THREE ESSAYS ON INSURANCE

by

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To my grandma, and my Lily

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ABSTRACT

A common assumption of in literature regarding unemployment insurance (UI) take-up is unemployed individuals will claim UI benefits immediately after job loss. I find that this assumption about immediate unemployment insurance take-up can not be supported in the data. I constructed a revised McCall search model to provide a mechanism to explain the delay of UI take-up found in the data. This dissertation contains three chapters. In Chapter 1, I provide evidence that UI application delay is significant. Many people delay at least one week - 87% of unemployed individuals delay at least one week, 37% delay at least 4 weeks and 27% individuals delay at least 12 weeks. The average delay is large - unemployed individuals on average have 12.99 weeks of delay before claiming UI benefits after job loss. I also analyze factors that correlate with application delay. I find a lower age, being disabled, being female, facing good economic conditions and fewer experienced number of job separations make delay more likely and increase length of delay. In Chapter 2, I provide a job search and separation model to explain the findings from the data in Chapter 1. I find that the application costs are large compared to benefits received. Counterfactual analysis show that reducing hassle of aplying for UI can have large impacts on delay of application. In Chapter 3, I extend the methodology to study the effect of availability of other welfare programs such as Supplemental Security Income (SSI) on the application delay of UI for people who have reported disability. I find that the availability of other welfare programs such as SSI is a contributing factor that make delay more likely and longer for people with disability.

1. WHY WAIT? APPLICATION DELAYS FOR UNEMPLOYMENT INSURANCE

Abstract

This paper documents that a standard assumption in the labor literature, that individuals will immediately take up unemployment insurance at the time of job separation, is not supported in the data. Using the SIPP 2008 panel, I find over 87% of individuals wait at least one week, and the average waiting time is almost 13 weeks. I show that demographics, experience with unemployment, and economic circumstances alter both the intensive and extensive margins of applying for unemployment insurance. I also find that although individuals still delay application even after multiple job separations, the average 'waiting time' decreases as the number of experienced job loss increase. This finding indicate there can potentially exist 'learning' as an individual is more experienced in job loss. The exists of 'learning' behavior is further explored in Chapter 2.

1.1 Introduction

Unemployment insurance (UI) is a widely (both within and outside of the US) used program that provides cash benefits to eligible workers who become unemployed through no fault of their own. The UI system serves two crucial functions. First, it provides unemployed workers with essential financial assistance when they are laid off, and gives them time to find a job that is a particularly good match. Second, it also acts as a form of countercyclical government spending to stimulate the economy during a recession. However, it is also well known that UI also creates adverse incentives for recipients– allowing workers to reduce search effort for a new job or encourage the unemployed to reject job offers that it would be efficient for them to match with (the disincentive effect or moral hazard). More generally UI distorts the relative price of leisure and consumption and makes leisure cheaper and more appealing for the unemployed. Optimal UI takes the trade-off between the insurance. and moral hazard effects. There is a large academic literature exploring optimizing design of unemployment insurance. Previous literature exploits important questions including the link between unemployment insurance and nonemployment duration Moffitt (1985)[1]; causal relation between unemployment insurance and unemployment rate Sargent and Ljungqvist (1998)[2];whether the connection between UI and unemployment would vary with economic conditions Schmieder, Wachter and Bender (2016)[3]and Kroft and Notowidigdo (2016)[4].

Unemployment Insurance Program: In the United States state unemployment insurance program (UI) is a social insurance funded by state and federal taxes on employers. UI provide people who are insured with income support if they lose their jobs. UI helps to sustain consumer demand during economic downturns by providing critical cash benefits. The unemployment insurance program is run by states under the guidance set by the U.S. Department of Labor. Subjected to the federal requirement, each state sets its own maximum duration of benefits and maximum amount of benefits. In most states under normal economic conditions UI provides up to 26 weeks of benefits and the replacement rate [1] is about half of the previous wage subject to a maximum benefit amount. In 2022 the maximum duration

[1]↑The replacement rate is the ratio of the claimants' weekly benefit amount (WBA) to the claimants' average weekly wage.

of benefits ranges from 12 weeks (Florida, North Carolina) to 26 weeks (majority of other states). During recessions when the unemployment rate is high the federal government may extend the maximum duration of benefits in the regular UI program to insure the welfare of the unemployed workers. For instance, during the Great Recession starting in December of 2007 the federal government enacted additional programs to regular UI as a response to the continuous high unemployment rate– Emergency Unemployment Compensation (EUC) and Extended Benefits (EB). Emergency Unemployment Compensation provides benefits to individuals who have exhausted regular unemployment benefits with up to 53 additional weeks of benefits. Extended Benefits are available to workers who have exhausted regular unemployment benefits and EUC and provide up to 20 additional weeks of benefits after the regular UI benefits and EUC are exhausted. With the additional programs to regular UI an unemployed worker can claim up to 99 weeks of unemployment benefits during the Great Recession period. Each state set up its own weekly maximum benefit level. In 2022, the maximum benefit level ranges from $\$235/week$ (Mississippi) to $\$823/week$ (Massachusetts) [5] and with an average of $\$474/week$ nationwide. UI in each state is typically aim to replace about half of a worker's previous earnings up to the maximum benefit level. Unemployment benefits are paid weekly and how the amount of weekly benefits are calculated also varies by states and will depend on the person's past earnings. For instance, Indiana sets the replacement rate to be 47% meaning a claimant's weekly benefit amount will be 47% of the average weekly wages earned in the base period [2]. In 2021, the most recent year that the data is available, on average UI replaces 42.4% of a worker's past earnings nationwide [6]. Since unemployment insurance is run separately in each state the exact requirements to qualify for UI varies by state. However each state follows general criteria in terms of the requirements of eligibility of unemployment. In general to qualify for unemployment benefits a person must:

- Have lost job through no fault of his/her own;
- Be able to work, available to work and actively seeking work;

[2]↑In most states the 'base period' is the first four out of the last five calendar quarters prior to the time the claim is filed.

- Have earned at least certain amount of money during the 'base period' before being unemployed [6].

The general requirements of eligibility of UI indicate the state unemployment insurance does not cover people who leave a job voluntarily [3], people who does not have enough work credits and people who are not actively searching for job [4]. Eligibility of UI is not a one time deal. Since UI is paid weekly a claimant must file weekly or biweekly claims in order to remain eligible to UI. With the weekly file UI recipients must report any job offers in each week to show they are actively seeking work. UI recipients must also report if they have refused job offers as they are required to accept any offer of suitable work [5]. Besides, UI recipients must be mentally and physically able and available to work. People that are not available to work due to illness or injury are likely to be denied of UI.

The existing literature on UI operates under the assumption that all eligible unemployed individuals will apply for benefits as soon as job separation. This paper challenges that assumption. Using panel data from SIPP 2008 I demonstrate that delay in UI application is important both on the extensive and intensive margin. Moreover, the decision of when (and whether) to apply for UI depends in systematic ways on experience, demographics and economic circumstances. Estimating a simple structural model I show that the costs associated with application are quantitatively large, and that policies to change these costs would have substantial impacts on the timing of UI uptake.

My findings raise the question of why researchers have traditionally assumed that UI uptake is immediate. The first reason is that states typically instruct individuals to apply for UI as soon as job separation occurs. Second, absent any significant costs of application, not applying for UI would be 'leaving money on the table' and irrational. My results suggest both that there are significant costs to applying, and that many individuals, in light of these costs, ignore the instructions of UI programs.

[3]↑Unless an individual has good, work-related reasons to quit, such as harassment at work, unreasonable changes of conditions of work by employers, moving to follow a spouse accepting a new job.

[4]↑Except for the individuals that are on involuntary furlough.

[5]↑A work offer is determined as suitable if it is reasonably similar in location, type of work and pay to the previous work. The longer a person remain unemployed the more likely a job offer will be determined as suitable.

Studies of Unemployment Insurance Application and Program Application Costs: As far as I am aware, there have been few studies specifically about application cost of unemployment insurance. There are however some studies about the takeup rates of UI. Motivated by the decline of UI takeup rate observed in the 1980s, Anderson and Meyer (1994) [7] was one of the first papers to study the effect of generosity of UI benefits on UI takeup rates after job separation. Theoretical arguments suggest that more generous UI benefits increase the value of applying for UI relative to its cost. This paper found more generous UI benefits would increase the takeup rate. In other words, the decision to file for UI benefits is affected by UI benefit levels. The paper argue that besides the unemployment effect (more generous benefits will increase duration of unemployment) of UI that a lot of papers have studied, there also exists the takeup effect (more generous benefits will also increase the UI takeup rates) of UI. The existence of takeup effect of UI is crucial when evaluating how changes in the UI system will affect program costs. Anderson and Meyer (1997) [8] investigated the determinants of UI takeup. They found a strong positive effect of the benefit level on takup as well as a positive effect of the potential duration of benefits. More specifically, a 10% increase of weekly benefits would increase the takeup rate bt 2% to 2.5%; a 10% increase of potential duration of benefits would increase the takeup rate by 0.5% to 1%. The paper also found that income taxation of benefits significantly reduces takeup. The tax change that lowers the after-tax value of UI benefits can explain the steep decline of UI takeup around the 1980s. Currie 2006 [9] provided a review of literature regarding the take up of social programs. She concluded that aside from the generally more common low takeup of means-tested programs, low take up of non means-tested social insurance programs (such as UI) are also a problem in the United States and other countries. Take up is enhanced by automatic or default enrollment and lowered by administrative barriers, although removing individual barriers does not necessarily have much effect. She also concluded that stigma cannot by the only cost facing participants of social programs, other more concrete types of transactions costs are likely to be more important. Ebenstein and Stange (2010) [10] study the question of whether inconvenience explain low take-up of UI. In the paper the authors examine the effect on takeup rates of UI after introducing of phone and Internet-based claiming for UI which reduced the time required to file for UI benefits. The authors found that the introduction of phone and Internet-based claiming did not have an appreciable impact on overall UI takeup. The finding of the paper suggests that reducing application barriers alone may not be an effective tool for increasing program participation. Auray, Fuller and Lkhagvasuren (2018) [11]studied the implications of 'unclaimed' benefits. In their analysis, they assume the UI collection costs along with past UI collections are private information for the worker and not known to the employer. The paper shows the take-up rate is lower with full information relative to private information. When past UI collections are observable firms prefer to dissuade some workers from collecting UI benefits by offering more wages in order to aviod paying the experience rated tax [6]. Under private information, firms have fewer options to provide an attractive alternative to collecting UI and the take-up rate remains higher in the private information economy.

Some recent papers studied the take-up and application costs of other programs such as SNAP (Supplemental Nutrition Assistance Program) and commonly known as food stamps. Gray (2019) [12] studied the retention of SNAP program. The paper found that retention in SNAP is low with about half of newly entering cases exiting within one year. A about a half of cases that have exited the program after one year are still eligible. Efforts to simplify recertification procedures will reduce exits or program and the effects found are concentrated among childless adults. The paper concludes that retention is an important part of program take up and simplifying recertification procedures and reducing administrative barriers (paperwork burdens) will meaningfully increase retention. Finkelstein and Notowidigdo (2019) [13] studied the welfare impacts of interventions to increase take-up of SNAP where the interventions were designed to reduce potential information barriers to enrollment and potential transaction cost barriers. The authors found that both information and transaction costs are barriers to take-up. The paper also find that barriers to take-up deter relatively less needy individuals from enrolling suggesting that reducing informational or transactional barriers decreases targeting. Murphy (2022) [14] examines both transaction costs and stigma on SNAP benefit take-up. The author finds individuals living in states with low transaction

[6]↑Experience rated tax is a tax tool used by state unemployment insurance programs that allows states to collect unemployment taxes from employers according to the amount of unemployment insurance benefits drawn by their former employees. In other words, UI tax accumulating only to those firms hiring a future UI collector.

costs are 19% more likely to take up SNAP benefits than those living in states with high transaction costs. Moreover, reducing stigma can increase the probability of benefits takeup by about 41%.

The rest of Chapter 1 proceeds as follows: Section 1.2 documents in detail the data I use and findings from data; Secion 1.3 explore factors that will have significant effect on application delay using both Probit, Linear regression and Cox regression analysis; Section 1.4 concludes.

1.2 Identifying UI Application Delay

This section begins by describing the data set used throughout the paper. It then turns to demonstrating the importance of delay in UI applications by by using fairly simple summary statistics. I first show that delay is an important issue on the extensive margin: the vast majority of individuals have at least some delay in their application. Thus, delay is not simply an issue concentrated among a small minority of potential UI applications. Second, I show that delay is important on the intensive margin. Conditional on not applying immediately, but eventually applying, the median delay is between 3.7 and 26 weeks. I have relatively large error bounds on these estimates because many individuals exit the survey with a job separation and not having yet applied for UI. Third, I show that delay are not due to inexperience: although individuals who have experienced more job separations shorten their delay for applying for UI on subsequent separations, they still delay by a significant amount.

1.2.1 Data Source and Description

The data set I use is the Survey of Income and Program Participation (SIPP) panel 2008. SIPP is a household-based survey collecting data on a variety of topics including demographic characteristics, social program participation, income, assets and etc. Other than demographic variables, SIPP provides weekly employment status and state unemployment benefit receipt data which are the crucial variables needed to study the waiting time of unemployment insurance claimants.

SIPP includes a series of panels with each panel having a duration of 2.5 to 4 years. All adults in the sampled households are interviewed every 4 months. Each time the interview is conducted is called a wave. The 2008 panel contains 16 waves covering the time period from May 2008 to November 2012. The 2008 panel has a large sample, 52031 eligible households were initially sampled. This long period of coverage is instrumental to study the dynamics of employment/unemployment transitions and UI claims over time. The 2008 panel occurs right after the Great Recession, which began at the end of 2007. This period is particularly useful for the issue examined in the paper, UI applications, because the Great Recession featured relatively high levels of employement/unemployment transitions and UI claims.

The 2008 SIPP panel samples 131892 individuals, among which 87910 (about 66.7%) are between the age of 18 to 65. I focus my analysis on this subsample because they are most likely to have be engaged in full-time work and are eligible to claim unemployment benefits. After dropping individuals who have either never worked, or have never been unemployed during the survey period (since these two categories are not relevant for the study of this paper) the sample is reduced to 54954 individuals. In each week, employment status is coded in the original data as one of the six categories: not applicable; with job- working; with job- on layoff, absent without pay; with job- not on layoff, absent without pay; no job- looking for work or on layoff; and no job-not looking for work and not on layoff. In order to construct the unemployment spells I need to recode the above employment status into only two categories: 'employed' and 'not employed' denoting whether a person is employed at current week. I recoded 'with job-working', 'with job-on layoff, absent without pay' and ' with job-not on layoff, absent without pay' as 'employed' and the others as "not employed". After recoding, the average unemployment spell is 51.21 weeks across all unemployment spells. If we instead look at the average length of unemployment across individuals over the course of the panel, it is 64.92 weeks. This is because many individuals experience multiple unemployment spells in their work history during the survey period. The reason to look at unemployment spells from these two different perspectives is to see if there is a difference of average unemployment spell at individual level (across all unemployment spells) and at spell level. Compared to looking across all unemployment spells, looking at the unemployment spells across individuals put less weight on people having more occurrences of job separations and more weight on people with fewer occurrences of job separations.

One potential issue with reporting only the unemployment spells across individuals is if there are extreme values for individuals with fewer than the average number of job separations the average unemployment spells reported will be affected more by these extreme values compared to the simple average across unemployment spells. Therefore as discussed I report both unemployment spells at individual level and spell level.

Table 1.1. Main Variables Summary Statistics

Variable	**Mean**	**Std.Dev**	**Median**	**Min**	**Max**	**N**
HouseIncome	\$5219.10	\$4637.36	\$4086.32	\$-6190.42	\$64565.96	28869
Age	37.03	15.26	35	18	65	54954
Education	13.45	3.07	14	1	23	54954
Unem Duration	51.21	69.02	19	1	279	94911
Individual	64.92	76.73	32.5	1	279	54954
UI Duration	45.87	29.26	35	4	99	9025

Table 1.1 shows summary statistics of main variables in the sample. Among the 54954 number of people sampled 25255 (45.9%) are male and 29699 (54%) are female. The average age of the sampled is 37.03 years old and the average education level is 13.45 years or 'some college, but no degree'. There are 28869 number of households remained in the sample. $HouseIncome$ is the average total monthly household income and is \$5219.1. $Unem\_Durarion$ is unemployment duration and captures how long unemployment spells last. There are two ways to look at unemployment spells. The first way is to treat each unemployment spell independently and not taking into account if it belongs to the same person, and unemployment duration in this case is at individual/unemployment spells level. The total number of individual/unemployment spells are 94911 with the average length of an unemployment spell 51.21 weeks. The second way is to take into account two or more unemployment spells may belong to the same person. I calculate the average unemployment spells within a person, and then take the average across all people to find the average unemployment duration at individual level. In this case, the 94911 number of unemployment

spells are comprised of 54954 people with an average of 64.92 weeks of unemployment spells at individual level. Every person on average has 1.7 times of job separations (54954 divided by 94911). Thus, using this aggregate statistic implies we are putting less weight put on individuals with more than 1.7 times of job separations and more weight put on those with less than 1.7 times of job separations. The average unemployment spells for people with less than 1.7 times of job separations are bigger than 51.21 weeks and the average unemployment spells for people with more than 1.7 times of job separations are smaller than 51.21 weeks. $UI\_Duration$ measures how long unemployment benefits lasts. Among 54954 people sampled, 9205 reported themselves to have been on UI, which gives about a 16.8% uptake rate of unemployment benefits. The average UI duration is 45.87 weeks at individual level. It is worth noting that this average UI duration is almost 20 weeks more than the maximum duration of unemployment benefits when economic condition are normal, as the majority of states have maximum UI duration of 26 weeks. The 45.87 weeks shown in the data indicates the majority of unemployment insurance claimants claimed extra weeks of unemployment benefits during big economy downturn. Unemployment insurance was extended due to 2007 recession and many states have the maximum duration extended to as long as 99 weeks during this time period. Therefore, a report of receiving longer than 99 weeks of unemployment insurance (UI) is treated as misreport and is replaced as 99 weeks in this paper.

