate that a typical American has worked in seven different locations within the first ten years of their career. These mobile workers were rewarded by higher wages. For instance, in the first ten years they experience a dramatic increase in wages. In the subsequent years, the rate of increase in wages subsides. This phenomenon is explained by Johnson's (1978) theory.

Booth et al. (1999) estimate that average British employees hold a total of five jobs over their lifetime. Half of the changes in jobs occur in the first ten years of employment. Horny et al. (2009) find in the Portuguese data that workers between the ages of 16-25 terminate their jobs to a greater extent than other groups. Farber's (1999) "stylized facts" show that the probability of job termination declines with age. Hall (1982) gives a very comprehensive analysis of job duration in relation to age using the data from 1978. By the age of 24, the average American has held four jobs and the probability that any of these jobs becomes a lifetime job is 2.2 percent.

In the late 1980's, almost one out of five Canadian employees quit their jobs (Morissette et al. (1992)). Young employees, below the age of 24, dominate the percentage of people quitting. While they constitute 17 percent of the workforce, their share in quits is almost 50 percent. Authors observe that young men were more likely to quit than women. Employees in the service industries have the highest numbers of quits. They represent 43.8 percent of all quits, followed by employees in public service (15.5 percent); employees in manufacturing (14.1); and employees in business services (10.9 percent), etc.

Johnson's theory considers only one side of the equation in job termination, namely, the supply side of labour. Booth et al. (1999) find that approximately half of job terminations in Britain are due to quits. Layoffs, on the other hand, represent 15 percent of job terminations for men and seven percent for women. It is interesting to look at the employer's side of the equation to find the answer to why quits occur.

Section 2.3: Employer's role in determining employees' job durations

Every year, more than a million Canadian employees are permanently displaced from their jobs. The displacement takes place during recessions, recovery or expansionary periods. This trend persists throughout the 70s, 80s and 90s.

There is no one single reason why businesses terminate jobs. These reasons may include decline in overall economic activity; drop in demand for the firm's product; seasonal nature of the job; business goes bankrupt; business moves to another geographical location; company outsources and abolishment of positions. All these reasons may be prompted by factors outside the firm's control. In these cases, job termination can come in the form of short term layoffs with the possibility of rehiring or, long term permanent layoff.

Dismissals are an involuntary employment termination which necessarily brings the relationship between employers and employees to an end. The employees who are affected, suffer shorter employment duration than if the dismissal had not occurred. Regardless of the employer's wishes, the firm also has a role to play in the mobility decision of workers.

Section 2.3.1: Theory of layoffs

Baily (1977) proposes a theory of layoffs, both temporary and permanent. Under a temporary layoff, the firm reinstates employees after a certain time. In the case of permanent layoff, the employee is unwillingly unemployed.

In this model, a risk neutral firm operates in the competitive market wherein the prices of the company's products, as well as the price for labour are set forward. Demand for the firm's products changes seasonally. Due to changes in demand, the firm must adjust its workforce, hours of work and the compensation per worker. Workers are aware of the state of the firm's demand and thus, whether or not they will be laid off. However, employees do not know the extent of the future decline in demand. In this model, the size of the workforce is such that each worker's marginal product of labour is equal to marginal cost per worker.

When the demand for the firms' products decline to a certain level, the firm reduces hours of work because it may incur unemployment insurance payment costs if employees are laid off. Further decline in demand forces the firm to lay off its workers which is, at this stage, more economically sound than the cost of wages.

In this model, the types of workers who are laid off first is not explicit. Tacitly, workers with the lowest marginal product of labour are the first ones to go. Workers with low marginal product of labour include young, less experienced and less educated workers.

Section 2.3.2: Empirical evidence for the theory of layoffs

Farber (2008) analyses job loss in the employer's side of the equation. His data comes from the Displaced Worker Survey which covers job loss resulting from plant closures, employers going out of business, layoffs from which the worker is not recalled, etc. In the period of 1981-2001, on average, one in ten job losses in the US was caused by the reasons mentioned above.

Booth et al. (1999) find similar results to Farber in the British labour market. Their findings show that 15 percent of the first jobs for British males end due to layoffs while only 6.9 percent of females lose their jobs due to layoffs. The gender difference is partly explained by women leaving the labour force for other reasons, for instance, pregnancy.

Picot et al (1997) conduct a similar analysis in the Canadian labour market. They notice temporary layoffs are counter cyclical and permanent layoffs have been stable accounting for 7 percent of the total job losses in the period of 1978-93. In the same period, temporary layoffs fluctuated around a mean of 8 percent.

Picot et al.'s (1997) study differs from the previous two in that it further divides permanent layoffs by industrial sector, age group, region, gender, firm size and earnings. On average, in the period of 1978-93, males are subject to permanent layoffs more often than women. Young adults are more likely to be laid off than their older counterparts. Firms in the Atlantic region dominate the permanent layoff category at 12 percent; followed by Quebec and BC at 8.5 percent; Alberta 7.3 percent; Manitoba and Saskatchewan at 5.7 percent; and Ontario at 5.2 percent. Industrial sector employees were more likely to be laid off; 28 percent of job losses in this sector are due to permanent layoffs. Finally, employees in the Health and Education sector enjoy relative stability in terms of layoffs; only 2 percent of job terminations were due to permanent layoffs.

Section 3: Data and sample construction

For analysing the determinants of job durations in Canada, we use the data from Workplace and Employee Survey (WES) provided by Statistics Canada. WES covers the period from 1999 to 2006. As we show further in this paper, we create two samples to estimate determinants of job durations. One of the sample covers all the survey periods for which workers were administered follow up questionnaires (years 1999-2004). The other sample covers the survey responses from wave 3 only (years 2003-2004). Thus the second sample is the sub-sample of the first sample. WES covers both workplaces and employees working in those workplaces. This survey stands out from previous surveys because it links employer and employee at a micro data level.

This section begins with an overview of WES followed by a definition and construction of job duration data. Finally, we present descriptive statistics of explanatory variables which encompass both employee and employer variables.

Section 3.1: Workplace and Employee Survey

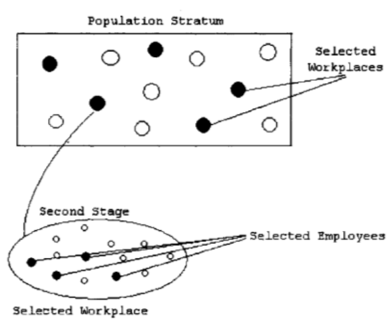
Workplace and Employee Survey (WES) is a longitudinal survey. It was conducted from 1999 to 2006 for workers and from 1999 to 2006 for employers. To construct the sample for the survey, all business locations registered in Statistics Canada Business Register (BR) are stratified into 252 relatively homogenous groups – strata. The stratification encompasses fourteen industries, six regions and three categories of firm sizes.

