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Contingent, Temporary Unemployment Insurance's Impacts on Employment and Unemployment Durations

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ABSTRACT

Contingent, Temporary Unemployment Insurance's Impacts on Employment and Unemployment Durations*

This paper studies contingent, temporary unemployment insurance (UI) coverage's impacts on employment and unemployment durations using a duration model extended with heaping considerations and a recent Canadian panel data. A unique source of identification here is the Employment Insurance (EI) reform of Canada in the 1996. Based on the estimated coefficients from the duration models, the simulations suggest that UI increases unemployment rates by 2% and 5% in the non-seasonal and seasonal sectors respectively.

JEL Classification: J65, J64

Keywords: unemployment insurance, unemployment durations, employment durations, heaping effect

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1. INTRODUCTION

Unemployment Insurance (UI) is an important public policy in many industrial economies. Since the 1990s, there is a strong motion of updating income support programs in these countries. Relative to other programs, UI has a closer connection with the labour market because of its coverage's employment requirement. That is, an unemployed worker's UI benefit treatment is conditional on his/her preceding employment history. UI's such contingent property is crucial to its benefit coverage's temporariness, i.e., workers could only collected UI benefit for a finite period. Without the contingency requirement, any worker could extend his/her UI collection by a quick return to work, thus making the temporary duration of UI coverage effectively infinite.

In the empirical literature, studies such as Green and Riddell (1997) and Baker and Rea (1998) have examined how UI's contingency affects workers' employment durations; others, such as Moffitt (1985), Ham and Rea (1987) and Meyer (1990), have examined how UI coverage's temporariness affects workers' unemployment spells. Though jointly these two sets of studies cover UI's impacts on both directions of employment/unemployment transitions, their datasets and econometric setups differ so much that makes it very difficult for readers to confidently merge the evidence together for an understanding of the overall picture. The purpose of this paper is thus to provide integrated and updated empirical evidence on UI's impacts on both employment and unemployment durations using a recently available Canadian panel data.

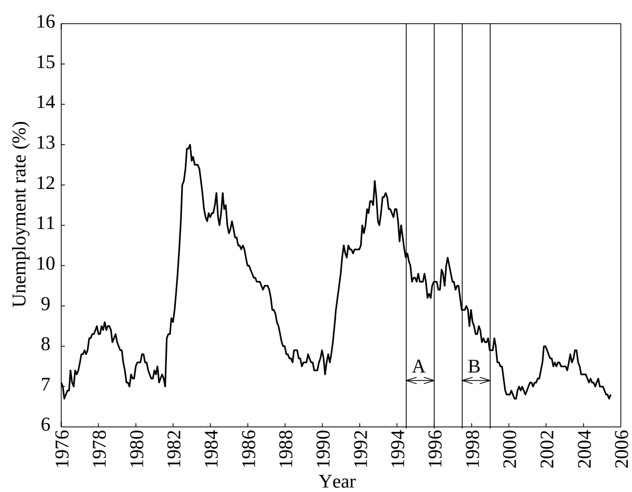
Because of UI's contingent and temporary nature, its impacts on workers' labour market durations are time-varying. In other words, the closer an employed worker is to his UI qualification week, the stronger the incentive is for him to stay employed; the closer an unemployed worker is to his UI benefit exhaustion week, the stronger the incentive is for him to leave unemployment.

Such time-varying impacts of UI are supported by previous studies. Using U.S. data, both Moffitt (1985) and Meyer (1990) show that unemployed workers' hazard rates (i.e. conditional probabilities of leaving the unemployment state) increase as they approach benefit exhaustion weeks. Ham and Rea (1987) provides similar results for male workers in Canada. On the employment stability side, both Green and Riddell (1997) and Baker and Rea (1998) show that employed workers' hazard rates (i.e. conditional probabilities of leaving the employment state) decrease as they approaching their minimum employment requirement weeks.

The identification in this literature critically relies on having exogenous variations of UI treatment (either workers' employment requirements or their benefit coverage durations). If, for example, all unemployed workers have the same number of weeks of UI benefit coverage, then the impacts of UI would be indistinguishable from the baseline hazard of unemployment spells. Unfortunately, this is very close to the situation in the U.S., where individuals' UI benefit durations are constant within state. In Canada, workers' UI benefit durations are functions of their previous employment histories and local unemployment rates. Thus generates a rich treatment variation for empirical researchers to explore.

There is but one problem for the Canadian studies. That is, the dependency of workers' UI benefit durations on their preceding employment potentially creates a serious endogeneity problem. It is arguably true that there could be common unobserved factors that affect both individuals' employment and unemployment durations, and therefore affect workers' UI treatment — the benefit durations — indirectly. To mitigate this endogeneity problem, this paper makes use of an unique exogenous source of treatment variation: the Canadian Employment Insurance (EI) reform in 1996.

FIGURE 1. Canadian Seasonally Adjusted Monthly Unemployment Rate



Note: A and B refer to pre- and post-reform periods respectively.

Source: Statistics Canada CANSIMII table V2062815

The EI reform took place in the later half of 1996. It is one of the most dramatic reform of the UI program in the Canadian history. Keeping the basic structure of this program unchanged, it made a whole package of changes. Using unemployment rate, figure 1 illustrates how the pre- and post-reform sample periods used in this paper relate to the overall macroeconomic movement. As shown in the figure, it happened in the middle of a period of economic recovery. Not surprisingly, evaluations of the EI reform constantly find labour market improvement in the post-reform period (Human Resources Development Canada, 1997-2002).

Although the usage of sample spells in two separate periods strengthen my identification by allowing an exogenous source of treatment variation: the EI reform. It also makes it necessary to take account of the pre- and post-reform periods' difference in macroeconomic conditions carefully. But since my key variables are all time-varying dummy variables, they differ across spells by flagging different weeks. It is unlikely for the estimated coeffients of these variables to be affected by any macroeconomic movement. Which could only be possible if the macroeconomic movement affect employment/unemployment hazard rates only at those weeks flagged differently across individual spells.

In terms of econometric setup, this paper follows the recent trend of the literature by using duration models, which could allow for incomplete (censored) spells and time-varying variables in a straightforward manner. Since the Canadian UI benefit is measured in weekly terms, my sample spells are thus measured in weekly terms. On the other hand, many of my sample spells ended at semi-monthly or monthly frequencies (hereafter, heaping). To accommodate this particular property of the data, I extend the usual duration model to allow for such heaping effect.

The results here confirm most of existing findings of the literature mentioned earlier in a new context, as well as uncover some new ones. In terms of aggregate impacts, the simulations here suggest that UI increases unemployment rates in the non-seasonal and seasonal sectors by 2% and 5% respectively. The rest of this paper is organized as follows: section 2 reviews theoretical implications of contingent temporary UI coverage. Section 3 discusses the data construction. Section 4 explains the econometric formulation. Section 5 presents empirical analysis. Section 6 concludes.