In summary, Table 1.1 shows among people who have worked and lost jobs during sample period they are on average 37 years old, have a $5219.1 monthly household income, with some college education level and an unemployment duration of 64.92 weeks. There are on average 1.7 times of job separations and about 16.8% of the unemployed (eligible and non-eligible) ended up taking up unemployment insurance.

1.2.2 Findings from Data

Figure 1.1 and Figure 1.2 show the PDF and CDF of 'waiting time' for all job loss, first time, second time, third time and more than three times of job loss. The x-axis is the number of weeks after job loss and the y-axis is the percentage of job separations. From Figure 1.1 we can see that about 12% of job separations 'wait' 1 week after job loss before claiming UI, about 10% job separations 'wait' 2 weeks after job loss before claiming UI and the proportion of job separations that 'wait' before claiming UI decrease as the time after job loss increases. The exception of the downward trend of the proportion of job separations that 'wait' are around week 17, 18 and week 35. This is due to the seam bias where more transitions are reported during the month that individuals are interviewed and individuals in the sample are interviewed every 4 months. Seam bias will be discussed in more detail in Section 13. First time, second time, third time and more than three times job separations follow the same trend. For first time, second time, third time and more than three times job separations respectively, the proportion of job separations that 'wait' before claiming UI decrease as time after job loss increases [7] [8].

Figure 1.2 shows the CDF of 'waiting time' for all, first, second, third and more than three times of job loss. We can see from Figure 1.2 that comparing to the first time job separation, the second time job separation takes less time before reaching 100% UI takeup. Similarly, comparing to the second time job separation, the third time job separation takes less time before reaching 100% UI takeup. 10 weeks after job separation, about 30% of first time job separations ended up taking up unemployment benefits, about 50% of second time job separations taking up unemployment benefits and about 60% of third time job separations taking up unemployment benefits. In other words, as the number of job separations increase, the time it takes to reach 100% UI takeup decreases.

Next I analyze the waiting time before taking on unemployment insurance in Table 1.2 and Table 1.3. There are two possibilities for unemployment spells that last until the end of survey period. One is that the person is still waiting to apply to or be approved for unemployment benefits and the other is that the person is never going to apply for UI

[7] ↑Note the y-axis shows the proportion of job separations for the specific time of job loss, therefore the length of y-axis between different time of job loss are not comparable.

[8] ↑Since I truncate the data to end at 99 weeks after job loss, Figure 1.1 shows a peak at week 99.

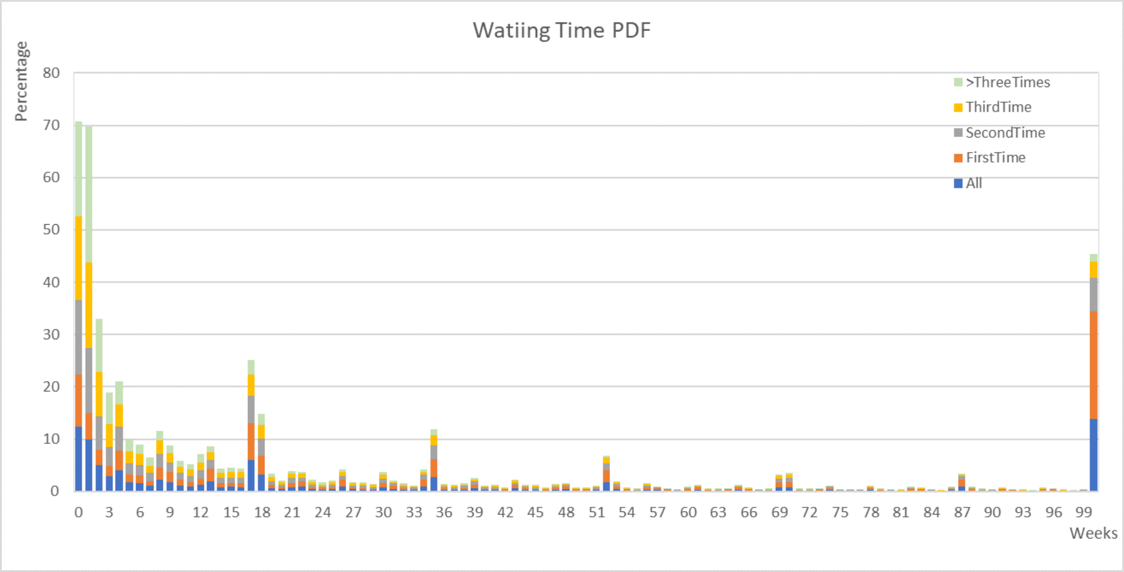


Figure 1.1. Waiting Time pdf

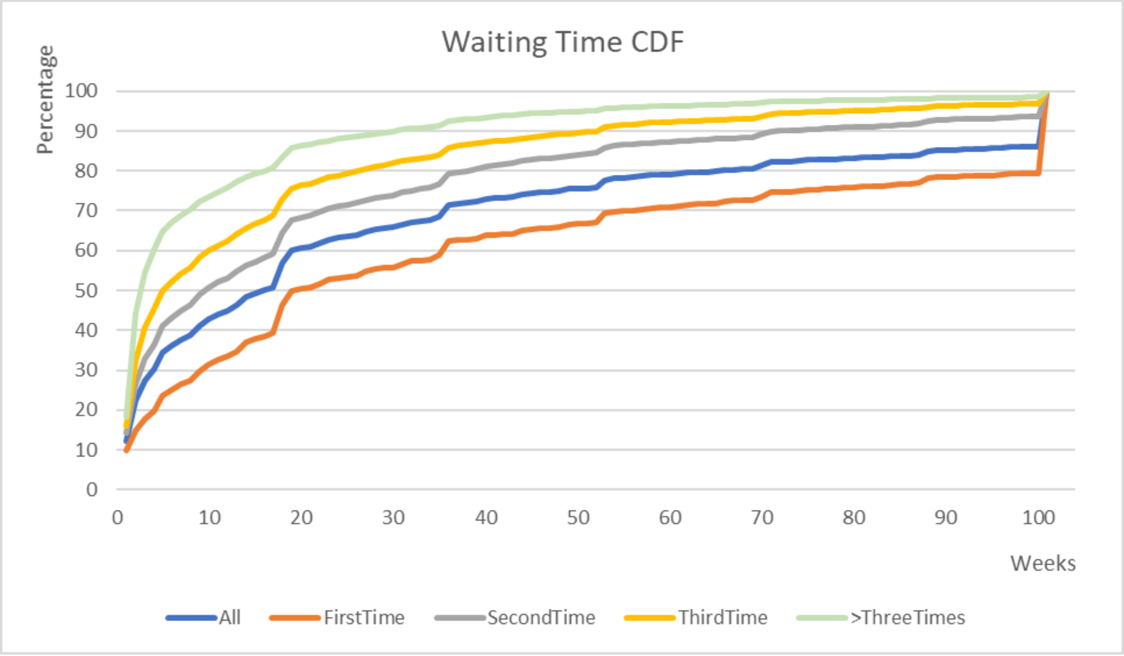


Figure 1.2. Waiting Time cdf

and/or is out of labor force [9]. I address these two possibilities in Table 1.2 and Table 1.3 respectively. It is worth mentioning that since the data is right and left censored, I will not be able to have perfect information on a complete employment history of each individual. However, random sampling of the survey would weaken this concern since at any time censoring should also be randomized so it should not be a big concern that data censoring will affect the analysis on the aggregate level. Also, according to the guideline of department of labor or department of workforce it may take up to 3 weeks before the unemployment workers to receive their benefits. In order to eliminate the possibilities that the 'waiting time' can be the administrative time it took for UI application to get processed and approved I recalculate the original 'waiting time'. Considering 3 weeks should be the maximum amount of time it took for the unemployed claimants to receive benefits if they are approved it will be shorter than 3 weeks for some applications I deduct the original 'waiting time' by 3 weeks if the original 'waiting time' is equal to or greater than 3 weeks. If the original 'waiting time' is smaller than 3 weeks I reassign it to be 0. This recalculation of 'waiting time' will take into account the period that people have already applied but still not receive the benefits. Therefore, the actual 'waiting time' to apply for benefits should be at least what are recorded in Table 1.2 and Table 1.3. Table 1.2 shows 'waiting time' summary statistics for all unemployment spells, including both the unemployment spells that end as taking up unemployment benefits and unemployment spells still last until the time survey finished. The 'waiting time' found in Table 1.2 is an upper bound. Table 1.3 includes only the unemployment spells that end as taking up unemployment benefits during survey period and should be a lower bound of 'waiting time'[10].

Similar as in Table 1.1, if a person has multiple unemployment spells, I took an average of an individual's averaged length of waiting time and report as the 'waiting time' at individual level. 'Waiting time' is defined as the time gap between job separation begins and

[9]↑I exclude individuals who never worked during survey period. All individuals in the selected data have some work history which makes it more reasonable to assume the majority of them should be eligible for UI. But there should still be a percentage that are not.

[10]↑The 'waiting time' calculated in Table 1.2 and Table 1.3 is not the same as unemployment spells reported in summary statistics of Table 1.1. In Table 1.1 unemployment spells are defined as any length of time that a person is unemployed whereas in Table 1.2 and Table 1.3 include only the unemployment spell after a job loss.

unemployment insurance begins. If there is no unemployment insurance claim during the whole period of unemployment spell, the 'waiting time' is counted as the length of job separation(that unemployment spell). 'Waiting time' is different than unemployment spells since 'waiting time' captures the time gap between job loss and unemployment benefits take-up while unemployment spells simply capture the time length that unemployment last. Therefore, the number of 'waiting times' should be smaller (91613 in Table 1.2) than the number of unemployment spells (94911 in Table 1.1) as some of unemployment spells does not end up as unemployment benefits take-up. I divide 'waiting time' into two subgroups: The first group comprises those individuals who claim UI immediately after their job loss (Imm in Table 1.2 and Table 1.3). The second group comprises those who wait at least one week after job loss before applying for UI (NotImm in Table 1.2 and Table 1.3).

I also look at whether there is any pattern or change of behavior in terms of 'waiting time' among the first, second, third and more times of job separations. More specifically, I decompose the sampled data into four subgroups: first time; second time; third time; and more than third time job separations. Decomposing 'waiting time' into the n^{th} time of job separation help to delve into the question that whether there is any pattern or trend in terms of unemployed workers' 'waiting time' as the number of job separations increase. This breakdown of the data can also shed light on the potential reasons of why the unemployed will choose to wait or even give up on taking up unemployment benefits after job loss. Table 1.2 and Table 1.3 show the summary statistics of the average waiting time under each subgroup.

Table 1.2. Waiting Time Summary Statistics -Upper Bound

		AvgWaitT	MednWaiT	Min	Max	Number
All						
	Indivl/WaitTime	44.53(67.65)	17	0	279	91613
	Imm	0	0	0	0	17063
	NotImm	54.59(71.28)	21	1	279	74550
	Individual	60.42(77.33)	26	0	279	54469
	Imm	0	0	0	0	7002
	NotImm	68.74(80.62)	34	1	279	47467
FirstTime						
	All	60.20(78.78)	22	0	279	54072
	Imm	0	0	0	0	6864
	NotImm	68.90(80.71)	34	1	279	47208
SecondTime						
	All	28.13(43.08)	12	0	274	18140
	Imm	0	0	0	0	4007
	NotImm	35.93(45.90)	17	1	274	14133
ThirdTime						
	All	20.31(32.62)	7	0	255	8303
	Imm	0	0	0	0	2174
	NotImm	27.28(35.44)	15	1	255	6129
>ThirdTime						
	All	16.62(28.28)	5	0	263	8425
	Imm	0	0	0	0	2083
	NotImm	21.85(30.85)	11	1	263	6342

Table 1.3. Waiting Time Summary Statistics -Lower Bound

		AvgWaitT	MednWaiT	min	max	N
All						
	Indivl/WaitTime	12.99(29.59)	2	0	262	18550
	Imm	0	0	0	0	9249
	NotImm	25.69(37.72)	13	1	262	9301
	Individual	15.24(33.48)	3.7	0	262	8723
	Imm	0	0	0	0	4659
	NotImm	31.73(46.25)	17	1	262	4064
FirstTime						
	All	14.33(34.48)	1	0	262	8326
	Imm	0	0	0	0	4521
	NotImm	31.21(45.57)	16	1	262	3805
SecondTime						
	All	13.54(28.71)	2	0	261	4440
	Imm	0	0	0	0	2105
	NotImm	25.54(35.54)	14	1	261	2335
ThirdTime						
	All	12.47(23.59)	2	0	200	2357
	Imm	0	0	0	0	1039
	NotImm	22.05(28.05)	12	1	200	1318
>ThirdTime						
	All	11.22(21.38)	3	0	209	2730
	Imm	0	0	0	0	1051
	NotImm	18.01(24.97)	9	1	209	1679

Finding 1 (Extensive Margin): The vast majority of individuals do not apply immediately for unemployment insurance

As shown in Table 1.2, among the 54469 people in the sample, over 87% (47467) wait for at least one week before getting on unemployment. At individual/waiting time level, among the 91613 number of total 'waiting time', over 81% (74550) have at least a week gap between job separation and being on unemployment benefits. Thus, the vast majority of job separations do not end up in immediate unemployment benefits take-up, which is contrary to both the common assumption made in previous literature and how the unemployment insurance guidelines are described. As mentioned in Section 1.1, previous literature use immediate unemployment benefits take-up after job separation as an assumption when designing optimal unemployment program. This assumption would even affect the design of other welfare programs. For instance, Low and Pistaferri (2015) assumes immediate unemployment take-up when designing disability insurance, since disability insurance would interact with unemployment insurance. My finding in the data implies this common assumption of immediate unemployment take-up in previous literature could potentially cause sub-optimal in the design of optimal unemployment insurance, therefore may lead to improvement in current policy regarding optimal unemployment program design. In reality, all states instruct applicants to claim UI right after job loss in their unemployment guideline. It is stated in the guideline that the delay of claim of the unemployment benefits can cause loss of benefits. However, both the UI program guideline and the administrative officials are very vague and unclear about questions like what is the consequence of delaying application; how the application time would effect the benefits received; or what is the maximum number of weeks an applicant can wait before taking unemployment benefits after job separation. This lack of information can cause confusion and even hesitance of applying for unemployment benefits for the job losers, and may even cause longer 'waiting time'.

Finding 2 (Intensive Margin) There are non-trivial weeks of waiting time before taking on unemployment benefits: the upper bound of the median waiting time is 26 weeks, while the lower bound is 3.7 weeks at individual level .

As documented in Table 1.2, the median waiting time is 17 weeks at individual/waiting time level and 26 weeks at individual level. These numbers should be an upper bound of median waiting time since the sample include those that are unemployed but neither find jobs nor are on unemployment benefits by the time the survey finished. The sample used here treats all these 'waiting time' as if the individual eventually take up unemployment benefits. Therefore the numbers shown in Table 1.2 should be the upper bound of 'waiting time'. I focused on median, not mean waiting time here since as shown in Table 1.2 the maximum number of weeks waited is 279 weeks. This large maximum number of 'waiting' weeks will lead to a large 'mean'. At both individual and individual/waiting time level and for both all sample and people who apply non-immediately, the median waiting time is around 40% to 50% of average waiting time indicating the data is skewed to the right and mean values are driven by a small number of large ‘waiting time’ occurrences. Which very likely captures those who are already out of the labor market and not looking for either jobs or unemployment insurance thus should not be the interest to my questions in this paper.