Workplaces are first randomly selected from each stratum to form the workplace component of WES. Then, employees are randomly selected from the sampled workplaces to form the employee component of WES. Figure 1 depicts this stage (Patak et al. (1998)). This survey provides us with micro data on the supply and demand side of the labour market. This method of matching workplaces and employees at a micro level makes WES unique in Canada.

The locations in the workplace component of WES, sampled in 1999, are followed through to 2006 with periodic adjustments so that the sample remains representative. Adjustments are made every second year of the survey (2001, 2003 and 2005) to take into account the birth of new workplaces.

The employees, in the employee component of WES, are randomly selected from sampled workplaces. Unlike workplaces, according to Picot et al. (1998), the employee component is not "a panel in the strictest sense." Sample selection of employees is done as follows. Employees sampled in 1999 are followed up in the year 2000. From the follow-up survey, employees are considered to be continuers or exiters[2]. The exiters are employees who report no longer working for the same employer as in the previous year while continuers are the ones who are still employed with the same employer.

Figure 1: Sample Selection of the WES



Source: Patak et al. (1998)

[2] Exiters and continuers are the terms defined and used by Statistics Canada.

Total of 9,337 distinct workplaces are surveyed in the period 1999 to 2005. In Table 1 we report the number of respondents for each year and the estimated population they represent. In 1999, WES surveyed 6,322 workplaces. In the second year of the first wave, 254 workplaces did not participate in the survey due to going out-of-business, seasonally inactive, holding companies or out-of-scope (WES Guide 2004). In the second wave, WES draws from 913 workplaces to maintain representativeness of the sample. In the same manner, 389 workplaces are lost in 2002 and 406 in 2004. WES draws from 1,133 in 2003 and 1,022 in 2005.

As for the employee component of WES, a total of 85,922 distinct employees are surveyed in the period 1999 to 2005. They are sampled and surveyed in the first year of each wave and are followed-up in the second year of each wave. In follow-up surveys, WES excludes employees in the workplaces that are excluded from WES (WES Guide 2004). In this manner, 3,373 employees did not participate in the follow-up year of the first wave, 3,539 of the second wave and 4,430 of the third wave. Employees sampled in last wave were not followed up in 2006. WES stores responses in the employee component of the survey. For each year, WES contains two sets of datasets: one for the employee component and another for the workplace component.

Table 1: WES sample size

		Workplaces		Employees	
	Year	Respondents	Estimated population	Respondents	Estimated population
Wave 1	1999	6,322	738,324	23,540	10,867,614
	2000	6,068	686,680	20,167	10,867,614
Wave 2	2001	6,207	734,127	20,352	11,640,536
	2002	5,818	668,876	16,813	11,640,536
Wave 3	2003	6,565	723,787	20,834	12,119,794
	2004	6,159	660,951	16,804	12,119,794
Wave 4	2005	6,693	670,812	24,197	12,215,309

Section 3.2: Sample construction

Given that we are interested in cross sectional variations in job durations, we look only at the cross-sectional aspect of WES (WES is a longitudinal survey). For this reason, we construct a new sample from WES to suit our needs.

The construction of the new dataset is as follows: step 1) employee responses from the first year of each wave are updated with the responses from the second and final year of each wave; step 2) observations in all four waves are pooled together; step 3) workplace responses are integrated into employee responses; step 4) we pool the observations from all four waves into single dataset.

By pooling observations from all waves into a single dataset, we are able to use all observations from all waves. We call this sample Sample 1. The software that we use to conduct our analysis fails to handle this large number of observations.[3] Therefore, we are obliged to construct a smaller sample that we call Sample 2. The construction of the Sample 2 follows only the first three steps outlined in the previous paragraph. Sample 1 covers the period of 1999 to 2005 and Sample 2 covers only the period of 2003 to 2004. In fact Sample 2 is a part of the Sample 1. There are 82,245 observations in the Sample 1 and 20,337 in the Sample 2.

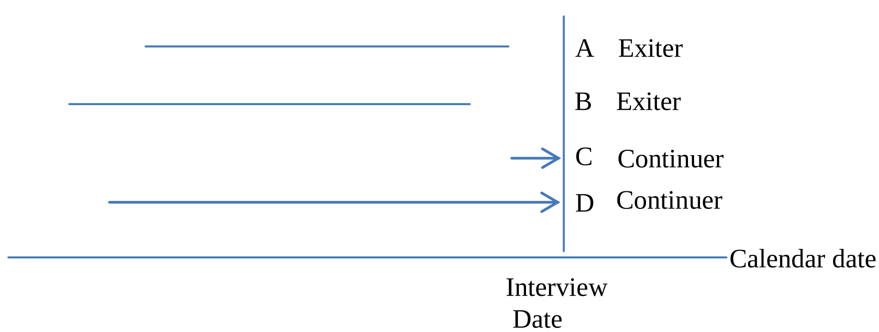
When updating responses from the first year of waves with those of the second year, we can differentiate between exiters and continuers. The employees who reported no longer to be working in the second year of the waves are considered exiters. Exiters are administered the exit questionnaire. Similarly, continuers are the employees who are observed to be working in both years of waves. Exiters indicate their departure date on the exit questionnaire.

[3] The software is discussed in Section 4.

Section 3.2: Duration data

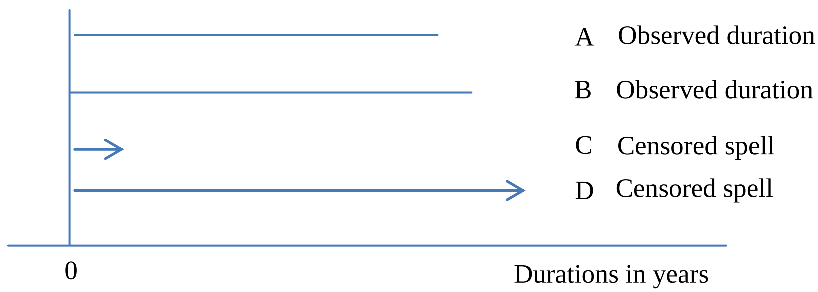
Calculation of the duration data differs for exiters and continuers. In general, the job duration (the length of time that one remains employed) is calculated by subtracting the beginning date of employment from the end date of employment. In our sample, we know the beginning and end date of employment relationship for exiters only. We calculate their durations using all available information. For continuers, we observe the beginning date of their employment but we do not have information on their last date of employment. When the survey was carried out they reported to be employed. Therefore, for continuers, we use the last week of March[4] as the end date of employment. By calculating the durations for continuers in this manner, we obtain right censored data. Right-censoring occurs when the failure event (an employment exit) occurs any time after the interview date and which we do not observe. In Figure 2 and Figure 3, we demonstrate distinction between exiters and continuers and the distinction between observed spell and censored spell.