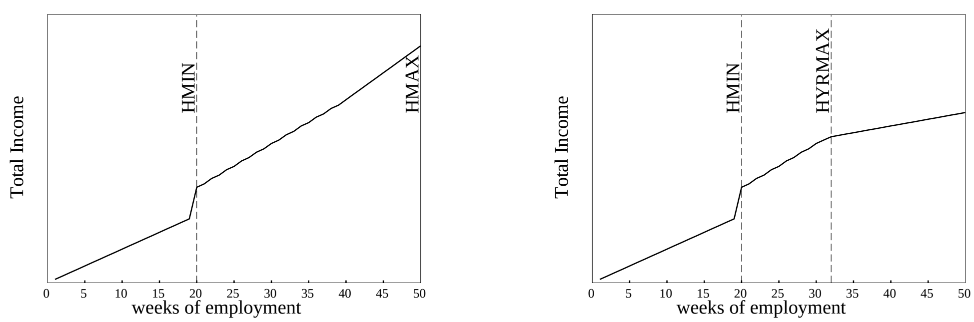
2. THEORETICAL IMPLICATIONS

A natural way to consider the contingent temporary UI coverage is to extend the static labour and leisure model. Here, a typical worker maximizes his utility by choosing the number of employment weeks. The UI we are concerned about is such that a worker can only collect UI if he has worked at least *HMIN* weeks prior to unemployment, and if qualified, his UI benefit weeks will increase as his preceding employment weeks increases up to a point, *HMAX*. This is a simple way to describe the Canadian UI program.

Figure 2 shows the non-linear impacts of such UI program on a worker's budget line. The part a of this figure shows that the worker effecively gets both the weekly wage and weekly UI benefit for additional weeks of employment if his planning horizon is infinite. The part b shows the worker gets only weekly wage beyond certain employment weeks, *HYRMAX*, if his planning horizon is 52 weeks.

FIGURE 2. Total Income

a: actual b: effective for seasonal workers



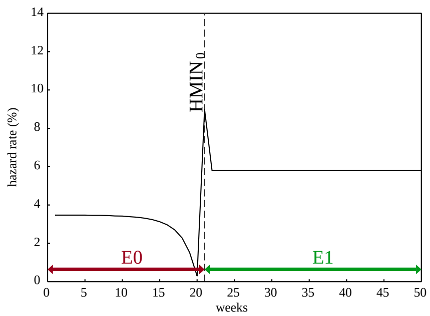
Note: Total income = wage income + UI benefit.

The idea that UI's impacts critically depend on the length of workers' planning horizon was emphasized by Green and Sargent (1998). Most seasonal workers in Canada have one-year planning horizon due to the weather and job season. Once their job season comes, they have to go back to work, otherwise, they will miss the whole season. As a result, these seasonal workers would only collect UI benefit prior to the start of their next season. Thus, the effective UI benefit weeks for them declines beyond *HYRMAX*, after which one more week of work means one less week of benefit collection. In terms of hazard rates, the static model thus predicts a higher employment hazard rates for weeks between *HMIN* and *HYRMAX*, and a spike of unemployment hazard rate around benefit exhaustion weeks, *BEW*.

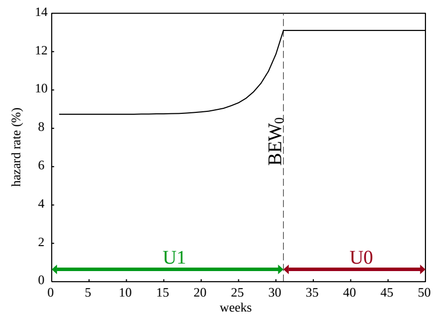
Seasonal workers, though repeatedly experience unemployment each year, often also interact with the same employer every year. Therefore, they could have a better idea about and better control over the timing and length of their employment and unemployment spells. This is also central to the above static model of labour and leisure. But it is less convincing to apply the same model to the non-seasonal workers, especially when we want to consider a contingent, temporary UI policy. Fig-

FIGURE 3. Predicted Hazard Rates with Contingent Temporary UI Coverage

a: employment spells



b: unemployment spells



ure 3 shows UI's time-varying impacts on employment/unemployment hazard rates according to Shen (2006)[1], where workers are considered to have an infinite planning horizon and face both re-employment and job loss uncertainties. In summary, the model predicts: 1) *entrance induction effect*: a gradual drop of employment hazard rates before *HMIN* and an employment hazard rates spike at *HMIN*[2]; and, 2) *benefit exhaustion effect*: a gradual rise of unemployment hazard rates before *BEW*[3].

3. DATA

The sample spells here are constructed using the Survey of Labour and Income Dynamics (SLID). Specifically, I use SLID's first and second panels, which cover the period from 1993 to 1998 and 1996 to 2002. SLID not only has a rich set

[1]This work is an extension of Green and Sargent (1998), which examine the contingent property of UI on employment spells and provide similar results on the employment part.

[2]Given the setup of UI in Canada, workers' potential benefit weeks will continue to increase with their employment weeks up to a maximum, *HMAX*. Thus, they still have incentive to stay employed beyond week *HMIN*. For that, we expect a potential *tailoring effect* of UI for workers after week *HMIN* but before week *HMAX* for non-seasonal workers (or *HYRMAX* for seasonal workers).

[3]In the empirical analysis, I also consider two new sets of rules introduced by the EI reform. First, *divisor rule*. It discourages workers from short, unstable labour market attachment by cutting workers' weekly benefit payment if the number of calendar weeks used to claim UI benefit is less than *HMIN+2*. Second, *worker-side experience rating rules*. Simply speaking, workers face increasingly higher benefit cut and benefit repayment amount as their previous 5 years' UI benefit collection weeks increase across each 20-week long interval. If the planning horizon is 53 weeks, considering the 2-week UI waiting period, that means a worker has to work at least 31 weeks in a year to avoid downgrade. Therefore, for the post-reform period, we expect hazard rates for leaving employment to be lower before week 31, and hazard rates for leaving unemployment to be higher before week 19.

of individuals' demographical information but also has detailed information about their jobs[4].

For the construction of employment/unemployment spells, I did not use the pre-derived weekly labour force states variable in SLID. This is due to the differences between the classical classification of the labour force states and those demanded by my research question. For example, although self-employment is one form of employment according to the standard classification, it is not UI-insurable employment nor eligible for UI benefit collection, which means we should not count self-employment as employed or unemployed here.

In this paper, the 'employment spells' mean periods working on paid jobs; 'unemployment spells' mean periods in-between those 'employment spells'[5][6]. All the sample spells are derived using the start and ending dates of individuals' jobs.