Similar as in Table 1.1, Table 1.2 reports ‘waiting time’ at individual level that helps to demonstrate the feature of distribution of ‘waiting time’. In Table 1.2, the median length of waiting time is bigger at individual level (26 weeks) compared to individual/waiting time (17 weeks) level, indicating the median ‘waiting time’ for individuals with less than 1.4 times of ‘waiting time’ after job separation is more than 26 weeks while for individuals with more than 1.4 times of ‘waiting time’ after job separation is less than 26 weeks. As mentioned earlier, it is necessary to also report result at individual/waiting time level as the reported average ‘waiting time’ will be affected more by the extreme values if there are extreme values for individuals with less than 1.4 times of ‘waiting time’ after job separation, because these individuals are assigned more weight at individual level calculation.

As shown in Table 1.3, if looking only at unemployment spells that end up on unemployment benefits during survey period, the median waiting time at individual/waiting time and individual level is 2 weeks and 3.7 weeks respectively. This could be treated as a lower bound for average waiting time. Since the sample excludes those cases that are waiting to apply for unemployment benefits but are still waiting by the time the survey ends. This subsample is convincing evidence that this ‘waiting time’ does exists since the sample includes only those people that clearly qualify for UI and have the knowledge and capability to apply for benefits. In other words, for those people who are observed to have applied for unemployment benefits their ‘waiting time’ before applying unemployment benefits after job loss is not trivial.

> **Finding 3 (Multiple Separations): Although the average waiting time decreases as the number of times job loss has been experienced increases, individuals still delay application even after multiple job separations**

As shown in Table 1.1, people on average have 1.7 (54954 divided by 94911) job separations. Compared to the 1.7 of job separations, Table 1.2 shows people on average have 1.4

instances(54469 divided by 74550) of delaying before taking up unemployment benefits. In other words, among the 1.7 of job separations, there are on average 1.4 times that individuals do not apply unemployment benefits right after job loss. This number shows the interesting phenomenon that 'waiting' before taking on unemployment benefits is consistent behavior for individuals. It is therefore of interest to explore why there is this 'waiting' before taking on unemployment benefits for people with multiple unemployment spells.

There is a very interesting trend demonstrated in both Table 1.2 and Table 1.3. By comparing $NotImm$ in the first time, second time, third time and more than third time job separation shows a clear descending trend of 'waiting time' as number of job separation increases. For instance, in Table 1.2 the median waiting time drops from 22 weeks to 12 weeks comparing first and second job separations in all data, and from 12 weeks to 7 weeks from second time to third time job separation. In other words, it seems like the more times UI claimants have been on benefits, the less delay there will be to claim benefits after job loss. There are a few potential explanations for this. First, claiming unemployment can be shameful or degrading for many people, making the first time application harder. This psychological burden however reduces with experience in applying for UI. This explanation indicates that individuals initially feel shame applying for UI, but become habituated to it over time. Therefore, waiting time decreases as the number of job separations increases. Second, it is possible there is a 'learning' process as number of job loss increases. This can be an individual's learning about his skill types or ability as more information gathered each time he is being laid off and goes on unemployment. For instance, a self-evaluated high ability worker may realize he is not as competitive and valuable as he thought in the labor market after being more 'experienced' in job loss. The individual is likely to learn and adjust his judgement based on information obtained from previous feedback or 'signals' and reduce waiting time for UI application after another job loss. It can also be 'learning' about the economic environment. For instance, an unemployed worker learns how tight the labor market is each time he is separated from job and adjusts his belief of market tightness accordingly after receiving these 'signals'.

1.3 What Influences Application Delay

The previous section demonstrated that waiting to apply for UI is a serious issue in the SIPP 2008. It demonstrated that a large fraction of individuals delay application, and that these delays are typically for a significant period of time. In this Section I explore the observables that influence the decision to delay, both on the extensive and the intensive margin. In Section 1.3.1, using Probit and linear regressions I look to see what kind of factors influence the extensive and intensive decision to delay. In Section 1.3.2 I conduct a more nuanced 'conditional application' analysis: I look at what influences behavior in any given time period, conditional on being unemployed without UI in the previous time period.

1.3.1 Probit and Linear Regression

Now I continue to explore the extensive margin to wait – the potential factors that could have effect on whether a person will wait before applying for benefits. First, I use the Probit model to explore how the explanatory variables chosen can explain whether the unemployed will apply for benefits. Specifically, I use the following as explanatory variables: *gender, race, age, education, marital status, total family income, indicator for disability, state unemployment rate at the specific month interviewed and number of times lost jobs.* [11] I interpret the state unemployment rate (by month) as a proxy for local economic conditions. SIPP unfortunately does not ask about the health status of respondents. I interpret the disability indicator as a crude proxy of health status.

Specifically the Probit regression I run is:

$$Wait_{i,t} = \beta_0 + \beta_1 jobloss\_time_{i,t} + \beta_2 unem\_rate_t + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{1.1}$$

In the above regression, dependant variable $Wait$ is whether there is time gap between job loss and being on unemployment insurance, or in other words, whether there is 'waiting

[11] ↑Gender is recoded as 0 for male and 1 for female. Race is recoded as 0 for non-white and 1 for white. Marital status is recoded as 0 for non-married and 1 for married. Education are recoded as number of years of education. Disability indicator is recoded as 1 for with work-limiting disability and 0 for without work-limiting disability.

time' before taking up unemployment benefits [12]. Explanatory variables are the 'n^{th}' time of job loss($jobloss\_time_i$), state unemployment rate at the month interviewed as proxy for local economic conditions($unem\_rate_{i,t}$), and the demographic characteristics including gender, race, age, education, marital status, total family income, whether disabled which are captured in $X_{i,t}$. Table 1.4 shows regression results for the Probit model. The regression include year and state fixed effect and cluster at industry level. The reason to cluster at industry level is to deal with the possibility that 'waiting time' for people working in the same industry might be correlated. The results for significant factors do not change if cluster at occupation level.

Next I analyze the intensive margin to wait –how the explanatory variables would effect waiting time using simple linear regression model as shown in Table 1.4. Dependant variable is number of weeks waited before taking on UI benefits. I included state and year fixed effect and cluster at industry level same as Table 1.4.

The Linear regression equation I used is,

$$WaitingTime_{i,t} = \beta_0 + \beta_1 jobloss\_time_i + \beta_2 unem\_rate_i + \beta_3 X_{i,t} + \epsilon_{i,t} \tag{1.2}$$

The dependent variable in the above linear regression is the number of weeks waited before taking up unemployment benefits after job loss. If the claimant took up the unemployment immediately, the 'waiting time' is 0. If an unemployment person is still unemployment and not on unemployment benefits at the time the survey ended, the 'waiting time' is the number of weeks unemployed after job loss until survey ends. There are a total of 73822 number of observations including 37085 number of people since one individual can have multiple job separations. The number of sample here is smaller than the sample in Table 1.2 (54469) after dropping individuals who never reported information on the industry they have worked in. Table 1.4 documents regression results for Probit and linear regression.

[12]↑The waiting time is calculated using the same interpretation as in Table 1.2. If a person is still not on unemployment benefits at the end of survey period the waiting time is calculated from the start of job separation until the end of survey period. Similarly, if a person 'waited' t weeks after job loss and not on unemployment benefits but at week $t+1$ report to find job the 'waiting time' is calculated from the start of job separation until the time the job is found again.

Table 1.4. Probit and Linear Regression Results

	Probit If_Wait	Linear Wait_Time
Age	-0.0131***	-0.0730**
	(-10.98)	(-3.02)
Education	0.00366	-0.713***
	(0.89)	(-3.46)
Gender	0.232***	8.462***
	(4.30)	(6.08)
Marital Status	-0.0337	1.345
	(-1.23)	(1.79)
White	-0.0249	-3.381***
	(-1.17)	(-6.27)
Disable	0.356***	18.25***
	(8.65)	(20.25)
State Unemployment Rate	-0.0572***	-1.021***
	(-7.07)	(-4.97)
Total Household Income	-0.0000160***	0.0000104
	(-10.31)	(0.35)
Number of Times Lost Jobs	-0.0656***	-1.102**
	(-10.58)	(-2.75)
Constant	1.804***	61.21***
	(13.93)	(11.15)
Observations	73822	73822

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finding 4:

- **A lower age, a lower household income, being disabled or being female make delay more likely**
- **Good economic conditions make delay more likely**
- **Fewer experienced number of job separations makes delay more likely**

As shown in the first column of Table 1.4, the effect of age on whether waiting is negative and statistically significant. Holding all other variables constant, one year increase of age will decrease the probability of 'waiting' by 0.0131, indicating younger unemployed individuals are more likely to wait before taking on unemployment benefits. This relation can be explained as young workers are more confident in their skills or ability to re-find jobs or less experienced in taking advantage of the opportunity to take up UI when separated from jobs compared to older workers. Older workers are one, likely to lack the skills required in modern working environment, such as computer skills to find jobs again; and two, more experienced in the labor market and likely to be more familiar with the unemployment benefit program.

The first column of Table 1.4 also documents that holding all other variables constant, being women will raise the probability of 'waiting' by 0.232 compared to men and the coefficient is significant at 1% level. This finding coincides with some of society's consensus about women and men such as women are in general more patient, less impulsive and more sensitive about self-esteem and self-image than men. Being more 'patient' implies women will more likely to 'wait' before taking on action, in this case applying for the unemployment, after a bad event such as job loss occur. Women in general care more about others' perception about them and in this case, applying for the unemployment is a psychological burden and potentially hurtful to a person's self-esteem and self-image. Therefore, as a way to protect self-esteem women are more likely to be reluctant on taking up the unemployment compared to men.

The first column of Table 1.4 indicates people with disability will raise the probability of 'waiting' by 35.6% compared to people who are reported to be healthy. The result is significant at 1% level. There is a possible explanation for a longer delay before applying for unemployment benefits for people with disability. Disabled individuals have other choices of benefit programs that they may be eligible for which have higher replacement rate and longer duration than unemployment benefits. People with disability may be eligible for programs such as SSDI (Social Security Disability Insurance) or SSI (Supplemental Security Income). Whether this explanation is the reason for the disabled individuals to wait longer before taking up UI will be investigated in more depth in Chapter 3.

Probit regression results shows one unit increase in unemployment rate decreases probability of 'waiting' by 0.0572, indicating individuals are less likely to wait before taking up unemployment insurance when economic conditions are not good. When the economic are in downturn, unemployment rate is high and labor market is tight. The unemployed workers expect themselves to be less likely to find jobs during economic downturn and then more likely to take up unemployment insurance right after job loss, or less likely to 'wait'. Therefore, the finding from data about relation between waiting time and economic conditions are consistent with our expectation.

One of the most interesting findings from Probit regression is that people are less likely to wait as the number of job loss increases. Table 1.3 showed that as number of job loss increases, the average 'waiting time' decreases. Finding in the first column of Table 1.4 is consistent with that in Table 1.3. The more times a person loses his job, the less patient he will be before taking up unemployment benefits after job loss, in other words less likely to wait. This phenomenon seen in the data is an indicator that there may be 'learning' behavior as individuals are more and more 'experienced' in job loss. An individual is likely to update his belief about his self-ability and capability of finding a new job each time he lost job. The existence of learning behavior provides a plausible explanation for the 'waiting' seen in the data and I will provide a model using 'learning' as a mechanism to account for this finding in the data in Chapter 2.

One factor that would also significantly affect the probability of 'waiting' is total household income. On the contrary to expectation, total household income is negatively correlated to the likelihood of waiting. In other words, the higher total household income is, the less likely a person will wait before claiming for UI. One possible explanation is higher total household income may indicate a higher regular expenditure and a more expensive lifestyle to maintain. A higher total family income means a possibility of more family members and more people to support. Therefore, in the event that one of the family members lost major source of income he is also under a big burden to collect as much other source of income as possible in order to maintain the regular expenditure and lifestyle of the family.

Finding 5:

- **A lower age, being disabled, being female, a lower education level, or being non-white increase the length of delay**
- **Good economic conditions increase the length of delay**
- **Fewer experienced number of job separations increases the length of delay**

As shown in the second column of Table 1.4, one year increases of age will decrease the number of weeks waiting by 0.073 weeks and the result is significant at 5% level. Younger unemployed workers will wait longer compared to older workers. This result is consistent with the effect of age on the extensive margin to wait shown in Probit regression. The younger workers are more likely to wait (extensive margin) and wait longer (intensive margin) before taking up unemployment benefits compared to older workers. These two phenomena can both be explained as young workers may be more confident in finding new jobs or in their abilities in finding new jobs therefore are willing to wait before taking up the unemployment. It is also possible that older workers are more 'experienced' in job loss and the process of applying for unemployment insurance therefore it is less costly for the older worker to apply unemployment benefits.

Education is not a significant factor on the extensive margin to wait but is a significant factor on the intensive margin. More specifically, one year increase of education decreases 'waiting time' by 0.713 weeks, and the result is significant at 1% level. One possible explanation for this phenomenon in the data is the more educated also have a higher ability to get familiar with the whole process of applying UI benefits, including whether he/she is qualified and what actions need to be taken to claim benefits. In other words, the process of applying for benefits is easier and less costly for more educated individuals. More educated individuals are not necessarily more likely to wait compared to less educated individuals (Education is not significant in Probit regression) but wait shorter if they wait (Education is significant in Table 1.5). This can be explained by that higher education does not necessarily mean higher probability of waiting since it is very possible that higher educated individuals have higher psychological burden and claiming unemployment is more likely stigma compared to less educated individuals. However, higher educated individuals do have shorter 'waiting time' implying it is possible the execution cost is lower for the more educated people so they wait shorter to apply if they decide to apply.

As shown in the second column of Table 1.4, being women will increase the number of weeks waiting by 8.46 weeks compared to men. This finding is also consistent with the finding in Probit regression. Women are more likely to wait and wait longer before taking up unemployment benefits after job loss compared to men. As previously analyzed, these findings are in accordance with the common gender difference agreed in the society. Women are in general more patient and have higher self-esteem and cares more about self-image compared to men. These traits would all help explain why women are more likely to wait and wait longer to take up unemployment. Further study can be done with respect to the gender difference in the behavior of claiming unemployment benefits.

Also, in terms of race white unemployed workers have shorter 'waiting time' compared to the unemployed who are non-white. Being white decreases the number of weeks wait by 3.381 weeks compared to non-white. The exact reason of why this would be the case is beyond the scope of this paper but one possible explanation I can think of is simply the unemployed white people are on average more familiar with the unemployment insurance system compared to non-white. Therefore, the process of UI application is executively less costly for white individuals. It is worth mentioning that race is not a significant factor of the extensive margin to wait as shown in Probit regression, meaning there is no evidence to show that white applicants are more likely to apply or being approved of unemployment benefits. Therefore, it should be of caution to attribute the finding in linear regression as race discrimination.

Lastly, being disabled will increase the number of weeks waiting by 18.25 weeks. This finding is consistent with finding in Probit regression, being disabled are more likely to wait and wait longer before taking up unemployment benefits after job loss. These results indicate the disabled individuals are less likely to be on unemployment insurance and more likely to resort to other welfare program, i.e. disability insurance. Disability insurance has higher replacement rate compared to unemployment and also will continue to provide support as long as the health condition does not improve. Therefore, from the data the disabled individuals are more likely to hold on applying for the unemployment and resort to other resources as support.

Second column of Table 1.5 shows the higher the unemployment rate is the shorter the 'waiting time' will be. I use unemployment rate by state by month as proxy for economic condition. One percent increase of unemployment rate will decrease 'waiting time' by 1.021 weeks. Higher unemployment rate indicates a tight labor market and the economic condition is not well. The unemployed workers 'adjust' their 'waiting time' as economic condition changes. When the economic is doing well and unemployment rate is low, the unemployed workers will wait longer before applying for unemployment benefits. On the contrary, when economic is not doing well and unemployment rate is high, the unemployed workers decrease their 'waiting time' and get on unemployment faster. This change of 'waiting time' as economic condition changes can indicate the unemployed would evaluate and adjust their beliefs when economic conditions change. I will provide a model to incorporate change of belief in the structural model in Chapter 2.

One of the most important findings of the second column of Table 1.4 is that a onetime increase of job loss decreases 'waiting time' by about 1.1 weeks. The result is significant at 1% level. This provides further evidence that people are 'less patient' as number of times separated from jobs increase. In other words, individuals have shorter waiting time before claiming and getting on unemployment insurance the more 'experience' they have in terms of job loss. This finding is important evidence to support the existence of 'learning' behavior when applying for unemployment insurance. Each time an individual lost his job he will update the belief of his skill level or ability as to how likely he will find a job again. Each time of job loss can be treated as a 'signal' sent to an unemployed individual of his skill level and his belief of skill level is updated every time a signal is sent, therefore a 'learning' process. This 'learning behavior' and update of beliefs will be the mechanism I model in later section to explain the major findings in the data.

Compare the two columns of Table 1.4, Age, Gender, Whether Disable are demographic factors that will have significant effect on both intensive margin and extensive margin to wait. Decrease of age, being women, being disabled will increase both the likelihood of waiting and the length of waiting time.

Education and race are not significant factors for extensive margin to wait but are significant factors for intensive margin to wait. Individuals with higher education and being white do not necessarily mean they are more likely to wait but individuals with higher education and being white will wait shorter before applying for benefits after job loss. One possible explanation for this phenomenon may be that executive cost for the less educated and non-white people to apply for unemployment is higher.