Figure 2: Exiters and Continuers in the survey



[4] From Guide to the Analysis of the Workplace and Employee Survey (2004) we learn that the reference period is March

Figure 3: Transformed duration data



The mean of durations for the Sample 1 is 9.15 years. The average duration for censored observation is 5.58 years and the average duration for observations with completed spell is 9.45. The statistics are provided in Table 2. In Figure A2, we plot the job durations for Sample 1 and Sample 2.

Table 2: Average job durations in years

	Sample 1	Sample 2
All observations	9.15	9.26
Completed spell observations	9.45	9.66
Censored observations	5.58	5.6

Section 3.3: Explanatory variables and descriptive statistics

In our model, explanatory variables include both employee and workplace observable characteristics. Employee observable characteristics include age, gender, educational attainment and part-time. Workplace observable characteristics include industry variable and multiple plant indicator. Next we define each variable, and then we present descriptive statistics of these variables.

Construction of the variable age is similar to the construction of the variable duration. Its value is calculated as of the last time the individual is observed in the sample. The exiters are last observed as of the last day of being employed. We observe the exit day of exiters and are able to calculate their age. The continuers are last observed as of the survey date. Their age is calculated as of the survey date. Table A1 presents definitions of the four dummy variables for age and their descriptive statistics.

Values for variable gender are obtained directly from the WES survey. We create a dummy variable which takes value 1 for the male employees and 0 for the female employees. Table A1 presents definitions of the dummy variable for the gender and its descriptive statistics.

We divide education into three categories: dropouts, completed secondary and postsecondary. In the secondary category there is variable dropout (those who have not graduated from high school) and variable secondary. The WES provides more details about level of education for those who have completed their secondary education. We take this information into consideration in the category postsecondary. The variable dropout is thus reference category for both categories. The postsecondary is education is divided into four variables: vocational, college, university, and other. The variable other represents employees who have industry certified diplomas.

Statistics Canada defines part time as hours worked less than 30 hours per week. We use the same definition for the construction the variable part time. Table A1 presents definitions of the dummy variable for part-time and its descriptive statistics.

Workplace observable characteristics include multiple plant indicators and the industrial sector in which the workplace operates. WES categorizes firm as being single small unit, or single big unit or multi-unit. For the purpose of this paper, we combine single units together. Variable multiple plant, thus, takes two values. Table A1 presents definitions of the dummy variable for the multiple plants indicator and its descriptive statistics.

The WES divides the Canadian industrial sectors into 14 groups. Due to the limits of the software, we combine four industrial sectors into two in order to reduce number of variables. We analyze North American Industry Classification System (NAICS) codes of industrial sectors of the WES and combine two industrial sectors that have similar NAICS codes. Table A2 presents NAICS codes for industry variables. We combine transportation, warehousing and wholesale trade with communication and other utilities into one variable. Similarity, we combine retail trade and consumer services with finance and insurance to form a new variable. We verify that transportation, warehousing and wholesale trade and communication and other utilities have very close coefficients. Similarity, retail trade and consumer services and finance and insurance share similar coefficients.[5]

In Table A3, we provide average durations for observable worker and firm characteristics. The first thing to notice on the table is that the average durations across both samples are very similar. We can conclude that in the study time window, average durations have not changed.

Males on average have longer durations than females. Picot et al.'s (1997) show that Canadian males are likely to get laid off and Morissette et al. (1992)) show that Canadian are more likely to quit. Since job separation occurs due to quits or layoffs, we would expect females to have longer duration. Although, the proportion of males and females are identical in our sample, maybe the composition of males and females in longer duration jobs is different.

[5] The verification is done using Frequentist approach. As we discuss in Section 4, we use different software to conduct Bayesian estimation and frequentist estimation. We refer to the limits of the software to conduct Bayesian estimation.

Univariate analysis of job durations shows that average durations increase with age. We cannot take this as an evidence for Johnson's theory. We will look at multivariate analysis in the next section to determine if young people are in fact more mobile.

As for education, there seem not to be large differences in average job durations for employees with postsecondary education. However, dropouts have longer durations on average than employees with secondary education. Part-time employees are on average exhibit 3 years shorter durations. This can be explained by the fact that part-time employments are mostly temporary jobs.

Turning to firm variables, workers in large organization have on average longer durations than in single business units. Large organizations offer internal labor market where an employee can move up the ladder. Small businesses do not offer such flexibility.

Employees in education and health services have on average longest durations while employees in retail trade, consumer services, finance and insurance have shortest durations. Again by looking at univariate finding of (Picot et al.'s (1997) for layoffs and (Morissette et al. (1992)) for quits, we see that quit rates and layoff rates are lowest in education and health and higher in retail trade, consumer services, finance and insurance.

Section 4: Model and Methodology

We estimate the determinants of job durations using the semi-parametric Cox Proportional Hazard Model (Cox (1972)). This model gives us the flexibility to estimate the coefficients of the model without specifying a functional form for the baseline hazard function.

To analyze the job durations, we express the durations as a hazard function. The relationship between the hazard function and the duration is given by:

where is time and is the actual job durations. The hazard function ( ) in the equation (1) denotes the probability of employment termination in the time interval given that the employee has been employed till time .

We express the hazard as a function of covariates using the proportional hazard model. We denote individual by (=1, 2, …) and firm by (1, 2…). The hazard as a function of covariates is given as

Equation (2) is termed Proportional Hazard (PH) model. Under the specification of PH, covariates are assumed to shift the hazard function proportionally. The function is the baseline hazard function. The baseline hazard depends only on time. In PH models no assumption is required on the shape of the baseline hazard; the shape of the baseline hazard is determined by the data. The individual and firm covariates are expressed by . In this paper, we refer to the equation (2) as model 1.

A Mixed Proportional Hazard (MPH) model is a proportional hazard model in the equation (2) with a mixing distribution. By allowing worker heterogeneity in the equation (2), we obtain

where is the the worker unobserved heterogeneity. We refer to the equation (3) as model 2.