FIGURE 4. Illustration of Sample Spells Construction

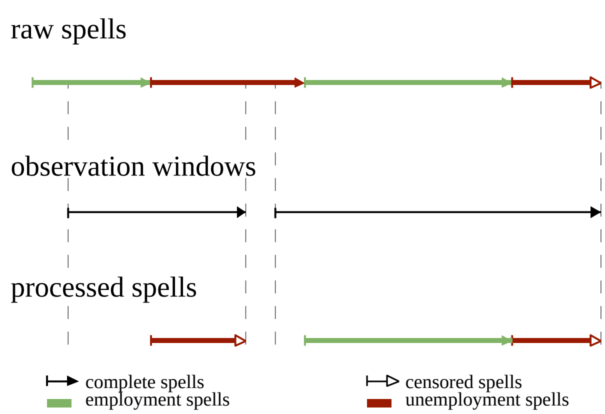


Figure 4 illustrates the three steps of the so-called 'observation window' procedure used here for data construction. First, raw employment spells are constructed. For each individual, these spells cover all of his/her dates working on paid jobs,

[4]It is of course reasonable to consider the exact, realized UI benefit collection durations information better than the derived ones in this current case. But in general that kind of information is only available from administrative data sets, which usually have only limited demographical information. Furthermore, administrative data sets usually do not have information of individuals' labour market activities beyond benefit collection spells.

[5]Since there is no search requirement imposed on the so-called "unemployment spells" in this paper, some might find it more appealing to call them *non-employment spells* instead.

[6]For new entrants of the labour market, such as students who just graduate from universities, my definitions means they are excluded from the sample. In this sense, this study is mainly about active paid labour market participants.

except those temporary layoff dates[7]. Once the raw employment spells are created, those dates left behind form my raw unemployment spells.

Next, individuals' observation windows are constructed. This is done by excluding periods of schooling, disability, non-paid employment, outside the ten Canadian provinces, less than 20 or more than 50 years old, from the entire set of dates of the six-year panel period[8]. These windows are periods of dates that an individual is considered to be in the labour force. For the two observation windows in figure 4, one possibility could be that the individual was attending school in the meanwhile.

Finally, raw employment/unemployment spells and observation windows are considered jointly to create my sample spells. Only raw spells started within observation windows are selected. Furthermore, they would be cut at the end dates of their starting observation windows and flagged as incomplete if necessary.

TABLE 1.
Unweighted Counts of Individuals and Spells

panel	1	2
years covered	1993-1998	1996-2001
Count of Individuals		
total	30,455	31,459
with observation windows	23,840	23,973
with a single panel-long observation window	12,108	10,534
Counts of Spells		
paid jobs	39,055	44,013
employment spells	32,880	34,816
Counts of Spells within observation windows		
employment spells	8,784	6,835
unemployment spells	10,133	7,664

Table 1 gives a basic set of counts of the sample data. In particular, it shows that, in my panel 1 data, only 12,108 out 30,455 individuals had no 'out of labour force' activities throughout their entire panel periods (i.e. those having a single panel-long observation window). As one can imagine, less sample individuals will remain in a longer panel. After all, being in the labour force is just one stage of the life cycle. By making the selection based on events, my 'observation window' approach not

[7]Since there is a two-week waiting period for workers' UI benefit collection in Canada, any two raw employment spells are merged together by adding the intermediate dates if they are apart from each other for less than 14 days.

[8]In case of a problematic job ending, any dates after the end date of a job that haveing a problematic job ending are also excluded. Here, 'having a problematic job ending' means the job ended because of the job was denied by the respondent or because did not receive information about the job in subsequent data collections.

only increases the sample size but also makes the sample selection independent of host panels' length.

In order to use the 1996 EI reform treatment variation, both spells before and after the reform are needed. Since only panel 1 spells cover the pre-reform period, it is natural to select pre-reform sample spells from it. Specifically, my pre-reform sample spells are panel 1 spells started in the period from July 4 1994 to December 31 1995[9]. To match with pre-reform sample spells in terms of the within-panel time frame, my post-reform sample spells are those panel 2 spells started in the period from July 4 1997 to December 31 1998.

TABLE 2.
Unweighted Counts of Employment Spells' by Starting Years

Panel 1			Panel 2		
year	counts	percentage	year	counts	percentage
		All Spells			
1993	1,936	19%	1996	1,591	21%
1994	2,019	20%	1997	1,495	20%
1995	1,575	16%	1998	1,426	19%
1996	1,536	15%	1999	1,205	16%
1997	1,515	15%	2001	939	12%
1998	1,552	15%	2002	1,008	13%
total	10,133	100%		7,664	100%
		Individuals' First Spells			
1993	1,703	33%	1996	1,404	33%
1994	1,165	23%	1997	858	20%
1995	636	12%	1998	700	16%
1996	568	11%	1999	471	11%
1997	534	10%	2001	405	9%
1998	560	11%	2002	455	11%
total	5,166	100%		4,293	100%

Note: The sample here are all within observation windows.

The main concern of the within-panel time frame here is the sample spells' attrition over time due to the nature of labour market transitions[10]: if we select a random sample of individuals and follow them over time, we will find more and more of these individuals will either find stable long-term jobs or leave the labour market, leaving only less and less of them continue their transitions between employment and unemployment. As a result, the sample of individuals having fresh employment or unemployment spells at the later part of each panel isn't random any more. Ta-

[9]Here July 3 1994 is the date of a previous major UI change. Although the EI reform's transition period started in mid 1996, December 31 1995 is chosen here to avoid distortion of workers' behaviour due to the anticipation of the reform. All spells are censored at June 30 1996 if necessary.

[10]Previous empirical studies in this literature mostly emphasize sample attrition in panel data set from a different perspective, that is, individuals' endogenous heterogeneity attitude toward survey participation (Van den Berg and Lindeboom, 1998).

ble 2 shows how in both panel 1 and 2, the unweighted counts of employment spells decrease over time. Moreover, the second part of table 2 shows the later a spell started within the panel the less likely that spell to be the first employment spell of the given individual. In other words, this spell is more likely to belong to a high turnover type individual in the labour market.

As emphasized earlier, I expect UI to have significantly different impacts on seasonal and non-seasonal sectors and I want to study these two sectors separately. The final data issue here is thus how to distinguish seasonal spells from non-seasonal ones[11]. Here a seasonal employment spell is one that started with a job that later ended for seasonal reasons; a seasonal unemployment spell is one that the preceding employment spell ended due to a job ended for seasonal reasons[12]. All other spells are classified as non-seasonal[13].

4. ECONOMETRIC SETUP: DURATION MODEL WITH HEAPING

The econometric model used here is a discrete-time duration model with heaping effect. The basic discrete-time duration model has been widely used in the study of labour market spells, e.g. Meyer (1990) and Green and Sargent (1998).

Specifically, let spell j lasted for d_j periods. Let c_j be 1 if this spell is complete, 0 if it is incomplete (censored). Let $\theta_{j,t}$ be the instantaneous hazard rate of this spell at time t, that is $\theta_{j,t} = prob\{d_j = t | d_j \geq t\}$; let $p_{j,t}$ be its discrete hazard at period t. Then

$$p_{j,t} = 1 - exp(-\theta_{j,t}) \tag{1}$$

If we specify $\exp(\alpha_t)$ to be the baseline hazard rate for all spells, and $x_{j.t}$ be the vector of control variables for this spell at period t, then it is common to set

$$\theta_{j,t} = exp(\alpha_t + \beta' x_{j,t}) \tag{2}$$

[11] Another option here would be to define spells' seasonality according to the characteristics of realize spell durations. But this way of taking spell durations as exogenous will make any study of UI's impacts on the spell durations absurd.