Total household income is a significant factor for the extensive margin to wait but not intensive margin to wait. The unemployed with higher total household income are less likely to wait before taking up unemployment but there is no evidence they will wait longer.

The findings of the effect of economic condition and number of times lost job on 'waiting' is consistent on the extensive and intensive margin. As economic condition worsened and number of times lost job increases both the likelihood and number of weeks waiting will decrease.

Probit and Linear Regression with Different State Backdate Policies: Different state has different backdate policies of claiming UI. Some states allow for backdate when applicants claim UI some states do not allow for backdate. For instance, Indiana does not allow for backdate when claiming UI. UI applicants are not allowed to go back and claim benefits for previous weeks and file dates can not be 'backdated' for weeks that the applicant has missed. The claim of UI for next week must be completed by Saturday of the week in order to receive benefits for the following week. On the other hand, Maryland allow backdate of UI claim. No matter when the applicant file the claim, the applicant becomes eligible for benefits starting the day after he/she separated from employment. The payment will be backdated to the date the applicant become unemployed and if determined eligible the applicant will be paid for all benefits due. Based on the variation of UI retroactive policies in different states I run Probit and linear regression to see how the difference of retroactive policies will effect waiting time of UI. The states are divided into three categories based on their UI backdate policies. The first category (Type I) includes states that allow backdate of UI claim and the process of applying for backdate payments is easy and straightforward and does not require additional paperwork; the second category (Type II) includes states that all backdate of UI claim under certain conditions and requires the applicants to fulfil additional procedures or fill out additional paperwork in order to decide whether he/she is eligible to claim retroactive benefits payment and how long the payments can be backdated to; the third category (Type III) includes states that do not allow backdate claiming of UI. Among the 50 states, 12 states are categorized as Type I, 11 are categorized as Type II and 27 are categorized as Type III. Type I include states such as Arizona, Idaho, Illinois, Maryland; Type II include states such as Delaware, Kentucky, Louisiana; Type III include states such as Alabama, Alaska, Michigan, New York.

Table 1.8 shows the main variable summary statistics for the three types of states that have different backdate UI policies respectively. We can see from Table 1.8 that all variables are not meaningfully different across the three states except for total household income. Type I states (states that UI backdate are easy) have the highest average and median total household income while Type III states (states that do not allow UI backdate) have the lowest average and median total household income. Average education level are the same for the three states types and is 'some college, without degree'. Table 1.9 and Table 1.10 show the upper and lower bound of waiting time summary statistics for states with different backdate policies. From Table 1.9, comparing the upper bound of waiting time across the three types of states we are see that type II (states that allow backdate but require additional paperwork or information) states have the longest average waiting time at both individual/waiting time level and individual level. Type I (states that UI backdate are easy) have the shortest average waiting time at both individual/waiting time level and individual level. This is an interesting finding and not fully within expectation. Unemployed individuals living in states that UI backdate are easy have the shortest waiting time shows that a more convenient backdate policy will reduce waiting time of unemployed individuals. Results in Table 1.10 are fully within expectation. From Table 1.10 comparing the lower bound of waiting time across the three types of states we can see that individuals living in Type I states have the lowest average waiting time at both individual/waiting time level and individual level. Moreover, individuals living in Type III states have the highest average waiting time at both individual/waiting time level and individual level. This finding shows a UI backdate policy that allows unemployed individuals to easily backdate their benefits will reduce the delay of claiming UI; whereas if the state does not allow UI backdate it will increase the delay before claiming UI. The findings in Table 1.9 and Table 1.10 are further evidence that reducing the barrier of claiming UI can reduce the application delay. This barrier to claim UI can also be attributed as part of total application costs (administrative costs). This is in line with the finding in Chapter 2 that a small reduction of the hassle of claiming UI can have meaningful impacts on delay of application.

I run Probit and Linear regression separately for the three different state types and compare the results to see how variation of retroactive policies will affect the 'waiting time'. Results are shown in Appendix 1.5.2. Table 1.11 shows Probit regression results and Table 1.12 shows linear regression results for different state types. Comparing the three columns in Table 1.11 race has significant effect on probability of waiting for Type I and Type II (allow backdate claim) states but does not have significant effect on probability of waiting for Type III (do not allow backdate claim) states. This is an interesting finding as the states different retroactive policies can potentially determine whether race will be a significant factor on probability of waiting. More specifically, for states that allow for retroactive claim of UI, being white has significant effect on the probability of 'waiting' and nonwhite applicants are more likely to wait before applying UI. However, for states that do not allow for retroactive claim of UI, race does not have significant effect on the likelihood of 'waiting'. It is not clear why the variation of states' UI backdate policies will effect race the way it is and the link between the two is worth further study. Table 1.12 shows how variation of states' UI backdate policies will affect the length of waiting. Comparing the three columns of Table 1.12 we can see for states that allow for UI backdate claim, marital status does not have significant effect on UI 'waiting time' whereas for states that do not allow for UI backdate claim marital status has significant effect on UI 'waiting time' at 10% significance level. For states that allow for UI backdate claim, economic conditions (proxy by state unemployment rate) does not have significant effect on length of 'waiting' while for states that do not allow for UI backdate claim economic conditions have significant effect on the length of 'waiting' at 1% significance level. For states that do not allow UI backdate claim, worse economic conditions will significantly reduce waiting time before claiming UI and applicants that are unmarried will significantly reduce 'waiting time' compared to those that are married. I think these findings make sense intuitively. For states that do not allow for backdate claim applicants will likely be more sensitive to the timing of applying for benefits since they are not able to claim any benefits retrospectively to make up for the time that they have missed after job loss without benefits. Therefore, in states that do not allow UI backdate claim, when economic conditions are bad UI applicants will have shorter waiting time. Unmarried applicants do not have a spouse to provide income to smooth consumption when separated from jobs and therefore will have shorter waiting time if backdate claim is not allowed.

1.3.2 Conditional Application

In this section I further study what happens in week $t+1$ conditional on unemployed without unemployment insurance at week t. There are three potential outcomes in week $t+1$ conditional on unemployed at week t: finding job, unemployed with unemployment insurance, and unemployed without unemployment insurance. I first draw Kaplan-Meier Curves to demonstrate the proportion of population that survive at time $t+1$ conditional on survived at time t. Then I run Cox proportional hazards regression to analyze the variables that will have significant effect on survival time.

Kaplan-Meier Curve

Kaplan-Meier curve is popularly used in the medical field to analyze how the introduction of a new treatment would effect the survival times of the subjects and shows the fraction of subjects living for a certain amount of time after treatment. The 'event' in these studies is usually death of the subjects. Kaplan-Meier estimates can also be used in other context to study more general questions with the 'event' being any event of interest. For instance it can also be used to measure the length of time people remain unemployed after a job loss [15]. Here I will use the Kaplan-Meier estimates to understand 'conditional' decisions to apply to UI, where the 'event' does not occur if during the number of periods that have passed since job separation UI has not yet been applied for. An 'event' occurs at week t if an individual takes up UI after idling for t weeks. Thus, I think of 'survivors' as individuals who are separated from jobs but still haven't applied for UI, while non-survivors are those who apply for UI.

I first draw Kaplan-Meier curves to visually represent the survival function. Kaplan-Meier curves show the probability of an event is at a certain time interval. Figure 1.3 shows the probability of still having not applied for UI at time $t+1$ conditional on being unemployed without UI benefits at time t. Subfigure 1.3a - Conditional Idle shows the probability of being still unemployed without either job or unemployment insurance at time $t+1$. Subfigure 1.3b - Conditional UI is the probability of unemployment with unemployment insurance at time $t+1$ and Subfigure 1.3c - Conditional Job shows the probability of transitioning into having job at time $t+1$ from unemployment.

The survival probability[13] of a regular Kaplan-Meier curve at any particular time is calculated using formula:

$$S_t = \frac{Number\ of\ Subjects\ Living\ at\ the\ Start - Number\ of\ Subjects\ Died}{Number\ of\ Subjects\ Living\ at\ the\ Start}$$

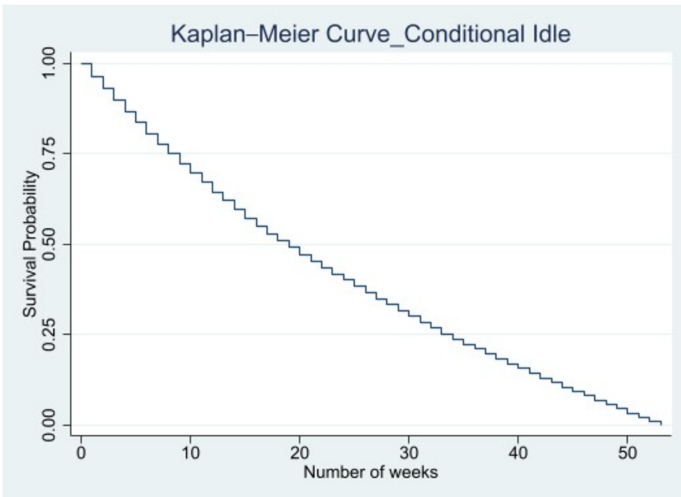
Corresponding to the above formula, in my study, the survival probability of Kaplan-Meier curve is calculated using:

$$S_t = \frac{Number\ of\ Subjects\ Idling\ at\ the\ Start - Number\ of\ Subjects\ Transitioned}{Number\ of\ Subjects\ Idling\ at\ the\ Start}$$

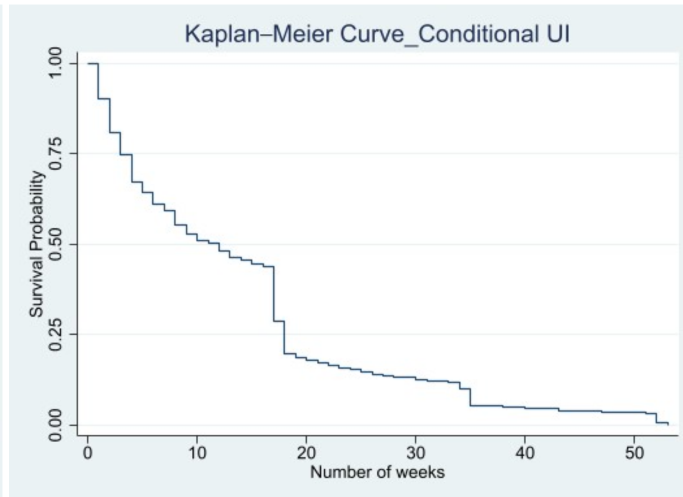
[13]↑$S(t)$ is also called a survival function and is the percentage of subjects surviving at time t.

Where the number of subjects transitioned will be number of subjects remained idling, number of subjects claimed UI or the number of subjects found jobs.

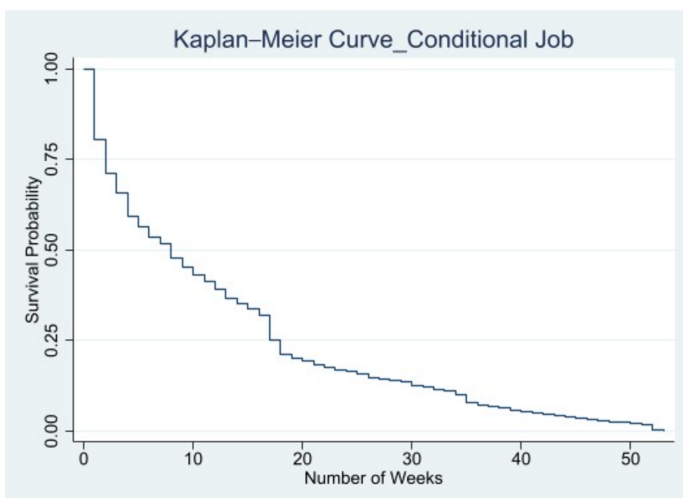
In Figure 1.3, the x axis of each of these sub-figures is the number of weeks since job separation and the y axis is the proportion of subjects 'surviving' where what survival means depends on the subfigures and the curve shows the progression of event occurrences. A vertical drop of Kaplan-Meier curve indicates individuals exiting that status. More specifically, a vertical drop of Subfigure 1.3a of Figure 1.3 represents the proportion of subjects transitioned out of being idle(unemployed without benefits) in week t. A vertical drop of Subfigure 1.3b of Figure 1.3 is the proportion of subjects claimed UI in week t. And a vertical drop of Subfigure 1.3c of Figure 1.3 is the proportion of subjects found jobs in week t. I truncate the curves to 53 weeks as the survival probability drops to close to zero after 50 weeks and longer time is also more susceptible to misreport.



(a) Conditional Idle



(b) Conditional UI



(c) Conditional Job

Figure 1.3. Kaplan-Meier Curve

Finding 6:

- **We observe large drops in transitions into unemployed and with UI over the first four weeks, and weeks 17, and 35**
- **We observe large drops in transitions into employment over the first four weeks and weeks 17 and 18.**

There are a total number of 2086441 'conditional idle events'. Subfigure 1.3a of Figure 1.3 shows the Keplan-Meier curve for conditional idle– the proportion of subjects remains idling in period $t+1$ given the idling in period t. In this case, an 'event' occurs in week t if an individual transitions out of the status of idling in week t. The vertical drop of Figure 1.3 is smooth and does not have drastic change meaning transitions out of idling is consistent in each week and there is not big or sudden occurrences in terms of the number of 'conditional idle events' in each week. Moreover, the vertical drop becomes smaller and smaller as the number of weeks increase indicating there is a decreasing number of 'transitions out of idling' events occur in each week as time increases. For instance, based on Subfigure 1.3a of Figure 1.3 conditional on idling at week 0, the vertical drop in week 1 is about 2.5 times of the vertical drop in week 50. This indicates the number of 'transitions out of idling' events occur in week 1 is about 2.5 times of that occur in week 50.

There are a total of 2227 'conditional UI' events, where 'conditional UI' events indicate that conditional on being unemployed without benefit(idle) at week 0 the number of subjects transition into unemployed with unemployment benefits in week t. Subfigure 1.3b of Figure 1.3 shows relatively big vertical drops for the first four weeks, weeks 17 and 18 and week 35 indicating a large number of 'conditional UI' events occur in these weeks.The big vertical drops for the first four weeks indicate that about 33%(1 minus 0.67) of 'conditional UI' events happen in the first four weeks. The other big drop at week 17 and 18 indicates about 23%(0.43-0.18) of 'conditional UI' events occur at week 17 and 18. The large number of 'conditional UI' events occur in the first four weeks are not surprising. Many literature have documented that the number of UI claimants decrease as the time after job loss increases [16][17][18]. What is noteworthy in Subfigure 1.3b is the big vertical drop around week 17, 18 and week 35 indicating a large proportion of subjects claim UI around week 17, 18 and week 35. The relatively large proportion transitions from idling to conditional UI should be caused by 'seam bias'. Since the survey interview is conducted every four month, studies (Moore 2008; Ham, Li and Sheppard 2009; Moore, Bates, and Pascale 2009; Martini 2009; Callegaro 2008) [19] [20] [21] [22] [23] have shown there are more transitions reported around the seam (month 4 of every interview) and this phenomenon is called 'seam bias'. The seam of survey interview corresponds to week 17 and week 35 of where more 'conditional UI' events occur. More discussion of the seam bias will be in Section 13 Cox regression Analysis.

There are 48293 'conditional job' events occurred, where 'conditional job' events indicate the number of subjects find jobs in week t conditional on idling in week 0. Subfigure 1.3c of Figure 1.3 illustrates big vertical drop for the first four weeks and week 17,18 indicating a lot of individuals found jobs in these weeks. About 20%(1-0.8) of 'conditional job' events happen in the first week and about 41%(1-0.59) of 'conditional job' events occur in the first four weeks indicating a large proportion of idling individuals found jobs in the first four weeks. About 11% (0.33-0.22)of 'conditional job events' occurs in week 17 and 18. Similar as in 'conditional UI' events, it is not surprising a big proportion of subjects find jobs soon after job loss. The relatively big transitions into jobs from idling around week 17 and 18 should be causes by 'seam bias' which will be discussed in more depth in the next section.

Cox Regression Analysis

'Seam bias' is a known limitation of SIPP data and is clearly evident in the Kaplan-Meier figures where transitions or changes in status within an interview are underreported and transitions and changes between interviews are overreported. The existence of seam bias has been documented for different longitudinal surveys including the Current Population Survey(CPS), the Panel Study of Income Dynamics(PSID) and the Survey of Income and Program Participation(SIPP).Seam bias is especially a concern for study of duration models since the spell starting and ending date may be misreported[20][19]. SIPP uses rotation group design which means the total household sampled are randomly selected and divided into four rotation groups. Members of one rotation group are interviewed regarding the previous four months in each calendar month.Therefore all rotation groups in a panel will be interviewed over a four month period. The existence of seam bias is likely to cause more reports of transitions around the seam, in the SIPP data, more transitions around the end of the 4^{th} reference month (Kalton and Miller, 1991; Martini, 1989; Ryscavage, 1993; Young, 1989) [24][25][23][26][27]. In order to improve the seam bias issue the U.S. Census Bureau revised the SIPP questionnaire using a more extensive and comprehensive procedure called dependent interviewing(DI) starting from the 2004 panel. The new DI procedures incorporated in 2004 panel explicitly link the wording of current interview questions to information provided in previous interview when designing the questionnaire [28]. With the improvement of DI procedures, Moore (2008)[19] has shown the seam bias is substantially lower in 2004 panel compared to previous panels but still visible and to a substantial extent. Due to the nature of question-by-question interviewing approach using calendar months as reference that SIPP currently use the seam bias will never be fully eliminated.