By allowing both workers' and firms' heterogeneity in the equation (2), we obtain

where is the worker unobserved heterogeneity and is the firm unobserved heterogeneity. We treat unobservable heterogeneity as random effects. Following Horny et al (2005), we assume these two random effects are non-nested and independent from each other and covariates. We refer to the equation (4) as model 3.

Treating unobservable heterogeneity (also called frailty) as random effects has both its advantages and disadvantages. Random effects allow us to estimate the parameters of frailty distributions. However, unlike fixed effect, for random effects one must assume a distribution and independence between random effects and covariates. Horny et al (2005) present list of studies in the support of treating unobservable heterogeneity as random effects.

Identification rule of MPH requires that covariates and random effects be independent from each other. And random effects have a finite mean (Elbers and Ridder (1982)). In order to estimate model 2 and 3 we assume the independence between the covariates and random effects and finite mean for random effects.

In all three models, the shape of baseline hazard is determined by the data i.e. no assumption is made on the shape of the baseline hazard. Covariates enter the model linearly. From equation (2) we can see that if all covariates are zero, expression equals to one. Then, baseline hazard is equal to the observed hazard rate.

Expression in equation (2) guarantees that the hazard is always non-negative. The sign of coefficient indicates the effect of the covariate on the hazard. The hazard increases (decreases) with a positive (negative) coefficient. Thus a positive (negative) coefficient reduces (increases) the duration. For example, we take dummy variable age in isolation. From equation (2) we can see that hazard for females would be and for males. The hazard rate for males would be that of females.

Unlike the classical approaches, Bayesian approach can compute complex pattern relating the random effects (Congdon (2007)), as it is in our case. All three models are estimated using semi-parametric Bayesian method. Since model 1 can also be computed using classical approaches (by maximum likelihood), we also provide frequentist estimates for model 1 using the Sample 1 and Sample 2. The results are presented in Table A5.

Section 4.1: Bayesian approach

The Bayesian approach combines prior belief with the sample data in order to obtain the posterior distribution. Posterior distribution conditional on data is proportional to the product of the likelihood and the density (prior belief) ((Gelman et al.(1995)):

Inferences on parameters are made from posterior distributions. In what follows, we discuss priors and sampling techniques from the posterior distribution.

Section 4.2: Prior distribution

Regression coefficients of the model are assumed to follow proper but uninformative priors. Horny et al. (2005) argue that proper but uninformative priors make the computation easier for the software that we use. Following Horny et al. (2005), regression parameters follow univariate normal distribution mean and precision (inverse of variance). Regression coefficients are assumed to be independent. The commonly used values for and precision (inverse of variance) are 0 and 10000 respectively (Hall (2012)).

Now we turn to the priors for random effects. Firm and worker random effects are assumed to follow Gaussian distributions. This choice is motivated by Horny et al. (2005). The Gaussian priors for random effects are justified by two reasons. First, unobservable heterogeneity could generate the positive or negative hazard. Second, the presence of unobservable heterogeneity may be the result of the omission of worker and firm specific unobservable covariates. The mean for both frailties are assumed to be zero. The zero mean assumption captures deviation from the mean. Precisions (inverse variance) of random effects (and) are assumed to follow gamma distributions.

The values of the baseline hazard are assumed to follow gamma distribution. If the parameters of the gamma distribution are small, the posterior of the gamma distributed priors is proportional to the partial likelihood (Kalbfleisch (1978) cited by Horny et al. (2005)). Horny et al. show that by assuming gamma non informative prior on baseline hazard, we can estimate the baseline hazard in the semi-parametric setting.

Section 4.3: Bayesian Estimation

In the Bayesian approach, inferences on parameters are made from posterior distributions. It is a daunting task to compute analytical solutions for posterior distributions given that it requires multidimensional integration. Even if the analytical solutions were available, the computational advances made it feasible to estimate the complex models using numerical techniques. One the available numerical approximation method is the Markov Chain Monte Carlo method (MCMC).

In order to sample from posterior distribution, we make use of MCMC methods, in particular Gibbs sampling. Markov Chain Monte Carlo method (MCMC) generates random samples of parameters from the posterior distribution. The initial samples are discarded (called burn-in) to avoid bias associated with initial values. If the chain is run long enough it converges to the stationary distribution which has the same properties as in the equation (6).

The inference on parameters is made from the samples generated in the stationary distribution. The Gibbs sampler (Gelfand and Smith, 1990) is a MCMC algorithm for sampling from lower dimensional conditional distributions. Each draw of the Gibbs sampler generates set of parameters. This procedure is called Markov Chain. The draws from Gibbs sampler eventually converges to the draws from joint posterior distributions.

One of the computational advances is the family of BUGS (Bayesian Inference Using Gibbs Sampling) software. For the estimation of our models we use the OpenBUGS software package. OpenBUGs is open source software than computes MCMC methods. OpenBUGS can estimate statistical models of “arbitrary complexity." The software estimates the model using an appropriate MCMC scheme (based on the Gibbs sampler). The software that we use recommends using either one long chain or many shorter chains. The use of many chains is common (Horny et al. (2005), Horny et al. (2009), Koissi and Hognas (2005) and others).The use of many chains offers some advantages. For example, by using many chains, there are more options to check for convergence.

We run simultaneously two chains with different initial values. For model 1, 10,000 iterations are discarded as burn-in while for models 2 and 3 burn-in period is much longer – 20,000 iterations. Convergence is assessed by visually inspecting the time series plot. Visual inspection alone is not sufficient to assess the convergence. We use Brooks, Gelman and Rubin Diagnostic (Brooks & Gelman (1998)) of the software to examine the convergence.[6] Once convergence has been assessed we check the values of the autocorrelation in the remaining iterations. We obtain the desired low values of autocorrelations indicating that remaining samples have been generated independently from one another.

Post convergence samples are used to draw the inference about the parameters of the model and to calculate the Deviance Information Criterion (DIC). Proposed by Spiegelhalter et al (2002), the DIC is a Bayesian model comparison criterion used in OpenBUGS. Similar to the Akaike Information Criteria (AIC), DIC measures the fitness of the model by taking into consideration the trade-off between the fit of the data and complexity of the model. The model with the lowest value of the DIC is said to best predict a replicate dataset. Thus, the model with a smaller DIC is preferred to those with a high DIC.