[12] When there are multiple jobs that started an employment spell, the seasonality of the employment spell is defined based on the job that lasted the longest. Similarly, for an unemployment spell, its seasonality is defined based on the longest job among all jobs that ended the preceding employment spell.

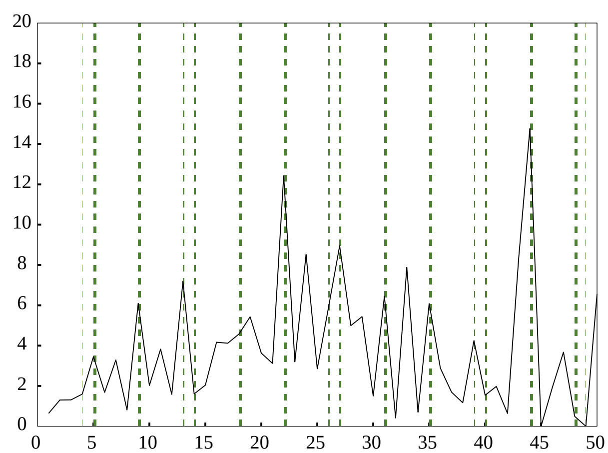
[13] The approach here could be problematic for spells started late in a panel. Because all spells on-going at a panel end would be counted as non-seasonal. Fortunately, both of my sample periods end three years earlier than their host panels do. This means I effectively take all spells lasted more than 3 years as non-seasonal, which should not be a problem at all.

Thus, the log likelihood function of this spell can be written as

$$\begin{aligned}\ln(f_{j,d_j,c_j}) &= c_j \ln(p_{j,d_j}) + \sum_{s=1}^{d_j-1} \ln(1-p_{j,s}) \\ &= c_j \ln\left(1 - exp\left(-exp(\alpha_{d_j} + \beta' x_{j,d_j})\right)\right) \\ &\quad - \sum_{s=1}^{d_j-1} \exp(\alpha_s + \beta' x_{j,s}) \end{aligned} \tag{3}$$

Often, empirical studies on the labour market find the actual baseline hazard rates (α_t) very volatile. My sample spells have the same property as figure 5 shows. Previous studies (e.g. Green and Sargent (1998)) deal with this observation by adding a time-varying dummy variable for end-of-month weeks on top of a non-parametric baseline. This approach is both readily accessible and conceptually straightforward[14]. But its ability to separately identify the baseline hazard and the coefficient for end-of-month dummy relies heavily on having rich variation across spells in their calendar properties[15].

FIGURE 5. Illustration of Empirical Hazard Heaping



In this paper, I use an extension of the above duration model with a heaping component added. By heaping effect, I mean the tendency of labour market spells to end at frequencies (e.g. monthly) lower than the frequency of the duration model (e.g. weekly). The spikes of empirical hazard rates have been a common feature in labour

[14]Since this semiparametric approach is relatively demanding on sample size, applications of this approach using my sample spells are not very sucessful, especially when I tried its multiple-spell version. The calendar spikes such as those shown in figure 5 are absorbed mostly by baseline hazards.

[15]By that, I mean the number of weeks/days in each sequential month.

market duration data[16]. As an illustration, figure 5 shows the presence of heaping effect in our pre-reform seasonal employment sample spells. The dashed vertical lines in the figure represent weeks that could possibly contain calendar month ending dates in the sample[17]. As this figure shows, the spikes of the empirical hazard rates match well with the vertical lines [18].

Let $\{a_0, a_1, a_2\}$ be the probabilities of reporting at weekly, semi-monthly, and monthly frequencies, where $\{a_0, a_1, a_2\} \in [0, 1]$ and $\sum_{l \in \{0,1,2\}} a_l = 1$. Then the likelihood of spell j with heaping considered could be written as a weighted sum of the likelihood of this spell in each of the three frequencies, $\{f^0_{j,d_j,c_j}, f^1_{j,d_j,c_j}, f^2_{j,d_j,c_j}\}$, that is

$$\tilde{f}_{j,d_j,c_j} = \sum_{l \in \{0,1,2\}} a_l \cdot f^l_{j,d_j,c_j} \tag{4}$$

For details about this duration model with heaping, please refer to Shen (2006).

Finally, with heaping component taking care of the fluctuations of baseline hazard rates, we no longer need to use the 'expensive' non-parametric baseline specifications. Instead, we can now use parsimonious parametric baseline. In this study, a 2nd order polynomial is used in the preferred setup.

5. EMPIRICAL ANALYSIS

5.1. Descriptives

The sample sizes of non-seasonal spells are about 2.5 to 3 times of those of seasonal ones. The seasonal spells have a higher proportion of married workers, male workers, non-immigrant workers, less educated workers and older workers than non-seasonal ones. Moreover, while non-seasonal employment/unemployment spells are more concentrated in Ontario and Quebec, seasonal employment/unemployment spells are more concentrated in Quebec and Atlantic provinces (that is, Newfoundland, Nova Scotia, New Brunswick, Prince Edward Island).

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[16]Baker (1992) made a similar observation and called it as *digit preference*, where he found respondents tend to "report the length of their current unemployment spell as an integer multiple of one month". To deal with digit preference, he used a formula to backup the underlying, smooth distribution of unemployment spells of the Current Population Survey. Limited by data, his formula did not consider variations of individual spells' calendar properties. Specifically, it assumes every spell's week 4, 8, 12, etc, correspond to "integer multiple of one month". The approach used in this paper not only allows heaping weeks to differ across spells but also allows spells to start at any day of a month, not just day 1 of a month. Torelli and Trivellato (1993) has raised similar concerns on the hazard spikes. They proposed an estimator that could deal with complete spells only.

[17]The vertical lines are generated as follows. Let there be 18 spells each started at day 1 of each one of the 18 months from July 1994 to December 1995, which is the period covered by the sample spells in this case. These vertical lines in the figure correspond to the set of weeks that these 18 spells could possibly contain the last day of a month. The thickness of these lines is proportional to the number of spells that happen to have month-end day in that week.

[18]In a similar manner, it can be shown that most of the spikes between the vertical lines coincide with mid-month weeks of the particular sample period.