Since the study of waiting time before UI take-up in this paper involves locating the start and end time of job separation and unemployment benefits claim, the existence of seam bias can potentially cause measurement error when calculating the 'waiting time'. There are potentially a lot more job separation and UI take-up reported in reference month 4 (on seam) compared to other months(off seam) due to seam bias. To address the concern of seam bias on the calculation of 'waiting time', I use one of the commonly used approaches which is adding a 'seam' indicator(Blank and Ruggles(1996) [29], Fitzgerald(2004)[30]), where the last reference month is included as a dummy variable. More specifically, adding dummy variable 'seam' where 'seam' is defined as 1 if the reference month is 4(where the interview is conducted) and 0 otherwise. During each interview information is collected about the previous 4 months, therefore month 4 is the 'seam month'.[14]

Cox proportional hazard model [32] is a regression model commonly used to investigate the relationship between the 'survival time' and the predictor variables. I use the Cox proportional hazard model to provide a quantitative analysis of conditional application, i.e.

[14]↑In the 2008 SIPP panel individuals surveyed are interviewed every 4 month over a 32-month period, where they are divided into four rotation groups. Each rotation group was interviewed in a separate month. The Four rotation groups constitute one cycle, i.e a 'wave'[31]. Thus in each calendar month only a quarter of people in the survey are interviewed. In each calendar month, depending on which rotation group the interviewed individual is in, he would be in 1,2,3 or 4 of the reference month where reference month 4 is the month the interview will be conducted for the rotation group the individual is in.

to evaluate what factors will have significant effect on the probability of the 'event' happening and how there factors will affect it. The 'event' here is UI take-up after 'surviving' n week(s) of idling (separated from jobs but still haven't applied for UI). Similar as described previously in the Keplan-Meier Curve section the 'survival time' is the number of weeks that have passed since job separation and that UI has not been applied for.

Cox regression models the natural log of a binary outcome y as a function of predictors and the follow-up time t. The formula used for Cox regression is generally written as,

$$h(t) = h_0(t)\exp(\beta X) \tag{1.3}$$

Or,

$$ln(h(t)) = ln(h_0(t)) + \beta X \tag{1.4}$$

Where $h(t)$ is the hazard[15] which is the risk (or probability) of having the event occur ($y = 1$) at time t and it is time-variant.[16] ($h_0(t)$) is the hazard that an event occur ($y = 1$) at time t when $X = 0$. β is the change of hazard that $y = 1$ for one unit change in X at any time in the follow-up (time-to-event) period. In Cox proportional hazard model e^{β} is referred as the hazard ratio and can be interpreted as the difference in hazard per unit difference in X at any time. One key assumption of Cox proportional hazard model is constant hazard ratio meaning even if the hazard changes over time the ratio between any two groups does not. If X is a categorical variable, the difference of hazard among different category of groups does not vary over time as β is constant over time. Since all subjects share the same baseline hazard $h_0(t)$, Cox proportional hazard model allows estimate of coefficient for predictors without the need to estimate the baseline hazard $h_0(t)$[17].

[15]↑hazard or hazard rate is an instantaneous probability of state transition at time t, conditional on already survived that long. It can be more formally defined as $h(t) = P(T = t \| T \geq t) = \frac{P(T=t)}{S(t)} = \frac{f(t)}{S(t)}$ where $f(t)$ is the probability density of failure at time t and $S(t)$ is the survival function. hazard rate is the probability of an event occur in the next few second given the event has not currently occurred.

[16]↑Sometimes the Cox regression are rewritten using natural log in order to have unconstrained estimation of the slope β since the hazard $h(t)$ can only be between 0 and 1 but the range of $ln(h(t))$ is $(-\infty, \infty)$.

[17]↑If there is one unit change of X , $\beta = ln(y = 1, X + 1) - ln(y = 1, X) = ln\frac{y=1,X+1}{y=1,X} = ln(hazard\ ratio)$ and$\mathrm{e}^{\beta} = hazard\ ratio$.

I run Cox Regression to estimate how the covariates of interest would affect the probability of 'survival', where the probability of survival is the 'hazard rate' in Cox regression model. In this case, the 'survival' is the number of weeks that have passed without getting on UI or finding jobs.

The Cox regression I run for transitions into unemployed and with UI in $t+1$ given unemployed and without benefits in t is ,

$$Hazd_{UI}(t)_i = Hazd_{0,UI}(t)_i + \beta_1 jobloss\_time_{i,t} + \beta_2 unem\_rate_t + \beta_3 seam_t + \beta_4 X_{i,t} + \epsilon_{i,t} \tag{1.5}$$

In the above Cox proportional hazard model, $Hazd_{UI}$ is found by calculating the maximum likelihood function using the observed occurring of an event for subject i at time t[18]. $jobloss_time$ is the number of job separations. $unem\_rate$ is state unemployment rate for the given calendar month. $seam$ is the dummy variable of whether the week an individual is interviewed is in the seam month. X are demographic characteristics including education, gender, age, whether white, total household income, whether disabled and marital states. Observations are clustered at individual level. Since the key assumption of Cox model is constant hazard ratio I test this assumption in Appendix 1.5.3. Figure 1.4 in Appendix 1.5.3 shows that assumption of constant hazard ratio is satisfied for Cox proportional hazard model.

Cox regression results for transitions into unemployed and with UI are shown in Table 1.5. I report both regression coefficient and hazard ratio in the result.The coefficients report the value of β. If coefficient is positive, then as the independent variable increases the hazard for the event to happen increases (since β is positively correlated to hazard rate in Cox proportional hazard model) and the time-to-event decreases. Whereas a negative sign of regression coefficient means the hazard is lower and time-to-event increases as the independent variable increases. The hazard ratio is the exponential of the coefficients ($h(t) = e^{\beta}$) and gives the effect size of covariates. If coefficient β is positive the hazard ratio is bigger than 1 and if β is negative then the hazard ratio is between 0 and 1. Hazard ratio shows when

[18]↑the number of weeks between an individual begin at risk to the time an event occur,and in this case, the time an idling individual start taking up unemployment benefits.

the dependent variable changes by one unit how much would the hazard rate (probability of event happening) change. The number in parenthesis is the z-score or the number of standard deviations a data point lies from the mean.

Table 1.5. Cox Regression-Conditional UI

	(1) Coefficient	(2) Hazard Ratio
Education	0.017	1.017
	(1.87)	(1.87)
Gender	-0.393***	0.675***
	(-7.79)	(-7.79)
Marital Status	0.106	1.111
	(1.74)	(1.74)
White	-0.633	0.939
	(-1.05)	(-1.05)
Disable	-0.369***	0.691***
	(-4.83)	(-4.83)
State Unemployment Rate	0.091**	1.095**
	(3.10)	(3.10)
Total Household Income	-0.0000327***	0.9997***
	(-4.94)	(-4.94)
Age	0.0227***	1.023***
	(12.99)	(12.99)
Number of Times Lost Job	0.0891***	1.093***
	(-4.61)	(-4.61)
Seam	5.473***	234.229***
	(21.34)	(21.34)
year==2012	-0.249*	0.779*
	(-2.29)	(-2.29)
Observations	2034558	2034558

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finding 7:

- **Being non-white, disabled, lower income, fewer previous job separations all decrease the hazard rate of transitions into unemployed with UI**
- **Being interviewed at a seam month increases the hazard rate of transitions into unemployed with UI**

As shown in 1.5, the coefficient is smaller than 0 for female applicants[19], hazard ratio is equal to 0.675 (exp(-0.393)). This result indicates that being female will decrease the probability of conditional unemployment benefits by 32.5% (1-0.675) compared to male applicants and the result is significant at 1% level. In other words, conditional on currently unemployed without benefits female applicants are less likely to get on unemployment insurance in the instant future (hazard is an instantaneous probability) and female will have a longer duration of 'waiting' before getting on UI. Moreover, a hazard ratio of 0.675 indicates female has hazard rate that is 67.5% of male. Previously in Table 1.5 we have seen female UI applicants have longer 'waiting time' compared to male. The result in Table 1.5 is consistent with that of Table 1.4 that female individuals has longer 'waiting time' and lower conditional UI compared to male.

Table 1.5 also shows that being disabled will reduce the hazard of conditional UI 30.9% (1-exp(-0.369)) compared to non-disabled individuals [20]. A hazard rate between 0 and 1 indicates disabled individuals have longer duration. Results in Table 1.5 shows disabled individuals are less likely to get on unemployment insurance in the close future and will have longer duration before taking up unemployment insurance, given currently idling without benefits. The result in Table 1.5 and Table 1.4 are consistent in a sense that the disabled individuals will have longer 'waiting time' and (Table 1.4) and a lower probability of getting on unemployment insurance in the instant future (Table 1.5) compared to the non-disabled. The likely reason for this phenomenon, as explained previously, is that the disabled UI applicants are very likely to have applied for (or already on) other welfare programs, such

[19]↑Female is recoded as 1 and male is recoded as 0 in the data.
[20]↑Disabled individuals are recoded as 1 in the data

as social security disability insurance (SSDI) or Social Security Income (SSI) program which will provide more and longer financial support than the unemployment insurance program would. I will study more about the behavior or disabled individuals in Chapter 3.

Table 1.5 shows that individuals with a higher total household income have lower probability of taking up unemployment insurance benefits. But although the difference is statistically significant the hazard ratio is very close to 1 when total household income changes. As total household income increases, the probability of getting on UI in the instant future is smaller but very close to the probability for the individuals with lower household income, given idling in the current time. Result in Table 1.5 indicates individuals with higher total household income do not have significant difference in terms of 'waiting time' compared to those with lower total household income. Table 1.5 shows even though total household income do not have significant impact on 'waiting time', it does statistically significantly increase the instant take-up of taking up unemployment benefits if currently idling. But the practical significance is very small and not significant. Results for Table 1.5 and Table 1.4 are also consistent. As discussed earlier, the reason for a slightly lower hazard rate for individuals with higher total household income can be that individuals with higher total household income are more likely to be in a bigger family and have higher level of expense to maintain every month. They will therefore be faster to take up any financial support to help maintain the expense every month when they find themselves idling.

Table 1.5 shows that as the number of job loss increases the probability of instant unemployment insurance take-up will increase as well (positive coefficient). A one time increase of job loss will increase the likelihood of instant UI take-up by 9.3% (exp(0.089)-1). Results in Table 1.4 showed a one time increase of job loss decreases 'waiting time' by about 1.1 weeks. The results in both Table 1.5 and Table 1.6 indicate a one time increase of job loss will decrease 'waiting time' before taking up unemployment insurance by 1.1 weeks after job loss and increase the hazard of taking up unemployment benefits by 9.3%. Results in Table 1.5 and Table 1.4 are consistent in the sense that individuals who have lost jobs multiple times are more and more likely to take up unemployment benefits and becomes more and more 'impatient' before taking up benefits as number of job loss increase. This interesting phenomenon indicates there is likely to be 'learning behavior' exists when unemployed individuals decide whether to apply for UI benefits. Each time a person lost job he receives a 'signal' with regard to his ability/skill level or the condition of the economy. As the individual becomes more experienced with job loss he/she will collect more past signals to determine that either the economy is not in a promising condition or he/she is not competitive enough in the labor market. Therefore it takes a person with more job loss experience less time to take up unemployment benefits.

Table 1.5 shows as age increases the hazard to take up unemployment benefits also increases (positive coefficient) and a one year increase of age will increase the hazard of conditional UI by 2.3%(exp(0.0227)-1). Linear regression results in Table 1.4 showed a one year increase of age would decrease the 'waiting time' before getting on unemployment program by 0.073 weeks and this result is also consistent with Table 1.5. A one year increase of age will drop the unemployed individuals' waiting time before taking up UI by 0.073 weeks and increase the probability of taking up UI in the close future by 2.3%. Young workers' more confidence in finding new jobs and being less familiar with the unemployment program may be the possible reasons for their longer 'waiting time' and less propensity to take up UI after job loss.

In the Kaplan-Meier curves we observed a big vertical drop around 17 and 18 weeks in the conditional UI graph. It has been documented that there are more transitions reported during 'seam month' which is the month that people are interviewed [19] [20] [21]. In Table 1.5, I use 'seam' as an independent variable to test whether being at seam will have significant effect on conditional application and second, to exclude the effect of 'seam bias' on the reported hazard ratio. I find that being at 'seam' increases the probability of reported conditional UI by 223 times and the result is significant at 1% level. This result is evidence that the big vertical drop observed in the Kaplan-Meier curve around 17 and 18 weeks are caused by seam bias.

Although understanding transitions from unemployment to jobs is not the main focus of this paper, in order to complete my analysis I also run Cox proportional hazard regression for conditional job events. All independent variables are the same as the conditional UI regression and I also report both coefficient and hazard ratio. The dependent variable is conditional job, i.e. the hazard of finding job in the instant future given unemployed without benefits in the current period. Observations are also clustered at individual level. The result is shown in Table 1.6.

The Cox regression I run for transitions into employment in $t+1$ given unemployed and without benefits in t is,

$$Hazd_{Job}(t)_i = Hazd_{0,Job}(t) + \beta_1 jobloss\_time_{i,t} + \beta_2 unem\_rate_t + \beta_3 seam_{i,t} + \beta_4 X_{i,t} + \epsilon_{i,t} \tag{1.6}$$

Table 1.6. Cox Regression-Conditional Job

	(1) Coefficient	(2) Hazard Ratio
Education	0.024**	1.024**
	(2.19)	(2.19)
Gender	-0.194***	0.824***
	(-18.98)	(-18.98)
Marital Status	0.00027	1.000
	(-0.02)	(-0.02)
White	0.108***	1.114***
	(8.91)	(8.91)
Disable	-0.543***	0.581***
	(-28.02)	(-28.02)
State Unemployment Rate	0.012*	1.012*
	(2.04)	(2.04)
Total Household Income	0.000008***	1.000***
	(9.8)	(9.8)
Age	-0.003***	0.997***
	(-6.05)	(-6.05)
Number of Times Lost Jobs	0.0475***	1.049***
	(5.87)	(5.87)
Seam	1.026***	2.791***
	(107.85)	(107.85)
year==2012	-0.230	0.794
	(-0.8)	(-0.8)
Observations	2034558	2034558

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.6 shows age, education, gender, race, whether disabled are the demographic characteristics that will have significant effect on the probability of getting jobs after being unemployed. A one year increase of education increases the probability of getting jobs by 2.3% after job loss and the result is significant at 5% level. This result is further evidence of the effect of education on labor market, more specifically, the effect of education on the likelihood of getting jobs for those individuals who recently lost jobs.

Result in Table 1.6 indicates male has higher hazard to get jobs compared to female after job loss [21]. More specifically, being female reduces the likelihood of getting jobs by a factor of 0.83 or 17% compared to male. This is further evidence of gender difference in the job market, specifically for the group of individuals who recently experienced job separation.

Being white increases the likelihood of getting jobs in the instant future by 11.4% compared to non-white individuals. This is further evidence of race difference in the labor market. The result is specifically for those individuals who recently experienced job loss.

A one year increase of age decreases the hazard of getting jobs by 0.3%. Even though age can be associated with experience in the labor market the result in Table 1.6 shows that increase of age may be a disadvantage for the unemployed individuals looking to find job again.

Moreover, it is also shown that being disabled has lower hazard to find jobs compared to people without disability after job loss. Disabled individuals are 41.9% less likely to find jobs again compared to non-disabled after losing previous jobs.

Table 1.6 indicates the hazard of getting jobs increases as number of job loss increases. A one time increase of job loss increases the hazard of getting jobs by 4.9%. This is not an obvious result since individuals with more job loss experience may have traits that will result in their previous job loss therefore have negative effect on the probability of finding jobs again. At the same time, people with more job loss experience are also likely to be those who are less picky on accepting jobs or have more experience in different jobs and as a consequence more likely to get a new job. This result shows the latter reason outweighs the former reason and makes these groups of people more likely to get new jobs after job loss.

[21]↑Female is recoded as 1 and male 0.

Result in Table 1.6 indicates that being on seam increases the hazard of reported job findings by 179%. This means the vertical drop observed in the Kaplan-Meier Curve for conditional job are likely to be caused by other factors. The result is significant at 1% significance level. Further study is needed for the other factors that could cause the transitions happen around 17 and 18 weeks for conditional jobs.