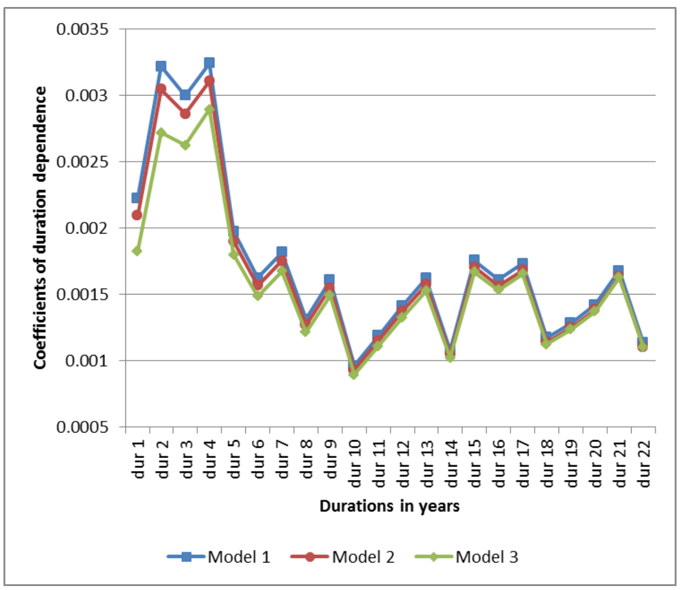
[6] Note: we have three models, at least 22 parameters per model, and three convergence testing techniques. It is not feasible to provide evidence for convergence in this paper.

Section 5: Results

Section 5.1: Duration Dependence

In the Cox PH model baseline hazard remains unspecified. It is determined by the data. The baseline hazard captures the effect of time on hazard rate. We can see it in (6). If all covariates are assumed to be 0, the hazard rate is explained by baseline hazard only. Baseline hazard on its turn is a function of duration only. Thus, from the baseline hazard we can infer about duration dependence in our sample.

Figure 4: Duration dependence for durations less than 22 years



In Figure 4, we plot baseline hazard for model 1 and model 3. We can observe negative duration dependence in both models[7]. We can see that in Model 1 duration dependence is more pronounced that in Model 3. Duration dependence arises from true state dependence or spurious state dependence (Huynh et al 2012). Model 1 takes the form if all covariates are assumed to be 0; while model 3 takes the form under the same assumption. In model 1 baseline hazard captures heterogeneity among employees as well as time effect. Model 3 distinguishes between unobserved heterogeneity and duration dependence.

[7] In fact duration dependence is significant in all models. They are presented in Table A1.

Duration dependence that we observe is the evidence for stylized fact number 3: the probability of job ending declines with tenure (Farber (1999)).

Negative duration dependence is observed for duration up to 10 years. Between duration 10 years and 30 years we observe flat hazard. Past duration 31 years, there is a reversal in duration dependence, i.e. probability of exit increases with tenure (Figure A1). This reversal in duration dependence can be explained partly by retirement.

The recent retirement pattern in Canada is documented by Lefebvre et al. (2011). They observe that probability of exiting labor force to retirement is fairly constant till the age 55. Past the age 55 the probability of exit increases very fast. The increase in probability is explained by retirement incentives. In many private firms retirement age is 55. QPP/CPP offer early retirement at the age of 60. Old Age Security pension is offered past the age 65. By the age 62 nearly half of Canadians retire and by the age 65 85% of them retire (Lefebvre et al.). Since baseline hazard, as we explained, is chiefly explained by the duration, the reversal in duration dependence past duration 32 (Figure A2) years is explained by retirement.

As we can see in Table 3, model 3 has the lowest DIC. In interpreting the result we refer to the estimates of model 3 unless we mention otherwise. As we noted above, the DIC measures the fitness of the model by taking into consideration the tradeoff between the fit of the data and complexity of the model.

Table 3: Bayesian estimation results			
	Model 1	Model 2	Model 3
Employee Variables			
Age			
16-25	1.57***	1.59***	1.67***
26-35	1.28***	1.29***	1.33***
36-55	0.22***	0.22***	0.23***
55-more	-	-	-
Female	-0.18***	-0.18***	-0.19***
Male	-	-	-
Education			
Dropout	-	-	-
Secondary	-0.08	-0.08	-0.09
Vocational	0.27***	0.28***	0.27***
College	0.10*	0.10*	0.10*
University	0.18***	0.18***	0.18***
Other	0.35***	0.36***	0.37***
Part Time	2.38***	2.39***	2.45***
Full Time	-	-	-
Firm Variables			
Multiple Plant	-0.39***	-0.40***	-0.44***
Single Plant	-	-	-
Industry			
Forestry, mining, oil, gas extraction	0.85***	0.85***	0.84***
Labour intensive tertiary manufacturing	0.78***	0.79***	0.75***
Primary product manufacturing	0.26*	0.26*	0.20
Secondary product manufacturing	0.32**	0.32**	0.26
Capital intensive tertiary manufacturing	0.61***	0.61***	0.56***
Construction	0.63***	0.63***	0.59***
Transportation, warehousing, wholesale	0.41***	0.41***	0.39***
Communication, other utilities, retail trade, consumer services	0.44***	0.44***	0.43***
Finance, insurance	0.44***	0.45***	0.44***
Real estate, rental and leasing operations	0.62***	0.63***	0.63***
Information, cultural industries	0.20	0.20	0.17
Business services	-	-	-
Random Effects			
Worker	NA	0.23***	0.23***
Firm	NA	NA	0.54***
DIC	17180	17190	17080
Total	20337	20337	20337
Workers	20337	20337	20337
Firms	6223	6223	6223

Note: Three stars (***) indicate significance at 1%, two stars indicate significance at 5%, and one stars indicate significance at 10%

Section 5.2: Employee variables

Employee variables in our sample are introduced in the Table 3. For the variable female, the reference category is male; for variable age, the reference category is age more than 55; for variable education, the reference category is dropout; and for the variable part-time, the reference category is full-time. All employee variables, except variable secondary and college are significant at 1%.

Women face lower chance of job termination compared to their male counterparts. In section 2 we see that men in Canada are more likely to get laid off (Picot et al.'s (1997)) or to quit (Morissette et al. (1992)) than women. It explains why in our sample men are more mobile than women.

Consistent with a Job Shopping theory, in our sample, young employees (employees less than 25 years old) are the most mobile. They are about 4.8 times (exp(1.57) = 4.8) more likely than older employee (reference category, age more than 55) to terminate their jobs. Mobility declines with the age. Employees in the age group 26-36 years old are almost 3.6 times more likely to exit employment state while the next age category reduces to only 1.25 times.

Employees having completed any level of postsecondary educations are more mobile than the dropout (the reference group). Only employees with secondary degree are less mobile. However, variable secondary is not significant.