Unemployment spells can be divided into seperate groups based on the reasons of unemployment and UI coverage. According to the Canadian UI rules, workers who left their preceding paid jobs voluntarily (such as family responsibility, or relocation) are not eligible for UI benefit coverage. So they have no UI coverage for their 'unemployment' spells. Other workers might get unemployed involuntarily (such as firm shutdown or layoffs). 76% non-seasonal pre-reform unemployment spells are not qualified for UI coverage from the beginning. Of the 76%, 34%, 37% and 5% are due to quit, permanent layoff and temporary layoff respectively. On the contrary, 61% seasonal pre-reform unemployment spells are qualified for UI coverage initially, with 41% and 20% due to permanent layoff and temporary layoff respectively[19]. For post-reform period, the basic pattern remains similar[20]. In short, not only seasonal unemployment spells are more likely to be eligible for UI coverage initially relative to non-seasonal ones, these spells are also more likely to be due to temporary layoffs. Thus unemployed seasonal workers are more likely to wait for returning back to their former employers in the near future rather than searching for new jobs.

The critical differences between seasonal and non-seasonal labour market turnovers are also evident in the figures of table 3. Table 3 presents the empirical hazard rates of my sample spells, both unemployment and employment spells, non-seasonal and seasonal ones. The figures show how the basic pattern of hazard rates are different between seasonal and non-seasonal spells. Hazards for leaving unemployment and leaving employment in the seasonal sector are higher, more volatile than in the non-seasonal sector. In addition, the empirical hazard figures for the seasonal sector also show vague humps in the later half of the year, which are absent in the non-seasonal sector.

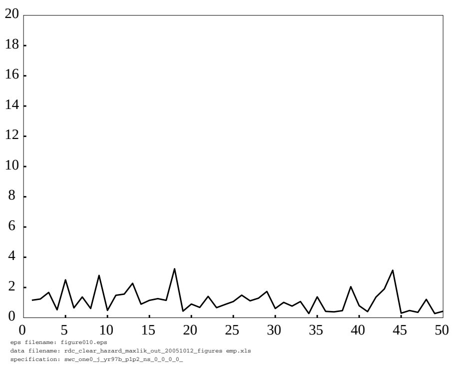
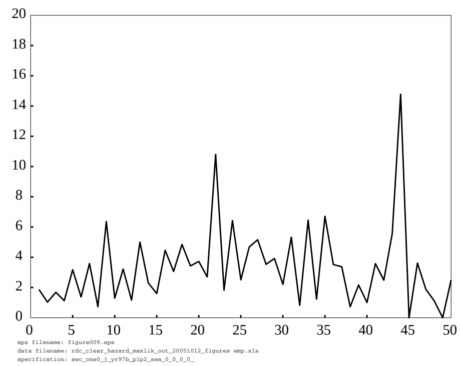
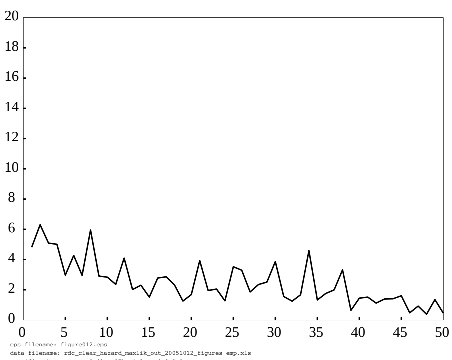
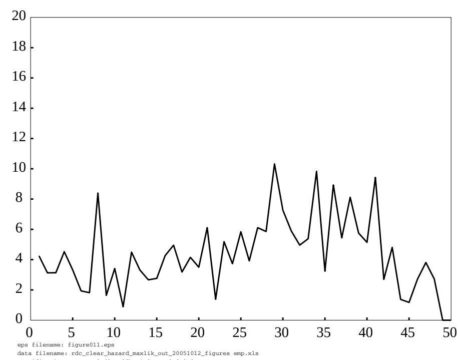
5.2. The preferred set of estimation results

The set of time-varying UI treatment dummy variables used here for estimating the behavioural impacts of UI may seem special, but they are commonly used in this literature. Unlike the usual case of time-constant variable, whose value remains the same for different weeks of a spell, the value of each time-varying variable is

[19]Since seasonal unemployment spells are defined to be those due to layoffs of seasonal reasons. The proportion of seasonal unemployment spells due to quit is zero by construction.

[20]One interesting difference is that there is a higher percentage of non-seasonal post-reform unemployment spells due to quit than in the pre-reform ones. This change perhaps is due to improving macroeconomic situation. A simple story could be, as labour demand increases, workers are more likely to get better jobs, so more job separations are initiated by workers rather than firms.

TABLE 3.
Empirical Hazard Rates

Non-seasonal	Seasonal
Employment spells	
	
Unemployment spells	
	

allowed to be different at different weeks of a spell. Accordingly, for any individual spell, a time-varying variable is a *vector* while a time-constant variable is a scalar.

Table 4 gives the full list of time-varying UI treatment dummy variables and their definitions. Here, the time-varying UI treatment dummy variables defined for unemployment spells are all related to the benefit exhaustion week (*BEW*) except the last one. For week t of an unemployment spells which are initially UI coverage of T weeks, there is $\max\{T-t, 0\}$ weeks of benefit left. Based on $\max\{T-t, 0\}$, a group of dummy variables (BEW_{21+}, BEW_{11-20}, BEW_{6-10}, BEW_{2-5}, BEW_{1}, BEW_{0}) is then created with thresholds of $\{20, 10, 6, 1, 0\}$. The threshold weeks are set to be closer and closer as they approach benefit exhaustion week. This is because the hazard rate of UI-covered unemployed workers is predicted to be increasing at an increasing rate before benefit exhaustion. Depending on the number of initial UI benefit coverage weeks, these *BEW*-related time-varying variables would differ

TABLE 4.
Definitions of Time-varying UI Treatment Dummy Variables

variable	definition
for unemployment spells	
BEW_{21+}	when there are at least 21 weeks to the benefit exhaustion week (BEW)
BEW_{11-20}	when there are 11 to 20 weeks to BEW
BEW_{6-10}	when there are 6 to 10 weeks to BEW
BEW_{2-5}	when there are 2 to 5 weeks to BEW
BEW_1	when there is only 1 week to BEW
BEW_0	the week of reaching BEW
$WK19$	week 19 (just before experience rating threshold week)
for employment spells	
$HMIN_{6-10}$	6 to 10 weeks before minimum employment weeks($HMIN$, also known as entrance requirement week)
$HMIN_{2-5}$	2 to 5 weeks before $HMIN$
$HMIN_1$	1 week before $HMIN$
$HMIN_0$	week of reaching $HMIN$
$HMIN_0$+1 to $HMAX_0$	after $HMIN$ and till week of achieving maximum benefit coverage ($HMAX$)
$HMIN_0$+1 to $HYRMAX_0$	after $HMIN$ and till week of achieving enough benefit coverage for the next job season ($HYRMAX$)
$HMIN_0$+1 to $HDIV$	after $HMIN$ and till the calendar week of $HMIN + 2$ ($HDIV$)
$HMIN_0$+1 to $HEXP$	after $HMIN$ and till the calendar week of 31 ($HEXP$)

across UI-covered unemployment spells[21]. Of course, these time-varying UI treatment variables are set to zero throughout for all unemployment spells with no initial UI coverage.