1.4 Conclusion

In this Chapter, I find that on the contrary to common assumptions about state unemployment insurance, there is significant 'waiting time' before applying for UI for the unemployed individuals. The vast majority (87%) of individuals do not apply immediately and the lower bound of average 'waiting time' is 12.99 weeks and median 'waiting time' is about 4 weeks. Regression analysis show a lower age, a lower household income, being disabled, being female, good economic conditions and fewer experienced number of job separations make delay more likely; a lower age, being disabled, being female, a lower education level, being non-white, good economic conditions and fewer experienced number of job separations increase the length of delay. I also run Cox regression to find factors that have significant effect on the conditional application of UI and the results are consistent with the findings in linear regression. Cox regression analysis also show that being interviewed at a seam month drastically increase the reported hazard rate of transitions into unemployment with UI. The finding that 'waiting time' decreases as the number of experienced job loss increase is particularly interesting. There is likely 'learning' behavior as individuals become more experienced with job loss and possibly UI application. The 'learning' can be individuals have acquired more knowledge of the economic conditions and their likelihood of finding jobs again under the economic conditions as they are experienced more job loss. 'Learning' can also be individuals have learned more about their true skill level in the labor market as the number of job separations increase. Each time a person is separated from or finding a job, he receive a 'signal' regarding his skill level or economic conditions and the individual will update his belief of 'good state' (high skill level or good economic conditions) based on the signal received. Existence of 'learning' behavior provides a logical mechanism of decreasing ‘waiting time’ as number of experienced job loss increases observed in the data. This mechanism is further explored in Chapter 2. The finding of application delay has important implication since the existence of delay means there may need improvement of current optimal UI design. The existence of application delay of UI indicates there is likely nontrivial application costs when unemployed workers applying for UI. More study of the application costs of UI is shown in Chapter 2. Current unemployment insurance may need to reduce the barrier of either the initial eligibility and/or the recertification of eligibility in order to prevent incomplete insurance of individuals in need of UI.

1.5 Appendix

1.5.1 Probit and Linear Regression Results Cluster at State Level

The following table shows the robust check for Probit and linear regression cluster at state level.

Table 1.7. Probit and Linear Regression Results Cluster at State Level

	Probit If_Wait	Linear Wait_Time
Age	-0.0130***	-0.0451
	(-16.64)	(-1.96)
Education	0.00350	-0.599***
	(1.28)	(-7.35)
Gender	0.232***	8.188***
	(15.11)	(15.22)
Marital Status	-0.0377	1.650***
	(-1.91)	(3.77)
White	-0.0354	-4.153***
	(-1.50)	(-5.45)
Disable	0.321***	18.71***
	(14.01)	(28.34)
State Unemployment Rate	-0.0397***	-0.361
	(-4.61)	(-1.37)
Total Household Income	-0.0000106***	-0.00000440
	(-8.45)	(-0.12)
Number of Times Lost Jobs	-0.0688***	-1.935**
	(-13.30)	(-3.19)
Constant	1.594***	32.60***
	(15.25)	(9.39)
Observations	73822	73822

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5.2 Variation of UI Backdate Policies

Summary Statistics for States with Different Backdate Policies

Table 1.8. Main Variable Summary Statistics for States with Different Backdate UI Policies

Variable Name	*Mean*	*Std.Dev*	*Median*	*Min*	*Max*	*N*
Panel A. State Type I						
HouseIncome	$5541.82	$4946.73	$4368.31	$-1691.67	$62983.79	9387
Age	38.22	15.42	36	18	65	17158
Education	14.15	3.07	14	1	23	17158
Unem Duration	4.48	20.15	1	1	279	288544
Individual	37.31	74.28	2.20	1	279	16874
UI Duration	44.22	28.90	35	4	99	2776
Panel B. State Type II						
HouseIncome	$5205.36	$ 4737.55	$4012.87	$ -874.53	$ 64565.96	6874
Age	38.50	15.38	37	18	65	13177
Education	13.87	3.03	14	1	23	13177
Unem Duration	4.48	20.23	1	1	279	232480
Individual	38.63	76.18	2.29	1	279	12932
UI Duration	46.08	29.41	35	4	99	2053
Panel C. State Type III						
HouseIncome	$ 4972.63	$4456.02	$3877.11	$-6190.42	$62687.67	14235
Age	38.74	15.46	37	18	65	27041
Education	14.03	3.03	14	1	23	27041
Unem Duration	4.57	20.60	1	1	279	473410
Individual	39.81	76.70	2.39	1	279	26715
UI Duration	45.35	29.30	35	4	99	4,530

Table 1.9. Waiting Time Summary Statistics for States with Different Backdate Policies - Upper Bound

Panel A. State Type I

		AveWaitT	*MednWaiT*	*Min*	*Max*	*N*
All						
	Indivl/WaitTime	43.47(66.66)	17	0	279	27946
	Imm	0	0	0	0	11216
	NotImm	53.48(70.36)	20	1	279	22658
	Individual	58.82(76.38)	24	0	279	16730
	Imm	0	0	0	0	2231
	NotImm	67.54(79.72)	32	1	279	14499
Panel B. State Type II						
All						
	Indivl/WaitTime	46.45(69.19)	17	0	279	21191
	Imm	0	0	0	0	3812
	NotImm	56.51(72.63)	22	1	279	17379
	Individual	62.25(78.43)	26.75	0	279	12813
	Imm	0	0	0	0	1617
	NotImm	70.77(81.63)	34	1	279	11196
Panel C. State Type III						
All						
	Indivl/WaitTime	45.70(68.60)	17	0	279	43696
	Imm	0	0	0	0	8045
	NotImm	55.88(72.14)	22	1	279	35651
	Individual	61.58(77.86)	26	0	279	26478
	Imm	0	0	0	0	3298
	NotImm	69.57(80.96)	34	1	279	23180

Table 1.10. Waiting Time Summary Statistics for States with Different Backdate Policies - Lower Bound

Panel A. State Type I

		AveWaitT	*MednWaiT*	*Min*	*Max*	*N*
All						
	Indivl/WaitTime	11.75(26.85)	1	0	257	5557
	Imm	0	0	0	0	2855
	NotImm	23.93(34.55)	13	1	257	2702
	Individual	13.21(29.35)	3	0	257	2683
	Imm	0	0	0	0	1473
	NotImm	27.98(40.92)	16	1	257	1210
Panel B. State Type II						
All						
	Indivl/WaitTime	12.93(29.54)	1	0	261	3992
	Imm	0	0	0	0	2020
	NotImm	25.98(37.81)	14	1	261	1972
	Individual	14.79(32.93)	3	0	261	1974
	Imm	0	0	0	0	1076
	NotImm	32.35(45.46)	17	1	261	898
Panel C. State Type III						
All						
	Indivl/WaitTime	14.03(31.46)	2	0	261	9197
	Imm	0	0	0	0	4456
	NotImm	27.00(39.66)	14	1	262	4741
	Individual	17.07(36.25)	4.17	0	262	4342
	Imm	0	0	0	0	2218
	NotImm	33.92(48.95)	17	1	262	2124

Probit Regression with Different State Backdate Policies

Table 1.11. Probit Regression Results with Different State Backdate Policie

	IfWait_State I	IfWait_State II	IfWait_State III
Age	-0.0148***	-0.0131***	-0.0120***
	(-12.19)	(-8.77)	(-9.02)
Education	0.00116	0.000247	0.00626
	(0.20)	(0.05)	(1.57)
Gender	0.269***	0.244***	0.203***
	(5.57)	(3.99)	(3.84)
Marital Status	-0.0145	-0.0247	-0.0563
	(-0.30)	(-0.87)	(-1.76)
White	-0.0647***	-0.118***	-0.00958
	(-3.70)	(-3.87)	(-0.35)
Disable	0.372***	0.274***	0.329***
	(7.03)	(4.56)	(9.09)
State Unemployment Rate	-0.0647***	-0.0402**	-0.0277**
	(-3.70)	(-2.97)	(-2.83)
Total Household Income	-0.0000129***	-0.00000837***	-0.0000110***
	(-4.95)	(-4.27)	(-6.08)
Number of Times Lost Jobs	-0.0887***	-0.0573***	-0.0685***
	(-10.19)	(-4.38)	(-8.20)
Constant	1.778***	1.410***	1.415***
	(8.58)	(6.89)	(10.43)
Observations	16955	22360	34507

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear Regression with Different State Backdate Policies

Table 1.12. Linear Regression Results with Different State Backdate Policies

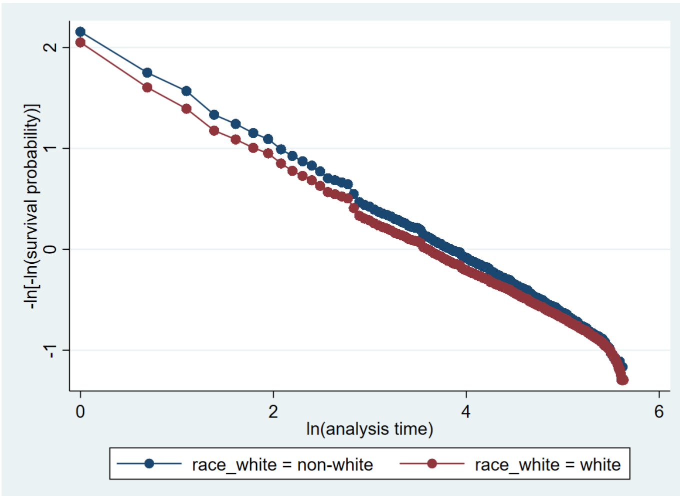
	WaitTime_State I	WaitTime_State II	WaitTime_State III
Age	-0.0311	-0.0455	-0.0390
	(-1.02)	(-1.60)	(-1.49)
Education	-0.735***	-0.578**	-0.550***
	(-3.40)	(-2.82)	(-3.61)
Gender	9.387***	7.400***	8.275***
	(8.26)	(6.00)	(6.62)
Marital Status	1.840	2.000	1.456*
	(1.45)	(1.81)	(2.10)
White	-3.349***	-4.883***	-3.604***
	(-3.92)	(-6.90)	(-4.74)
Disable	19.64***	17.92***	18.60***
	(14.56)	(13.63)	(16.82)
State Unemployment Rate	-0.471	-0.194	-1.116***
	(-1.16)	(-0.52)	(-3.61)
Total Household Income	-0.0000192	-0.00000499	0.00000630
	(-0.32)	(-0.09)	(0.15)
Number of Times Lost Jobs	-3.429***	-3.017***	-1.411*
	(-11.92)	(-10.40)	(-2.25)
Constant	23.63***	30.75***	26.46***
	(5.52)	(5.32)	(7.07)
Observations	16955	22360	34507

t statistics in parentheses

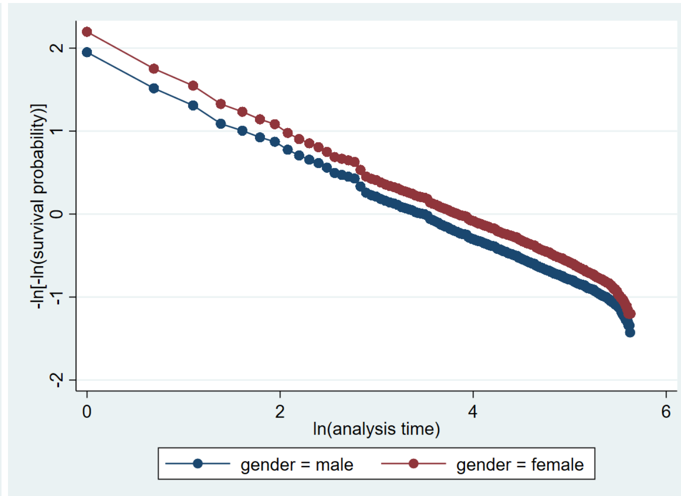
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5.3 Test Assumption for Cox Proportional Hazard

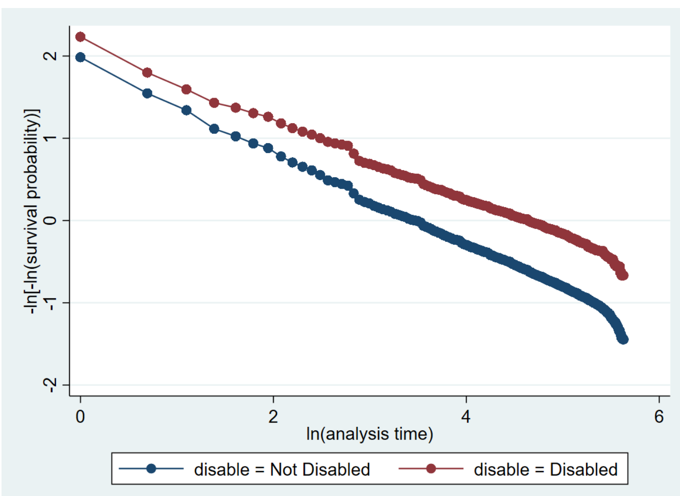
The following figures test the assumptions for Cox proportional hazard model.



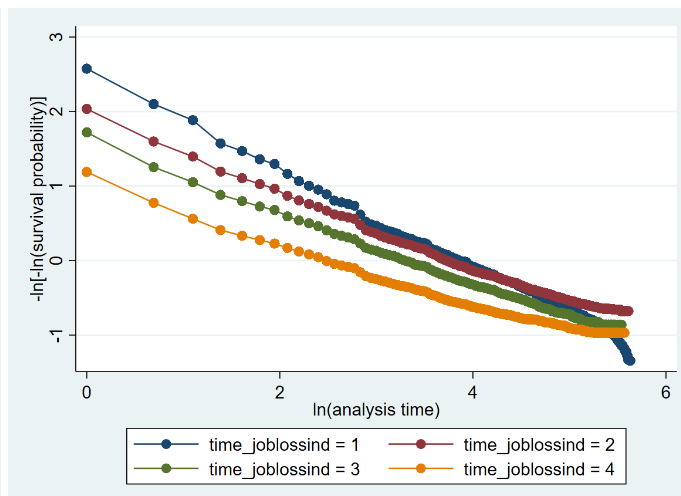
(a) Conditional Idle



(b) Conditional UI



(c) Conditional Job



(d) Conditional UI

Figure 1.4. Test Assumption for Cox Proportional Hazard

2. STRUCTURAL MODEL TO PROVIDE A MECHANISM TO EXPLAIN APPLICATION DELAY OF UI

Abstract

Given UI application delay is an important empirical fact found in previous chapter, it is necessary to establish a mechanism of how and why it happens. This paper constructs a job search and separation model with UI benefits to establish a mechanism that can explain the previous findings in the data. The model has two key feature: application requires fixed cost and workers are uncertain about the current state. I use Simulated Method of Moments (SMM) to estimate the key parameters in the model and find the total application costs are about 9 times of the benefits received. The large total application costs are more likely to be driven by the psychological costs or stigma associated with claiming UI. Counterfactual analysis show that reducing application costs such as the hassle of applying for UI can have large impacts on delay of application. A 1% decrease of application costs will decrease UI waiting time by over 11%.

2.1 Introduction

In Chapter 1 I documented that 'waiting' before applying for unemployment benefits is nontrivial at both the intensive and extensive margin in the data. The findings in Chapter 1 indicate that delay in UI applications shrinks as workers experience more unemployment spells in the past. This is indicative of some kind of learning going on. For example it could be that workers are learning about the economic conditions and how much they should wait until applying. Moreover, the fact that there is a delay indicates some kind of cost for UI application, which shouldn't be surprising. Although there is no monetary cost of applying for UI, there are non-trivial amounts of time and effort for application. They must fill out forms, figure out eligibility and benefits (which has both an explicit, as well as an implicit cost — forgone time for job search). Moreover, claiming unemployment benefits can also be psychologically very costly. The shame and stigma associated with the idea of being unemployed and having to claim government welfare could be a crucial reason of why the unemployment would wait before applying for unemployment benefits. Of course, these costs may decrease with experience — the unemployed become more familiar with the application process if they have done it before, and the stigma associated with UI may be reduced if they have already received UI. Thus the reduced form results demonstrated in Chapter 1 lead to the conclusion that there are likely two key features that need to be captured by any mechanism that purports to explain the application delays: learning about the environment and a fixed cost of application.

In this chapter I rationalize these observations using a job search model which incorporates fixed time/effort costs, as well as psychological/stigma costs of application, and learning about the economic circumstances. I structurally estimate the model and show that the application costs are 9 times the weekly unemployment benefits. Counterfactuals indicate that relatively small changes in these costs can lead to significant improvements in applications. I use a revised McCall job search model [33] incorporating the two key elements 'learning' and cost to model the dynamic of employment and unemployment with benefits and unemployment without benefits transition.

The rest of this chapter proceeds as follows: Section 2.2 explains the setup of model; Section 2.3 shows simulation and counterfactual results from the model; Section 2.4 concludes.