Mobility first rises than drops with years of schooling. We can see it with rising than dropping hazard rate for education variables. Employees with vocational diploma are more mobile than college graduates. Among postsecondary education, employees with college degree are least mobile. Past college, mobility rises again for university variable (employees with undergraduate degree, diploma, master's degree or doctorate degree).

Our findings with education variables support the second argument of Johnson (1978) about education, namely “the function of education in giving workers information about their abilities.” He argues that if education gives employees the knowledge about their skills and abilities, then educated workers are mobile than uneducated ones. It follows from the argument that educated workers start off their careers with “risky job.” Their mobility stems from the quest to stable job. Part-time employees are more mobile than full-time employees.

Section 5.3: Firm variables

Turning to firm-level variables, we look at mobility at multiple plants and different industrial sectors. Employees in multiple plants are less mobile than those in single unit factories.

Among industrial sectors, employees at primary industries (forestry, mining, oil and gas extraction) face highest hazard. They are about 2.3 times more likely to face job termination than those in education and health sector (reference category). In section 2, we see that employees in primary industries face highest incidence of layoffs. On the other extreme, employees in educational and health services (reference category) sector are the least mobile; the face the lowest hazard.

Following primary industries, employees in labor intensive tertiary manufacturing face second highest hazard. Previous literatures look at combined effect of all manufacturing sectors. In the WES, manufacturing is divided into four distinct categories: Labor intensive tertiary manufacturing; Primary product manufacturing Secondary product manufacturing; And capital intensive tertiary manufacturing.

By looking at these manufacturing sectors separately, we see that employees in these four manufacturing sectors face different hazard. Among the four industry sectors, employees in labor intensive tertiary manufacturing face highest hazard (2.12) followed by capital intensive tertiary manufacturing (1.75), secondary product manufacturing (1.30), and primary product manufacturing (1.22).

In terms of hazard, employees in business service sectors face third highest hazard, followed by construction sector; real estate sector; retail trade, consumer services, finance and insurance; transportation, warehousing, wholesale trade, communication and utilities; secondary product manufacturing; primary product manufacturing; and information and cultural industries. While high layoffs at primary industries are contributing factor to a high hazard, mobility in other industrial sectors stems from layoff and quits rates equally (Morissette (2004)).

The coefficients of all industry variables are positive; meaning compared to the reference category, the hazard is higher in all industry variables. The reference category is education and health services.

Section 5.4: Random effects

Table 3 provides Bayesian estimates of standard deviations of random effects for model 2 and 3. Model 1 contains only observable worker and firm characteristics. In Model 2 we allow only worker random effect. Only few beta coefficients of observable characteristics change from Model 1 to Model 2. In Model 3 we allow both worker and firm random effects. We assume these random effects to be non-nested. By allowing both random effects, in column 3 of Table 3 we notice beta coefficients of firm characteristics to change. By allowing both random effects, DIC drops.

Table 4: Standard errors of worker and firm heterogeneities			
Random Effects	Model 1	Model 2	Model 3
Worker	NA	0.23***	0.23***
Firm	NA	NA	0.54***
DIC	17180	17190	17080

Turning to standard errors of random effects (Table 4), worker effect in Model 2 and 3 are identical (0.23). We reject the null that there is no worker heterogeneity in both models. However, only worker heterogeneity does not significantly improve the model. The DIC of model 2 is bigger than of that model 1. By allowing both worker and firm heterogeneity (model 3), the predicting power of model improves (the DIC drops). Standard error of firm heterogeneity is significantly different from zero. It implies that the firm observable characteristics in our model cannot fully explain observed durations. Standard error of firm heterogeneity is almost twice of that standard error of worker heterogeneity. It implies that there is a considerable amount of heterogeneity at the firm level. This finding is similar to Horny et al. (2009). In their study, standard error of the unobserved firm heterogeneity distributions is almost three times than of that unobserved worker heterogeneity distributions.

Section 6: Conclusion

In this paper, we estimate the determinants of employment durations using Canadian data coming from the Workplace and Employee Survey from Statistics Canada. Prior studies on the Canadian labor market (Christofides et al. (1993), Morissette et al. (1992), Picot (1997)) uses the Labor Market Activity Survey. WES differs from the Labor Market Activity Survey in that it provides matched worker and employer data at a micro level. From our dataset, we obtain evidence for the stylized facts of job durations (Farber (1999)).

We are interested in worker and firm variables as well as unobservable worker and firm characteristics as determining factors of employment durations. The role of employee is well-studied and well-known. Arguably due to lack of data connecting workers and employers at a micro level, there is a limited number of studies that considers both employees' and employers' heterogeneities.

Following Horny et al (2009), we estimate the determinants of job durations under three specifications. In the first specification, we consider only observable worker and employee characteristics. The first specification is thus a standard Cox model; we refer to it as model 1. In the second specification (model 2), we allow only workers' heterogeneities. In the third specification (model 3), we consider both worker and firm unobservable characteristics. In the model 3, we assume that worker and firm unobservables are independent from one another. Unlike the first model, the last three models are in the family of Mixed Proportional Hazard.

We rely on the Bayesian approach to estimate the parameters of all three models. Since posterior distributions do not allow for analytical solutions, we approximate them using the Markov Chain Monte Carlo (MCMC) algorithm, particularly Gibbs sampling method.

Model 1 is a standard Cox model. We estimate model 1 using the sample 1 and 2. When comparing model 1 estimated using Bayesian and classical approach, we notice that the sign of coefficients in both approaches are the same. Only the magnitudes of coefficients are different in both approaches. However, Bayesian and frequentist results do not contradict. In both approaches, the model predicts that mobility decreases with age. Part-time workers face shorter job durations while females and employees in large workplaces face longer job durations. Among industrial sectors, employees in business services face lowest hazard while their counterparts in health and education services enjoy long durations.

By adding worker heterogeneity to the standard Cox model (model 1), the predicting power of the model decreases. When taking into account both workers' and firms' heterogeneity, the predicting power of the model increases. Among the three models, model 3 has the best predictive power.

As for duration dependence, we observe negative duration dependence in all models. This is an evidence for one of stylized fact of job durations: the probability of job ending declines with tenure. Similar to the regression coefficients, only the magnitudes of dependence are different. Duration dependence in model 1 is more pronounced than those of model 2 and model 3. It implies that in Model 1, the baseline hazard captures the unobservable firm and worker heterogeneity.