The estimated coefficients of hazard model from unemployment spells are given in table 5. A coefficient $\hat{\beta}$ here means the hazard rate is proportionally increased by $e^{\hat{\beta}}$. Thus, a negative coefficient means the conditional probability of reemployment is lower. In each estimation, pre- and post-reform sample spells are pooled together. The identification of UI impacts here is thus from both within- and across-period UI treatment differences. Given the setup of Canadian UI program, the within-period UI treatment differences are mainly due to variations of individuals' local unemployment rate movement across region and over time as well as their potentially endogenous employment history[22], while the across-period UI treatment variation should be exogenous.

The coefficients for BEW_{21+} to BEW_0 in table 5 suggest that the more remaining UI benefit weeks an unemployed worker has, the less likely his unemployment spell

[21] The last UI variable *WK19* is set to 1 for the 19th week of post-reform seasonal unemployment spells with initial UI coverage. It is mainly to recognize potential tailoring effect in the seasonal industry due to the experience rating rules introduced after the reform.

[22] Just a cautionary note, since a dummy for post-reform is included in the model, the identification of the coefficient of unemployment rate is mainly based on within period variations. Since both pre- and post-reform sample periods are only 18 months long. It is probably more sensible to interpret the coefficients of unemployment rate as short-run impacts of local labour market conditions on employment/unemployment cycles.

will end. In particular, for the non-seasonal spells, the coefficients increase from $-1.51(s.e.\ 0.17)$ when there are at least 21 weeks of benefit to $-0.54(s.e.\ 0.34)$ when the worker just exhausted all his benefit. Seasonal workers are also shown to be responding to the experience rating rules by increasing their reemployment process just prior to the threshold week, at week 19. In particular, the estimated coefficient for *WK19* is shown to be $0.61(s.e.\ 0.29)$.

The top two figures of table 6 illustrate the impact of temporary UI benefit coverage on unemployment hazard based on coefficients from table 5[23]. Specifically, it is assumed that this worker has 28 weeks of UI benefit coverage. The solid lines give the hazard rates for him to leave unemployment with UI coverage while the dashed lines gives his hazard rates without UI. The impacts illustrated here are very much consistent with theoretical predictions, especially for the non-seasonal part: with less and less weeks of UI benefit left, the worker's hazard rate becomes closer and closer to the baseline rate.

It is worthnoting that there is an obvious difference in baseline hazard trend between non-seasonal and seasonal unemployment spells as shown in the figures. Non-seasonal unemployment spells' hazard is downward sloping, which means the longer a worker being unemployed, the less likely it is for him to get reemployed (i.e. negatively duration dependency). This finding is very similar to what was found in previous studies in this literature (such as Ham and Rea (1987)). On the other hand, seasonal unemployment spells' hazard is upward sloping, or positively duration dependent. An explanation for this could be based on the notion of 'seasonal', where workers are expected to end their unemployment spells within a year.

The definitions of time-varying UI treatment dummy variables used for employment spells is presented in the second panel of table 4. In particular, the first four of them ($HMIN_{6-10}$, $HMIN_{2-5}$, $HMIN_1$, $HMIN_0$) are defined relative to individuals' minimum employment weeks (*HMIN*), also known as entrance requirement week. As discussed earlier, workers' benefit weeks increase up to a limit even beyond *HMIN*, two additional UI variables ($HMIN_0 + 1$ to $HMAX_0$, $HMIN_0 + 1$ to $HYRMAX_0$) are used here for non-seasonal and seasonal employment spells respectively to catch any possible tendency for workers to response to the incentive of additional benefit weeks with extra employment weeks[24]. The last two UI related time-varying variables listed in the table are for post-reform seasonal employment

[23] Although *WK19* is included in the estimation for post-reform seasonal unemployment spells, the figure presented does not consider it as the focus here is not on the impacts of the EI reform.

[24] Depending on individuals working hours each week and on-going local unemployment rate, *HMIN* is recalculated in each week for each employment spells. So are *HMAX*, *HYRMAX*, *HDIV*.

TABLE 5.
Maximum Likelihood Estimates Using Pooled Pre-/Post-Reform Unemployment Spells

	non-seasonal	seasonal
sample size	3107	1406
post reform	0.19 (0.05)⋆	0.29 (0.07)⋆
ln of hourly wage	−0.00 (0.06)	0.20 (0.09)‡
unemployment rate	0.02 (0.01)	−0.06 (0.02)⋆
quit [so, no UI]	−1.86 (0.17)⋆	—
permanent layoff, no UI	−1.98 (0.17)⋆	−2.13 (0.14)⋆
permanent layoff, with UI (omitted group)	—	—
temporary layoff, no UI	−0.37 (0.19)‡	−0.47 (0.16)⋆
temporary layoff, with UI	0.88 (0.11)⋆	0.74 (0.09)⋆
time-varying UI treatment variables		
BEW_{21+}	−1.51 (0.17)⋆	−1.12 (0.16)⋆
BEW_{11-20}	−1.61 (0.18)⋆	−1.20 (0.15)⋆
BEW_{6-10}	−1.21 (0.22)⋆	−0.86 (0.17)⋆
BEW_{2-5}	−0.91 (0.24)⋆	−0.66 (0.18)⋆
BEW_1	−1.24 (0.45)⋆	−0.33 (0.33)
BEW_0	−0.54 (0.34)	0.08 (0.30)
$WK19$	—	0.61 (0.29)‡

Note: other control variables include gender, age, maritial status, immigration status, education dummies and regional dummies

spells only. They are meant to catch the impacts of divisor rule and experience rating rules introduced by the 1996 EI reform[25].

The estimated coefficients of hazard model from employment spells are given in table 7. The signs of the UI-related coefficients for both non-seasonal and seasonal spells are all consistent with theoretical predictions except for $HMIN_{2-5}$ for non-seasonal spells. Most of the coefficients for seasonal spells are statistically significant while none of the coefficients for non-seasonal spells are statistically significant.

To further appreciate the estimation results, the bottom two figures of table 6 illustrate the impact of UI on employment hazard using coefficients from table 7[26]. The left figure for non-seasonal spells shows that UI incentives only have minimal impacts on the distribution of non-seasonal employment spells, while the right figure shows UI has significant impacts on that of seasonal employment spells. The closer seasonal workers are to the minimum employment week *HMIN*, the stronger their tendency to postpone job-separation. Even after *HMIN*, these workers still tend to postpone job-separation before they accumulate enough benefit weeks for the rest of the year.

[25] There are little impacts of these rules on non-seasonal spells based on alternative estimations. Therefore, the discussion here focus on tests that only consider divisor rule and experience rating rules on seasonal employment/unemployment spells only.

[26] Here *HMIN*, *HMAX* and *HYRMAX* are set at 14, 40, 24 weeks respectively.