2.2 Model Setup

The modified McCall model I use will rely on three distinct value functions, each of which captures the value to an individual of being in a particular state: Employed (V_{e}), Unemployed with benefits (V_b) and unemployed without benefits (V_0). There will be an uncertain underlying state of the world, which can be either high (h) or low (l) (for simplicity we restrict ourselves to two state). Workers do not know the state of the world. The state variable in all three value functions is the belief (ϕ) of high state of current status, which could be the belief of economic environment or the belief of the the worker's skill level. This state variable, which evolves over time, will allow us to capture learning. The two states correspond to the expectations of the worker about their ability to find an keep a job. In the high state job arrivals are higher and separations are lower, while in the low state arrivals are lower and separations higher.

In each period, there is a possibility λ_z that a job will arrive. Where z indicates the state. We assume $\lambda_h > \lambda_l$, so that a good state indicates a higher chance of finding a job. Conditional on a job arriving, it's Wage offer is drawn randomly and independently from an uniform distribution.

$$w_t \sim U(0,1)$$

The agent observes wage at the start of t and there is no reservation wage which means the agent will always accept wage offer if a wage arrives [1]. The agent is infinitely lived and aims to maximize the expected discounted sum of earnings,

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t y_t$$

[1]↑If a person receives unemployment benefits in the current period and a job arrives, the person will take the job offer and become employed in the next period.

Where β is discount factor and $\beta \in (0,1)$ and y_t is the income at time t and is wage w_t if the agent is employed and is unemployment benefits $b(w)$ if the agent is unemployed and on unemployment benefits. The unemployment benefits $b(w)$ can depend on w, the wage of the past job that an individual held prior to being separated. While individuals are employed, they could lose a job, which happens at rate δ_z. We assume $\delta_h < \delta_l$, so that a good state indicates a smaller chance of being separated. Let c indicates the cost of applying for UI. The agent is assumed to know the distribution of wage and can use it when computing expectations. We assume that the agent updates their beliefs about the state of the world using Bayes' Rule. We denote ϕ_{ee} as the belief of high state in the next period if employed in the current period and remain employed in the next period. $\phi_{\text{e}u}$ is the belief of high state in the next period if employed in the current period and lost job and become unemployed in the next period. $\phi_{u\text{e}}$ is the belief of high state in the next period if unemployed in the current period and find employment and become employed in the next period. ϕ_{uu} is the belief of high state in the next period if unemployed in the current period and remain unemployed without job in the next period.

Given these definitions, we can construct the three value functions that govern the decision-maker's policies, as well as constructing the belief functions

The Value Functions

Equation 2.1 shows the value of employed. When an agent is employed in the current period he receives wage w in the current period and in the next period there he will either remain employed with possibility $1-\delta$ or lose job with probability δ. If the agent lose job in period $t+1$ then he will make the decision of whether to apply for unemployment benefits or not by comparing the value of applying for benefits and spend cost c and the value of not applying for benefits and spend no cost. Assume the agent's UI application will not be rejected if they decide to apply. The agent will make the decision of whether to apply for benefits by computing

$$\max\left\{\beta V_b(\phi^{'}) - c, \beta V_0(\phi^{'})\right\}$$

If the agent decide to apply for benefits, he will spend cost c in the current period t and receive value of V_b in period $t+1$. If decide not to apply for benefits, the agent will not spend any cost and become unemployed idling.

Value of Being Employed

$$V_{\mathrm{e}}(\phi) = w + \mathbb{E}_{\phi}\left[\beta(1-\delta_z)V_{\mathrm{e}}(\phi_{\mathrm{ee}'}) + \delta_z \max\left\{\beta V_b(\phi_{\mathrm{eu}'}) - c, \beta V_0(\phi_{\mathrm{eu}'})\right\}\right] \tag{2.1}$$

Equation 2.2 shows the value of unemployed receiving benefits in the current period. In this case, the agent receives benefit b in current period t and benefit is a function of his past wage. In the next period, there is a possibility λ that the agent will find job and receive the value of V_{e} and a possibility of $1-\lambda$ that there is no job offer and he will remain unemployed and continue receiving benefits b.

Value of Unemployed with Benefits

$$V_b(\phi) = b(w) + \beta\mathbb{E}_{\phi}\left[\lambda_z V_{\mathrm{e}}(\phi_{u\mathrm{e}'}) + (1-\lambda_z)V_b(\phi_{uu'})\right] \tag{2.2}$$

Equation 2.3 shows the value of unemployed idling and not receiving benefits. In this case the agent receives 0 in the current period t and in period $t+1$ there is still a possibility λ that the agent will find a job and receive value V_{e} and if he will not find a job he will then decide whether to apply for unemployment benefits. If applying for benefits in period $t+1$ he will spend cost c during period t and receive V_b in period $t+1$. If deciding not applying for benefits, the agent will remain idle and continue receiving value V_0.

Value of Unemployed without Benefits

$$V_0(\phi) = \mathbb{E}_{\phi}\left[\beta\lambda_z V_{\mathrm{e}}(\phi_{u\mathrm{e}'}) + (1-\lambda_z)\max\left\{\beta V_b(\phi_{uu'}) - c, \beta V_0(\phi_{uu'})\right\}\right] \tag{2.3}$$

Belief Updates Using Bayes Rule

The only state variable in the model is the belief of high state ϕ. Equations 2.4 to 2.7 provide how the next period belief will update based on Bayes' rule. Equation 2.4 gives how the belief of high state will be updated if employed in period t and remain employed in period $t+1$ which is $\phi_{\text{ee}'}$. Using Bayes rule, $\phi_{\text{ee}'}$ is equal to the belief of high state in period t which is ϕ times probability of remain employed in period $t+1$ if it is the high state $(1-\delta_{zh})$ divided by the sum of belief of high state times of the probability of remain employed if it is the high state and the belief of low state times the probability of remain employed if it is the low state. Where next period's belief is updated using Bayes rule,

$$\phi_{\text{ee}'} = \frac{\phi(1-\delta_h)}{\phi(1-\delta_h)+(1-\phi)(1-\delta_l)} \tag{2.4}$$

Equation 2.5 gives how the belief of high state will be updated if employed in period t but lost job and become unemployed in period $t+1$ which is $\phi_{\text{e}u'}$. Using Bayes rule, $\phi_{\text{e}u'}$ is equal to the belief of high state times the probability of losing job δ_{zh} if it is high state divided by the sum of belief of high state times the probability of losing job if it is the high state and the belief of low state times the probability of losing job if it is the low state.

$$\phi_{\text{e}u'} = \frac{\phi\delta_h}{\phi\delta_h+(1-\phi)\delta_l} \tag{2.5}$$

Equation 2.6 gives how the belief of high state will be updated if unemployed in period t but find job and become employed in period $t+1$ which is $\phi_{u\text{e}'}$. $\phi_{u\text{e}'}$ is equal to belief of high state ϕ in period t times the probability of finding job if the state is high λ_{zh} divided by the sum of belief of high state times the probability of finding job if the state is high and the belief of low state times the probability of finding job if the state is low $\lambda_z l$.

$$\phi_{u\text{e}'} = \frac{\phi\lambda_h}{\phi\lambda_h+(1-\phi)\lambda_l} \tag{2.6}$$

Equation 2.7 gives how the belief of high state will be updated if unemployed in period t and remain unemployed in period $t+1$ which is $\phi_{uu'}$. $\phi_{uu'}$ is equal to belief of high state times the probability of not find job in period $t+1$ if the state is high which is $(1-\lambda_{zh})$ divided by the sum of belief of high state times the probability of not find job if the state is high and the belief of low state times the probability of not find job if the state is low.

$$\phi_{uu'} = \frac{\phi(1-\lambda_h)}{\phi(1-\lambda_h)+(1-\phi)(1-\lambda_l)} \tag{2.7}$$

Based on the model, when $c = 0$ the unemployed individuals will always immediately apply for UI after job loss. Given our previous findings, it's clear c should be strictly larger than 0. The cost of claiming unemployment benefits is the key parameter to capture the delay of application of UI. The parameter c in the equation captures the total cost induced in the process of applying or claiming benefits. As discussed previously, these costs could be both physical (time and effort) and psychological (stigma). Given our data, it is hard to distinguish the relative extent of the different kinds of costs.

Given the value functions, the next thing I turn to is understanding the optimal behavior of the individual. In particular, we want to understand when the individual will apply for UI. The next proposition shows that the individual follows a simply threshold policy in terms of their belief — fixing the cost of application and the unemployment benefits, an individual has a threshold policy in terms of their beliefs — if their beliefs are high enough (i.e. place a large enough weight on the high state) they do not apply for UI. Once beliefs drop below a threshold, they apply for UI.

Claim 1. *If unemployment benefits $b(w)$ and application cost c satisfy $c-\beta c(1-\lambda_{zh}) < b(w) < c-\beta c(1-\lambda_{zl})$ then there exists a threshold belief ϕ^* such that if $\phi > \phi^*$, $V_b({\phi^*}_{uu'})-c < V_0({\phi^*}_{uu'})$; if $\phi < \phi^*$, $V_b({\phi^*}_{uu'})-c > V_0({\phi^*}_{uu'})$. The threshold belief is $\phi^* = \frac{1}{\lambda_{zh}-\lambda_{zl}}\left[\frac{b}{c}+(1-\lambda_{zl})-\frac{1}{\beta}\right]$ and $\phi^* \in (0,1)$ iff $\frac{1-\beta}{\beta}+\lambda_{zl} < \frac{b}{c} < \frac{1-\beta}{\beta}+\lambda_{zh}$. If $\frac{b}{c} > \frac{1-\beta}{\beta}+\lambda_{zh}$ then $\phi^* = 1$; If $\frac{1-\beta}{\beta}+\lambda_{zl} > \frac{b}{c}$ then $\phi^* = 0$.*

Proof. Suppose $\widetilde{\phi}' > \phi^{*\prime}$, then $V_b(\widetilde{\phi}')-c < V_0(\widetilde{\phi}')$ and equation (2)-(3) becomes,

$$V_b(\widetilde{\phi}) - V_0(\widetilde{\phi}) = b + \beta\mathbb{E}_\phi\left[(1-\lambda_z)(V_b(\widetilde{\phi}')-V_0(\widetilde{\phi}'))\right].$$

Then,

$$
\begin{aligned}
V_b(\widetilde{\phi}) - V_0(\widetilde{\phi}) - c &= b + \beta \mathbb{E}_\phi \left[(1-\lambda_z)\left(V_b(\widetilde{\phi}') - V_0(\widetilde{\phi}')\right)\right] - c \\
&= b + \beta \left[V_b(\widetilde{\phi}') - V_0(\widetilde{\phi}')\right]\left[\phi(1-\lambda_{zh}) + (1-\phi)(1-\lambda_{zl})\right] - c \\
&= b + \beta \left[V_b(\widetilde{\phi}') - V_0(\widetilde{\phi}')\right]\left[\phi(\lambda_{zl}-\lambda_{zh}) + (1-\lambda_{zl})\right] - c
\end{aligned} \tag{2.8}
$$

Since $V_b(\widetilde{\phi}') - V_0(\widetilde{\phi}') < c$ and $\lambda_{zl} < \lambda_{zh}$, we will have

$$
\begin{aligned}
V_b(\widetilde{\phi}) - V_0(\widetilde{\phi}) - c &< b + \beta c\left[\phi(\lambda_{zl}-\lambda_{zh}) + (1-\lambda_{zl})\right] - c \\
&< b + \beta c(1-\lambda_{zl}) - c
\end{aligned} \tag{2.9}
$$

Hence if $b < c - \beta c(1-\lambda_{zl})$ there will be $V_b(\widetilde{\phi}) - c < V_0(\widetilde{\phi})$

Similar as the previous case, if suppose $\widetilde{\phi}' < \phi^{*\prime}$, then $V_b(\widetilde{\phi}') - c > V_0(\widetilde{\phi}')$ and equation (2)-(3) becomes,

$$V_b(\widetilde{\phi}) - V_0(\widetilde{\phi}) = b + \beta \mathbb{E}_\phi\left[(1-\lambda_z)c\right]$$

Then,

$$
\begin{aligned}
V_b(\widetilde{\phi}) - V_0(\widetilde{\phi}) - c &= b + \beta \mathbb{E}_\phi\left[(1-\lambda_z)c\right] - c \\
&= b - c + \beta c\left[\phi(\lambda_{zl}-\lambda_{zh}) + (1-\lambda_{zl})\right]
\end{aligned} \tag{2.10}
$$

Since $\phi(\lambda_{zl}-\lambda_{zh}) + (1-\lambda_{zl}) > 0$ and $\lambda_{zh} > \lambda_{zl}$ and $\phi \in [0,1]$ then if $b - c + \beta c(1-\lambda_{zh}) > 0$ or $b > c - \beta c(1-\lambda_{zh})$ there will be $V_b(\widetilde{\phi}) - c > V_0(\widetilde{\phi})$

The threshold belief ϕ^* can be solved by using $V_b(\phi^*) = V_0(\phi^*) - c$, at threshold belief ϕ^* equation (2)-(3) becomes,

$$
\begin{aligned}
V_b(\phi^*) - V_0(\phi^*) &= b + \beta \mathbb{E}_\phi\left[(1-\lambda_z)c\right] \\
&= b + \beta c\left[(1-\lambda_{zh})\phi(*) + (1-\lambda_{zl})(1-\phi(*))\right]
\end{aligned} \tag{2.11}
$$

Substitute $V_b(\phi^*) - V_0(\phi^*)$ using c, there is

$$c = b + \beta c\left[\phi^*(\lambda_{zl} - \lambda_{zh}) + (1 - \lambda_{zl})\right]$$

Solving ϕ^* from the above equation,

$$\phi^* = \frac{1}{\lambda_{zh} - \lambda_{zl}}\left[\frac{b}{c} + (1 - \lambda_{zl}) - \frac{1}{\beta}\right]$$

Since belief should be between 0 and 1, solving $0 < \phi^* < 1$ using above equation we will have $\frac{1-\beta}{\beta} + \lambda_{zl} < \frac{b}{c} < \frac{1-\beta}{\beta} + \lambda_{zh}$. $\square$

2.3 Simulation and Counterfactual

We would now like to take the economic model we constructed in the previous subsection to the SIPP 2008 data, and see what kind of parameters can rationalize observed behavior. In this section I use simulated method of moment (SMM) [34] to estimate the two major parameters in the model: the total UI application costs c and the initial belief of high state (ϕ_0). The parameter of the most interest is the benefit application cost c compared to benefit $b(w)$ received or the ratio of of benefit and cost $b(w)/c$. The estimation of c or b/c tells us how much the total cost is to unemployment insurance applicants compared to the weekly unemployment benefits they receive. The cost estimated include all potential costs induced by UI application, including the psychological cost or stigma experienced when claiming unemployment as well as the time and effort spent weekly to be continually eligible for benefits. The other parameter needs to be estimated is the initial belief of high state ϕ_0. The discount factor β is set to be 0.98 [35]. The job finding rates (λ_z) are chosen based on the aggregate job-finding rates found during the survey period of 2008 and 2012 using CPS (current population survey) data by Birinci Amburgey and Tran (2021) [36] and is shown in Figure 2.1. The job finding rate shown in Figure 2.1 is reported monthly. Since the model parameter is estimated using weekly data, the job finding rate is converted from monthly to weekly value for estimation [2]. From Figure 2.1, the monthly job finding rate range from around 18.5% to 34% during 2008 to 2012. The corresponding weekly job finding rate ranges from 5% to 9.9%. Therefore, I select the job finding rate in low state λ_l to be 0.05 and the job finding rate in high state $\lambda_h$to be 0.099. The job destruction rate is chosen based on

[2]↑Monthly non-job finding rate = (weekly non-job finding rate)^4.

the findings in Shimer (2012) [35] which reports of monthly job destruction rate from 2008 to 2010 (shown in Appendix 2.5.1). I select the job destruction rate in low state δ_l to be 3% and 2.5% in high state (δ_h) and the corresponding weekly job destruction rate is 0.63% and 0.76% [3]. Wage is set to be drawn from a uniform distribution [0,1] [4]. After wage is drawn, benefit b is set to be 50% of wage w as UI claimants will approximately receive 50% of their previous earnings as UI benefit.