Appendix

Table A1: Explanatory variables and descriptive statistics for the Sample 1

Variable	Value	Definition	Mean
Female	=1 =0	For females For males	**.52** **.48**
Age			
Less than 25	=1	If employee is younger than 25	**. 0**
26-35	=1	If employee is younger than 35 and older than 25	**.22**
36-55	=1	If employee is younger than 55 and older than 35	**.55**
More than 55	=1	If employee is older than 55	**.13**
Education			
Pre-secondary			
Dropout	=1	If individual did not graduate from high school	**.16**
Secondary	=1	If individual graduate from high school	**.84**
Postsecondary			
Vocational	=1	1) Trade or vocational diploma or certificate,	**.14**
College	=1	2) Some college, CEGEP, institute of technology or nursing school, 3) Completed college, CEGEP, institute of technology or nursing school,	**.43**
University	=1	4) Some university 5) Teachers' college, 6) University certificate or diploma below bachelor level, 7) Bachelor or undergraduate degree or teachers' college, 8) University certificate or diploma above bachelor level, 9) Master's degree, 10) Degree in medicine, dentistry, veterinary medicine, law, optometry or theology or 1-year B.Ed. after bachelor's degree 11) Earned doctorate	**.36**
Other Education	=1	Industry certified and other	**.07**
Part Time	=1 =0	If weekly hours worked is less than 30 hours Full Time	**.18** **.82**
Multiple plant	=1 =0	Mall or large business with a complex statistical structure. More than one statistical location Large business with a simple statistical structure Small business with a simple statistical structure	**.37** **.63**
Industry			
Forestry, mining, oil, gas extraction	=1	For forestry, mining, oil, and gas extraction	**.01**
Labour intensive tertiary manufacturing	=1	For labour intensive tertiary manufacturing	**.05**
Primary product manufacturing	=1	For primary product manufacturing	**.03**
Secondary product manufacturing	=1	For secondary product manufacturing	**.03**
Capital intensive tertiary manufacturing	=1	For capital intensive tertiary manufacturing	**.05**
Construction	=1	For construction	**.04**
Transportation, warehousing, wholesale	=1	For transportation, warehousing, wholesale	**.11**

Communication, other utilities, retail trade, consumer services	=1	For communication, other utilities, retail trade and consumer services	**.27**
Finance, insurance	=1	For finance and insurance	**.02**
Real estate, rental and leasing operation	=1	For real estate, rental and leasing operations	**.10**
Information and cultural industries	=1	For information and cultural industries	**.03**
Business services	=1	For business services	**.26**

Table A2: Industry definitions

Industry		
Forestry, mining, oil, gas extraction	For forestry, mining, oil, and gas extraction	113, 1153, 211, 212, 213
Labour intensive tertiary manufacturing	For labour intensive tertiary manufacturing	311, 312, 313, 314, 315, 316, 337, 339
Primary product manufacturing	For primary product manufacturing	321, 322, 324, 327, 331
Secondary product manufacturing	For secondary product manufacturing	325, 326, 332
Capital intensive tertiary manufacturing	For capital intensive tertiary manufacturing	323, 333, 334, 335, 336
Construction	For construction	231, 232, 236, 237, 238
Transportation, warehousing, wholesale	For transportation, warehousing, wholesale	411, 412, 413, 414, 415, 416, 417, 418, 419, 481, 482, 483, 484, 485, 486, 487, 488, 493, 221, 491, 492, 562
Communication, other utilities, retail trade, consumer services	For communication, other utilities, retail trade and consumer services	441, 442, 443, 444, 445, 446, 447, 448, 451, 452, 453, 454, 713, 721, 722, 811, 812, 521, 522, 523, 524, 526
Finance, insurance	For finance and insurance	531, 532, 533
Real estate, rental and leasing operations	For real estate, rental and leasing operations	541, 551, 561
Information and cultural industries	For information and cultural industries	611, 621, 622, 623, 624, 8132, 8133, 8134, 8139
Business services	For business services	511, 512, 513, 514, 711, 712

Table A3: Average durations in years by observable characteristics

	Sample 1	Sample 2
Employee Variables		
Male	9.73	9.87
Female	8.66	8.72
Age		
16-25	2.50	2.66
26-35	4.72	4.79
36-55	10.74	10.75
55-more	15.30	14.92
Education		
Dropout	10.24	10.46
Secondary	9.00	9.05
Postsecondary		
Vocational	9.50	9.75
College	8.57	8.88
University	8.64	8.53
Other	9.64	9.18
Part Time	6.55	6.77
Full Time	9.73	
Firm Variables		
Multiple plant	10.76	10.81
Single unit	8.25	8.38
Industry		
Forestry, mining, oil, and gas extraction	10.37	9.85
Labour intensive tertiary manufacturing	9.99	9.58
Primary product manufacturing	13.18	13.04
Secondary product manufacturing	10.46	11.16
Capital intensive tertiary manufacturing	9.82	10.61
Construction	8.31	8.32
Transportation, warehousing, wholesale	9.66	9.77
Communication, other utilities, retail trade, consumer services	7.10	7.40
Finance, insurance	7.2	7.25
Real estate, rental and leasing operations	7.50	7.19
Information and cultural industries	9.42	8.85
Business services	11.33	11.45

Table A4: Frequntist estimates for Model 1 using Sample 1 and Sample 2

	Sample 1	Sample 2
Employee Variables		
Age		
16-25	1.71***	1.62***
26-35	1.42***	1.34***
36-55	0.38***	0.31***
55-more	-	-
Female	-0.18***	-0.13***
Education		
Dropout	-	-
Secondary	.008	0.03
Vocational	0.25***	0.28***
College	0.10***	0.31***
University	0.16***	0.21***
Other	0.15***	0.39***
Part Time	2.46***	2.45***
Full Time	-	-
Firm Variables		
Multiple Plant	-0.39***	-0.35***
Single Plant	-	-
Industry		
Forestry, mining, oil, and gas extraction	1.04***	1.08***
Labour intensive tertiary manufacturing	.97***	1.03***
Primary product manufacturing	.55***	0.52***
Secondary product manufacturing	0.69***	0.58**
Capital intensive tertiary manufacturing	0.98***	0.85***
Construction	0.87***	0.89***
Transportation, warehousing, wholesale	0.66***	0.63***
Communication, other utilities, retail trade, consumer services	0.57***	0.62***
Finance, insurance	0.67***	0.66***
Real estate, rental and leasing operations	1.03***	0.82***
Information and cultural industries	0.59***	0.40
Business services	-	-