TABLE 6.
Illustration of UI's Impacts on Hazard Rates: Based on Estimations Using Pooled Pre-/Post-Reform Spells

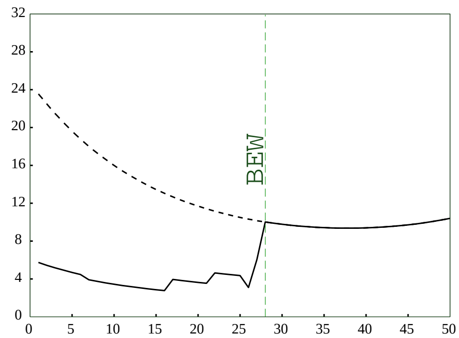
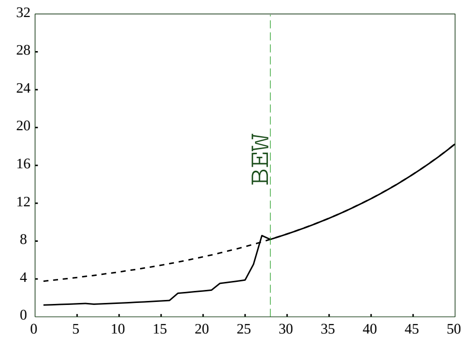
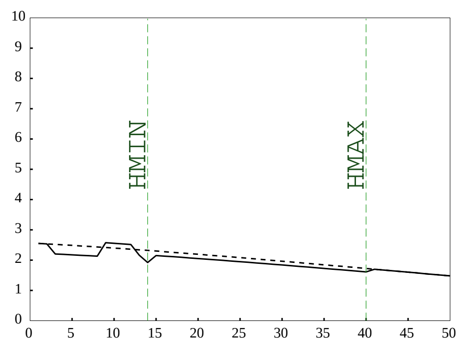
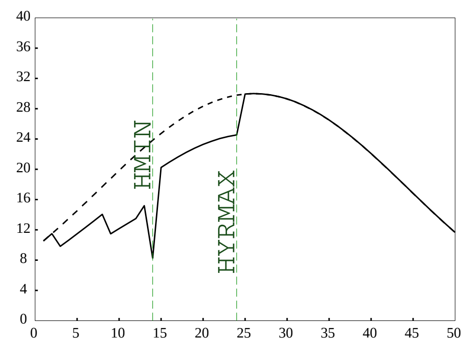
non-seasonal	seasonal
unemployment spells	
	
employment spells	
	

TABLE 7.
Maximum Likelihood Estimates Using Pooled Pre-/Post-Reform Employment Spells

	non-seasonal	seasonal
sample size	3338	982
post reform	-0.18 (0.05)⋆	-0.19 (0.10)†
ln of hourly wage	-0.19 (0.07)⋆	-0.86 (0.10)⋆
unemployment rate	0.03 (0.02)‡	-0.05 (0.02)‡
time-varying UI treatment variables		
$HMIN_{6-10}$	-0.14 (0.09)	-0.25 (0.14)†
$HMIN_{2-5}$	0.06 (0.11)	-0.53 (0.15)⋆
$HMIN_1$	-0.08 (0.25)	-0.45 (0.27)†
$HMIN_0$	-0.12 (0.24)	-0.92 (0.37)‡
$HMIN_0 + 1$ to $HMAX_0$	-0.07 (0.11)	—
$HMIN_0 + 1$ to $HYRMAX_0$	—	-0.23 (0.12)‡
$HMIN_0 + 1$ to $HDIV$	—	-0.17 (0.21)
$HMIN_0 + 1$ to $HEXP$	—	-0.22 (0.15)

Note: other control variables include gender, age, maritial status, immigration status, education dummies and regional dummies

5.3. Robustness check

Here I mainly focus on one set of maximum likelihood estimation results[27]. That is, I check how our preferred estimation results are affected by considering individuals' unobserved heterogeneity. By that, I mean individuals' inherent tendency of labour market attachment. An important weakness of single spell hazard model often mentioned in the literature is its lack of power to distinguish individuals' unobserved heterogeneity from 'true' duration dependence of the baseline hazard rate (see Heckman (1991)). Among others, Van den Berg (2000) and Lancaster (1990) both recommend multi-spell hazard models to tackle this problem. By using multi-spell hazard model, researchers hope to know (implicitly) individuals' type (strong or weak labour market attachers) and use that information to adjust the composition of unobserved individual quality at different weeks of each type of spells.

In the context of duration analysis, Lancaster (1990) argues that ignoring unobserved heterogeneity could lead to spurious negative duration dependency of the estimated baseline hazard. This is because it is more likely to have workers who consistently have long spells at the later periods of the sample spells. For example, in the case of unemployment spells, the later the week, the higher the proportion of individuals with *consistently* longer unemployment spells. Without considering the fact that these individuals have longer unemployment spells repeatedly, the estimated baseline hazard rate will be biased down for later weeks. Or in other words, we would get the wrong conclusion that the later the week in the unemployment spells, the harder for a typical individual to get reemployed (i.e. negative duration dependence). Therefore, the slope of the baseline hazard estimated from multi-spell hazard model is expected to be higher than that of the baseline hazard from single spell model.

If the impacts of these unobserved person-specific factors are important, then single-spell hazard models will produce un-reliable evident. To extend the previous single spell hazard model with heaping effect to the case of multi-spell multi-state, let $\{\epsilon_1, \epsilon_2\}$ be a random vector of standard joint normal distribution $N(0, I)$. Without loss of generosity, we can rewrite equation (2) as follows,

[27]Many more specifications are tested. In particular, I have also checked how my results are affected by pooling spells of two periods together, by the heaping part of the model, and by the order of baseline hazard polynomials. They do not change the main message of this paper.

$$\text{for an employment spell } \theta^e_{j,t} = \exp(\alpha^e_t + \beta^{e\prime} x_{j,t} + a_{1,1}\epsilon_1) \tag{5}$$

$$\text{for a unemployment spell } \theta^u_{j,t} = \exp(\alpha^u_t + \beta^{u\prime} x_{j,t} + a_{1,2}\epsilon_1 + a_{2,2}\epsilon_2) \tag{6}$$

Let the corresponding likelihood function of an employment and unemployment spell be $\hat{f}^e$ and $\hat{f}^e$ respectively. Then the likelihood function for individual i is,

$$L_i = \int_{\epsilon_1,\epsilon_2} \left\{ \prod_{j=1}^{N_i^e} \hat{f}^e_j \prod_{k=1}^{N_i^u} \hat{f}^u_k \right\} dF(\epsilon_1, \epsilon_2) \tag{7}$$

The construction here is quite similar to studies such as Hedeker et al. (2000) and Carneiro et al. (2003)[28]. Since $F()$ is the CDF for standard joint normal distribution, it is straightforward to use the method of Gaussian quadrature for numerical integration.