Figure A1: Duration dependence for durations more than 22 years

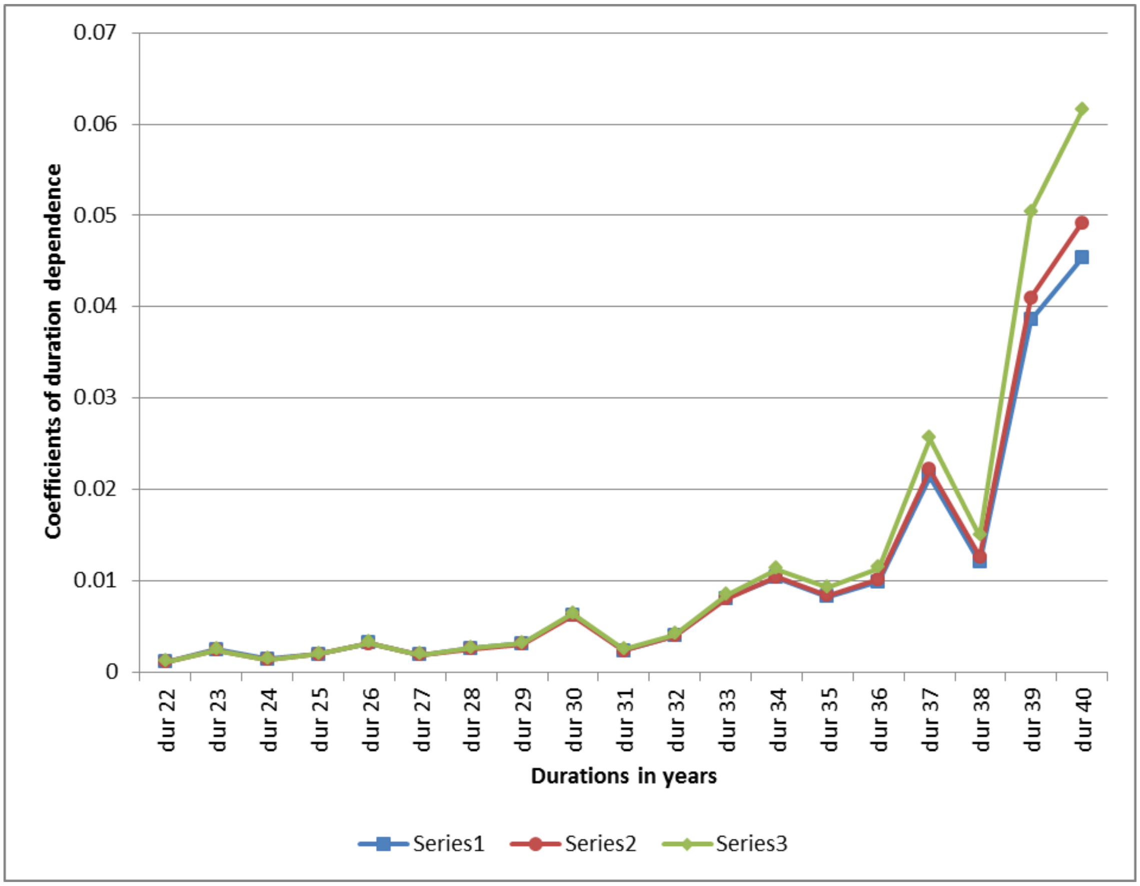
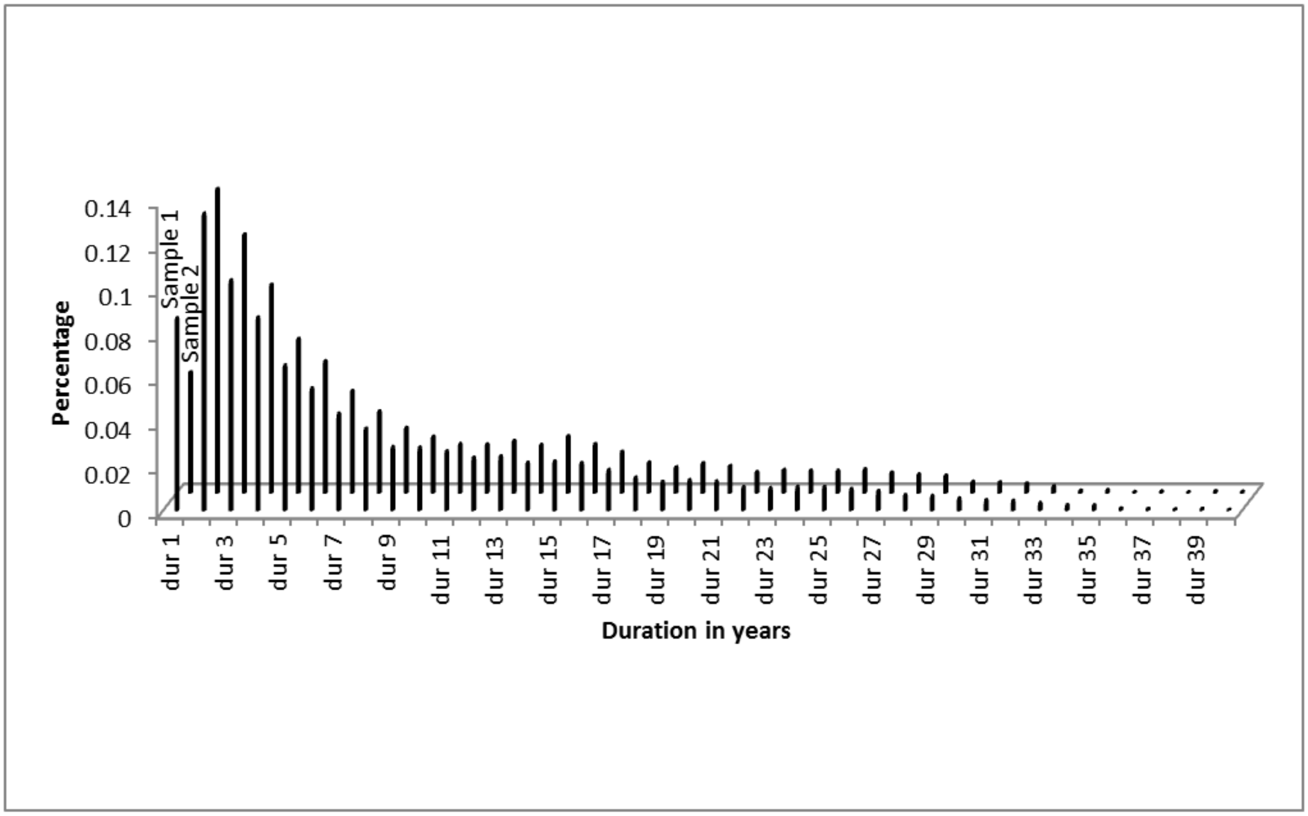


Figure A2: Duration data



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