TABLE 8.
Maximum Likelihood Estimates Using Pooled Pre-/Post-Reform Non-Seasonal Spells with Unobserved Heterogeneity Considered

	employment hazards	unemployment hazards
ϵ_1	0.75 (0.11)⋆	0.02 (0.10)
ϵ_2	—	0.65 (0.10)⋆
post reform	−0.18 (0.06)⋆	0.23 (0.06)⋆
log of hourly wage	−0.23 (0.08)⋆	−0.02 (0.07)
unemployment rate	0.03 (0.02)‡	0.01 (0.02)
time-varying UI treatment variables for employment spells		
$HMIN_{6-10}$	−0.15 (0.10)	—
$HMIN_{2-5}$	0.05 (0.12)	—
$HMIN_1$	−0.10 (0.26)	—
$HMIN_0$	−0.15 (0.10)	—
$HMIN_0 + 1$ to $HMAX_0$	−0.09 (0.11)	—
quit [so no UI]	—	−2.06 (0.20)⋆
permanent layoff, no UI	—	−2.24 (0.20)⋆
temporary layoff, no UI	—	−0.41 (0.22)†
temporary layoff, with UI	—	1.05 (0.14)⋆
time-varying UI treatment variables for unemployment spells		
BEW_{21+}	—	−1.79 (0.20)⋆
BEW_{11-20}	—	−1.79 (0.20)⋆
BEW_{6-10}	—	−1.34 (0.23)⋆
BEW_{2-5}	—	−1.02 (0.25)⋆
BEW_1	—	−1.33 (0.45)⋆
BEW_0	—	−0.63 (0.37)†

Note: the sample is consisted of 3796 individuals and the mean loglikelihood is -3.870. Other control variables included are gender, age, maritial status, immigration status, education dummies and regional dummies.

[28] An often used alternative approach in the literature is to follow Heckman and Singer (1984) and use non-parametric specification of the heterogeneity part. But results of Baker and Melino (2000) suggest that the non-parametric approach could generate biased estimates in certain cases in their Monte Carlo studies.

Only non-seasonal spells are used here. Both because we have more sample individuals in the non-seasonal sector and because the kind of unobserved heterogeneities that we are concerned about is mainly relevant in the non-seasonal sector. Our earlier evidence shows the length of seasonal workers' employment/unemployment durations are heavily affected by the cycle of four seasons. The inherent seasonality makes the heterogeneity story less applicable. We are not expecting the relative length of these durations to be very informative for individuals' future durations.

Table 8 gives the estimated results using pooled pre- and post-reform non-seasonal spells[29]. Table 8 shows that, overall, there are no dramatic differences between the multi-spell multi-state estimation results and the corresponding single spell estimation results as shown in table 5 and 7. The similarity of the two sets of estimation results is comforting in the sense that for most researchers it is much cost-effective to use single spell hazard models than multi-spell multi-state hazard models. But on the other hand, table 8 suggests that unobserved heterogeneity is statistically significant for both employment and unemployment spells in our case. In particular, we have the coefficient for ϵ_1 in the employment spell part to be 0.75 with s.e. 0.11; while the coefficient for ϵ_2 in the unemployment spell part to be 0.65 with s.e. 0.10.

Also quite interesting is the change in the coefficients for UI related variables in the unemployment spell part. Intuitively, we would imagine the estimated coefficient for a dummy variable will increase if the average unobserved heterogeneity of the group of individuals covered by the dummy is negative; decrease if the average unobserved heterogeneity is positive. For unemployment spells, it means if a group of individuals tend to experience longer unemployment spells repeatedly, then the estimated coefficient of the dummy for this group will increase after unobserved heterogeneity is considered. Applying such logic, a comparison between table 8 and 5 suggests that on average, individuals that on layoffs (both temporary and permanent) with initial UI coverage tend to have long unemployment spells repeatedly.

5.4. Policy implications

Finally, it is interesting to translate previous estimation coefficients into aggregate measures of UI's impacts on the labour market. Assuming the hazard rates remain constant from week 50 on, table 9 gives the estimated average durations of each type of spells. Then the unemployment rates in each sector by seasonality is presented in

[29] As a practical note, to reach a reasonable distribution of the unobserved heterogeneity vector, I utilized an intermediate step rather than set arbitrary starting values of the covariance matrix. Specifically, I first estimated the multi-spell multi-state hazard model without UI variables. Then, using that set of estimated coefficients as starting values, I estimated the model with UI variables added.

the lower panel of this table. Three scenarios are considered: no UI program, under pre-reform UI rules, and under post-reform UI rules. Table 9 suggests UI program increased the unemployment rate in the non-seasonal sector by 2% and that in the seasonal sector by 5%.

TABLE 9.
Summary Statistics from Simulations

	no UI	pre-reform UI rules	post-reform UI rules
average duration (weeks)			
non-seasonal unemployment spells	23	28	29
non-seasonal employment spells	117	124	121
seasonal unemployment spells	12	18	18
seasonal employment spells	30	35	35
unemployment rate(%)			
non-seasonal sector	17	19	19
seasonal sector	29	34	34

Note: All of the simulations are based on average characteristics of post-reform spells and estimated coefficients using single spell hazard model. .

There are several reasons to consider the above 2% and 5% increase in unemployment rate to be upper bound of the true values. First of all, this study defines unemployment and employment differently from the LFS does. Only paid employment is considered in this study. Although some out of labour force periods are excluded in the data used here, there is no searching requirement in the definition of unemployment here. Moreover, individuals who have no fresh employment/unemployment spells are excluded from our sample. Many of these individuals could be those with very stable employment.

6. CONCLUSION

This empirical work is related to the bigger question of income support program's labour market consequences. It extends the literature by using a common data source and common econometric setups when investigating UI's impacts on both directions of employment/unemployment cycles. This study also pays attention to the different nature of seasonal and non-seasonal labour market by studying them separately. Most importantly, this study utilizes UI treatment variations due to the EI reform as an unique exogenous source of variation.

The results confirm both findings of previous studies about UI's impacts on employment (Green and Riddell (1997), Baker and Rea (1998)) and those about UI's impacts on unemployment spells (Ham and Rea (1987), Meyer (1990), and Moffitt (1985)). In particular, the empirical results presented above show, both non-seasonal and seasonal workers' reemployment probabilities are pushed down when they still have some UI benefit coverage left; and, seasonal workers' probabilities of employment separation are also pushed down before their entrance requirement weeks. Furthermore, simulation results suggest upper bounds of the increases in unemployment rates due to UI are 2% and 5% in the non-seasonal and seasonal sectors respectively.

Broad interpretations of our estimation results should take into account several choices made here. First, our sample spells are constructed using an event-based selection procedure; second, the definitions for 'employment' and 'unemployment' here are adapted to UI legislation; and last, the usual discrete-time hazard model is extended by a heaping effect component here.

Interpretations of the results here also need to be clear about some limitations of the research. In particular, both seasonality and wages are taken as exogenous here. It would be interesting to explore how the size and composition of seasonal sector is affected by UI parameters. Knowing those, we could then know the overall aggregate impacts of UI. Also since all the employment/unemployment cycles should be coupled with wage or reservation wage dynamics, it would be interesting to know how robust our results would be if wages are endogenized.

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