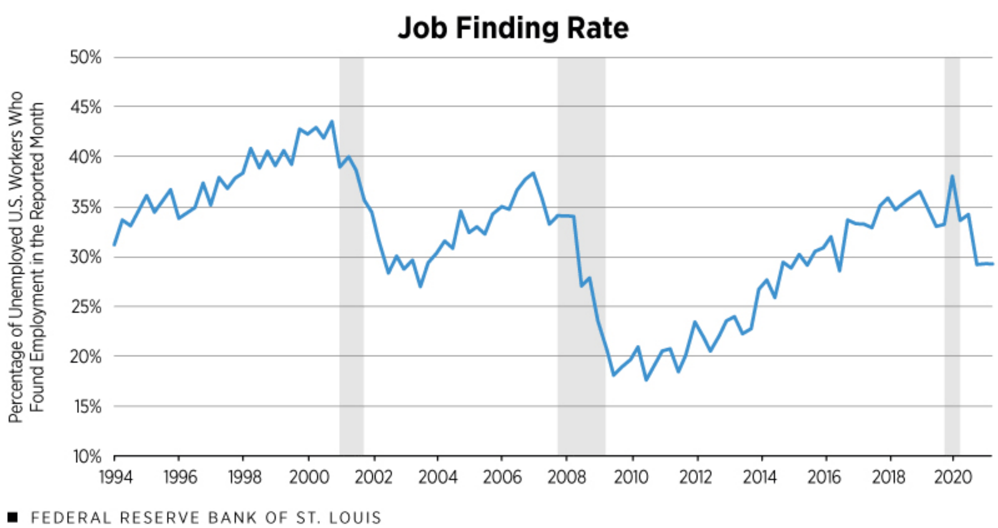


Figure 2.1. Job Finding Rate 1994-2020 [36]

2.3.1 Simulation

I use simulated method of moments (SMM) [34] to estimate the two parameters of interests ϕ_0 and c in the model. There are two moments used to estimate these two parameters: The number of weeks to find jobs after job loss (job finding time) and the number of weeks between job loss and being on unemployment benefits (UI waiting time). UI waiting time has been calculated in Table 1.3. There are on average 12.99 weeks of waiting period to take on unemployment benefits after job loss in the data. I then calculate the average job finding time in the data. In the data, I select people who have lost jobs in the survey period and find

[3]↑Monthly non-job destruction rate = (weekly non-job destruction rate)^4

[4]↑I changed the assumption of wage distribution to be a normal distribution $\mathcal{N}(\mu, \sigma^2)$ and the it does not qualitatively effect the estimation results.

the time difference between the time lost jobs and the time finding jobs again and record it as job finding time (if the unemployment period lasts until the end of survey period the job finding time is calculated from the time of job loss to the end of survey period). The job finding time calculated from the data is 25.04 weeks. Therefore 12.99 weeks as UI waiting time and 25.04 weeks as job finding time are the two moments used for SMM.

Use the parameters set up above, the simulation is completed in two steps. Step one is to find the threshold belief under different costs c. Step two is to use the simulated two moments, i.e. job finding time and UI waiting time and the moments calculated from the data to estimate application cost c and initial belief ϕ_0. In step one, I use discrete dynamic programming with belief ϕ as state variable where the state space is discretized and updated using Bayes' rule in each period. The cost c is also discretized within the lower bound and upper bound derived in Claim 1. The policy function found in step one shows the threshold belief to apply for unemployment benefit under different value of application cost c. Step two uses the threshold beliefs under different values of c generated in step one and simulate two moments: job finding time and UI waiting time. In this part, I simulate 1000 individual for 1000 period of time. The state space is discretized with two dimensions: one is initial belief of state ϕ_0 and the other is the value of c. The idea is to find how the job finding time and UI waiting time would change under different values of ϕ_0 and c. We begin by assuming all individuals are employed in period 0. For each individual starting with $t = 1$, program compares a randomly drawn number with the job destruction rate to determine whether the person is fired in $t = 1$. If the individual mains employed, then the program updates the belief of the individual $\phi' = \phi_{\text{ee}}$. This process loops until the randomly drawn number in some period t is below the job destruction rate, implying that individual loses their job in period t. If an individual loses their job in a given period, the program updates their belief using Bayes' rule $\phi' = \phi_{\text{e}u}$ and records the the period and belief (ϕ_{fire}) the job loss occurred. Next, let's consider what happens with an individual who begins a given period t without being employed, and without UI. compare the simulated value in period $t + 1$ with job finding rate. If simulated value in time $t + 1$ is smaller than job finding rate the person finds job in period $t + 1$. The program uses Bayes' Rule to update their beliefs $\phi' = \phi_{u\text{e}}$, and records the period that the job was found in [5]. If the randomly drawn number is larger than the job finding rate, no job offer is forthcoming to the individual in period t. This person now needs to decide whether to apply for UI. If their belief about the high state is below the threshold belief, they will apply for UI, otherwise they won't. The program then updates their beliefs $\phi' = \phi_{uu}$ and if they applied for benefits, records the time the person applies for benefits. This entire process continues looping until $t = 1000$. In the procedure described above, for each individual in the simulation, I am able to record when they lost jobs, when they find jobs, when they apply for UI, and what their beliefs are.

To generate simulated job finding time I look at each time period for each individual when they lost a job, and find the subsequent period when they found a job, and take the difference. The simulated job finding time will only depend on the current state of the world (high or low) based on the model or cost of UI application c since a person will always accept job offers once it arrives. The initial belief of high state ϕ_0 can be determined by making the weighted average of the simulated job finding time in low and high states equal to 25.04 weeks (observed job finding time in the data).

To generate simulated moment of UI waiting time I consider for each worker, each period a they are separated from a job if there is a corresponding UI application period (i.e. a UI application period that occurs prior to a job finding period). I take the difference between those two time periods. I then take an average over all workers and UI application occurrences within a simulation. I then average over simulations (i.e. average over different realizations of the high and low state of the world). Using the initial belief determined previously cost the c can be found by calculating the minimal distance between the simulated weighted average of UI waiting time and 12.99 weeks (the corresponding UI waiting time in data).

In order to ensure that the estimates found are consistent with the model, we need to ensure that the ratio $\frac{b(w)}{c}$ falls within the bounds required to generate an interior belief threshold for UI application (as shown in Claim 1), where $\frac{1-\beta}{\beta} + \lambda_l < \frac{b}{c} < \frac{1-\beta}{\beta} + \lambda_h$.Using the calibrated parameters (β is set to be 0.98, λ_h is 0.099 and λ_l is 0.05) we find that $\frac{b(w)}{c} \in (0.07, 0.119)$. Table 2.1 shows the estimation result of benefit over cost $\frac{b(w)}{c}$ and the initial belief of high state ϕ_0 where $\frac{b(w)}{c}$ is set as grid between 0.07 and 0.119. In the sim-

[5]↑ According to the model a person will always accept a job offer once a job arrives.

ulation, benefit $b(w)$ is set to be half of the wage [6], where wage is drawn from a uniform distribution in $(0,1)$ [7].

Finding 9: Initial belief of high state ϕ_0 is estimated to be only about 10% and estimated UI application cost is on average about 9 time of the amount of weekly unemployment benefits.

Table 2.1 shows that the estimated ratio of unemployment benefit over application cost ($\frac{b(w)}{c}$) is 0.111, which means the application cost is on average about 9 times of the amount of weekly benefit received. This result shows application of unemployment benefit is very costly compared to the benefit received. As mentioned earlier in the paper, the application cost can be interpreted as the overall cost in the process of applying for unemployment benefits: Including the time and effort spent on the application process as well as the psychological stigma induced in the process of applying for unemployment insurance. The large cost induced in the process of claiming unemployment benefit can explain UI applicants' behavior of waiting before applying for benefits found in the data. It is beyond the scope of this paper to quantify how much percentage of cost is caused by the actual application process including time and effort spend with the local department of workforce or department of labor and how much percentage of cost is caused by the stigma to apply for government welfare program. However, it's still very informing to see the overall application cost have a significant impact on the fact that UI applicants wait on average 12.99 weeks to apply for unemployment benefits after job loss. Table 2.1 also shows that the estimated initial belief of high state is only about 11%. The initial belief of high state can be interpreted as either that people on average belief there is about 11% probability that they are in the high state of the economy and 89% probability that they are in the low state(recession) of the economy; or that from the data there are about 11% of individuals who belief they are high skill workers and 89% who belief they are low skill workers. This estimation result is in line with the fact that the

[6]↑As discussed in the description of unemployment insurance program, UI is designed to replace about half of the previous wage [37]

[7]↑As discussed, the results are robust to alternative assumptions about the wage distribution.

data is sampled from 2008 to 2012 when the economy is during recession, therefore people's belief of high state is not large.

Table 2.1. Simulation Result-Model Parameters

b/c	ϕ_0
0.119	0.010
0.118	0.044
0.116	0.078
0.115	**0.111**
0.113	0.145
0.111	0.179
0.110	0.213
0.109	0.247
0.107	0.280
0.106	0.314
0.105	0.348
0.103	0.382
0.102	0.416
0.101	0.449
0.100	0.483
0.098	0.517
0.097	0.551
0.096	0.584
0.095	0.618
0.094	0.652
0.093	0.686
0.092	0.720
0.091	0.753
0.090	0.787
0.089	0.821
0.088	0.855
0.087	0.889
0.086	0.922
0.085	0.956
0.085	0.990
0.084	
0.083	
0.082	
0.081	
0.081	
0.080	
0.079	
0.078	
0.078	
0.077	
0.076	
0.075	
0.075	
0.074	
0.073	
0.073	
0.072	
0.072	
0.071	
0.070	

Table 2.2. Simulation Result–Simulated UI Waiting Time

c	**b(w)/c**	**sim__waitH**	**sim__waitL**	**mix__wait**
3.94	0.119	1.00	1.00	1.00
4.00	0.118	3.40	5.50	5.26
4.05	0.116	5.43	8.15	7.85
4.11	0.115	7.18	10.13	9.81
4.16	0.113	8.68	11.79	11.45
4.22*	**0.111***	**9.86**	**13.28**	**12.90**
4.28	0.110	11.04	14.40	14.02
4.33	0.109	12.15	15.42	15.05
4.39	0.107	13.13	16.27	15.92
4.44	0.106	13.99	17.40	17.02
4.50	0.105	14.91	18.35	17.96
4.56	0.103	15.78	19.27	18.88
4.61	0.102	16.52	20.05	19.66
4.67	0.101	17.30	20.80	20.41
4.72	0.100	18.10	21.65	21.26
4.78	0.098	19.03	22.36	21.99
4.84	0.097	19.65	32.95	22.58
4.89	0.096	20.41	23.37	23.04
4.95	0.095	21.23	24.01	23.70
5.00	0.094	21.82	24.57	24.26
5.06	0.093	22.31	25.00	24.70
5.12	0.092	22.85	25.71	25.39
5.17	0.091	23.55	25.81	25.55
5.23	0.090	24.27	26.31	26.09
5.28	0.089	24.86	27.19	26.93
5.34	0.088	25.33	27.62	27.36
5.40	0.087	26.36	28.47	28.24
5.45	0.085	27.18	28.91	28.72
5.51	0.086	28.02	29.44	29.28
5.56	0.085	28.50	29.87	29.72
5.62	0.084	29.18	30.22	31.10
5.68	0.083	30.11	30.72	30.65
5.73	0.082	31.09	31.27	31.25

Note: This table used the benefit calculated as 50% of wage drawn and initial belief of high state ϕ_0 estimated as 0.1114

Table 2.3. Simulated Job finding Time in Low and High State

ϕ	**sim_jobH**	**sim_jobL**	**waited_avg**
0.111	4.15	27.65	25.04

Table 2.2 shows more details about the estimation of application costs c and initial belief of high state ϕ_0. More specifically, the estimated benefit to cost ratio $b(w)/c$ is 0.111 indicating the application cost is about 9 times of the benefits received [8]. After a wage is drawn from a uniform distribution, benefit b is set as half of wage. The range of the application costs c is then determined by benefit $b(w)$ and the upper and lower bound of $\frac{b(w)}{c}$ derived previously. Initial beliefs about the high state ϕ_0 need to be estimated before estimating the application cost c. Table 10 shows the simulated job finding time in the high state and the low state as 4.15 and 27.65 weeks respectively. Note that simulated job finding time does not vary by application cost c. This is because we assume that a UI applicant will accept jobs once a job arrives. Therefore the job finding time only depend on the job finding rate λ and not the application cost c [9]. The initial belief of high state ϕ_0 can be estimated by finding the ϕ that will minimize the distance between the weighted average of the simulated job finding time in high and low state and the job finding time found in the data which is 25.04 weeks. Then application cost can be found using the estimated ϕ_0 so that it will minimize Euclidean distance between the weighted average of simulated waiting time before getting on UI and the waiting time in the data, which is 12.99 weeks. Table 2.7 in the Appendix provide the complete table of the weighted average of simulated waiting time as $b(w)/c$ and ϕ_0 changes.

An interesting feature of in Table 2.2 is that a relatively small changes in $b(w)/c$ can cause big changes in waiting time. Figure 2.2 gives a clearer illustration in this relation by graphing the percentage change of waiting time as the percentage change of $b(w)/c$ when

[8]↑In Table 2.1 change of $b(w)/c$ will generate simulated UI 'waiting time' in high and low state. Using the estimated initial belief $b(w)/c$ is chosen so that the weighted average of 'waiting time' equal to that in the data 12.99 weeks.

[9]↑This is not completely in accordance with the reality and the model can be revised to add more features and better conform with the real world. However, it is still informative to see the relative size of application cost compared to the benefit received by assuming that the unemployment applicant will accept a job offer when it arrives.

$b(w)/c$ decreases from 0.119 to 0.07 shown in Table 2.2. Figure 2.2 uses percentage decrease of $b(w)/c$ as x-axis and percentage increase of simulated waiting time as y-axis. The figure is a U shape showing that as $b(w)/c$ decreases the change of simulated UI waiting time first decreases then increases. At the beginning when $b(w)/c$ is big, a small decrease of $b(w)/c$ will cause a drastic increase of UI waiting time. More specifically, a 1.42% decrease of $b(w)/c$ will cause the UI waiting time to increase by 80% when $b(w)/c$ is around the upper bound. As $b(w)/c$ getting smaller, the increase of waiting time getting smaller and smaller and as shown in Figure 2.2, a 1% decrease of $b(w)/c$ will cause the waiting time to increase by around 1%-2% when $b(w)/c$ is in the middle part of its range. As $b(w)/c$ gets close to the lower bound change of waiting time increase drastically again. When $b(w)/c$ is at the lower bound, the increase of waiting time is close to 60%.

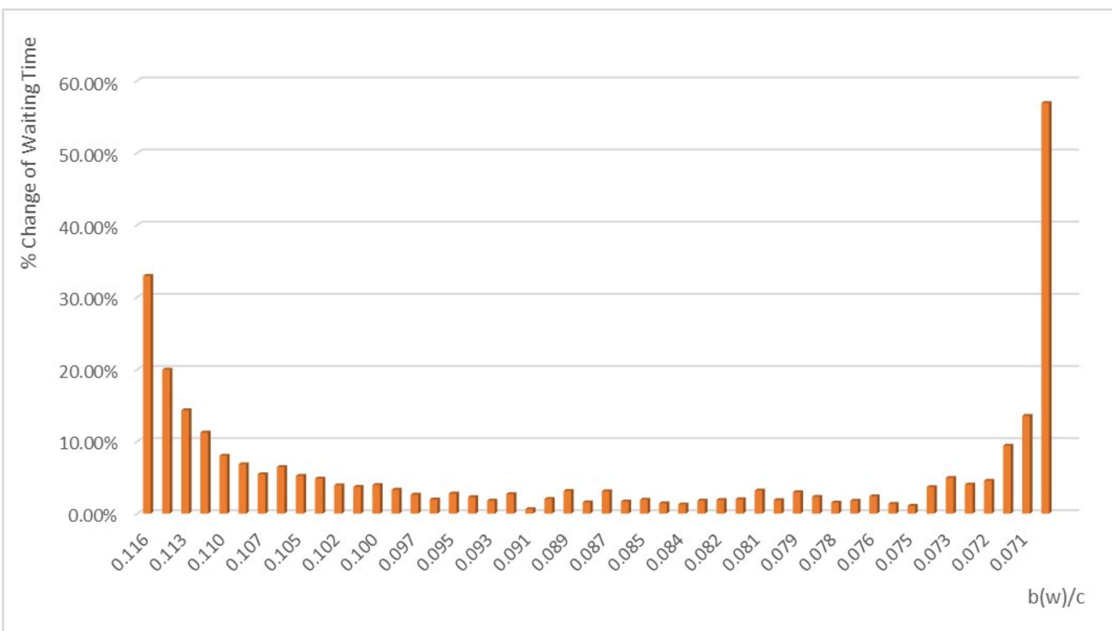


Figure 2.2. Percentage Change of Waiting Time as $b(w)/c$ Changes

2.3.2 Counterfactual

The results of the estimation indicate that application costs are relatively large. This raises the question of whether changes in the environment (e.g. via government policy), such as a reduction in application costs, might help significantly reduce delays in UI applications. In order to explore this, I conduct some counterfactual exercises.

First I did two counterfactual exercises by keeping the initial belief that the state is high ϕ_0 the same as the original estimation (0.111)and change benefit to application cost ratio $b(w)/c$ and effects the estimated waiting time of UI and job finding rate. The results are shown in Table 2.4, where *mix_waitT* is the weighted average of waiting time before applying for benefits and *mix_jobT* is the weighted average of job finding time. Table 2.4 shows when $b(w)/c$ is smaller than the original estimation the estimated weighted average of waiting time is large. More specifically, when $b(w)/c$ decreases from the original estimation 0.111 to a counterfactual value 0.096, which means if application cost c is increased from 9 times of unemployment benefit to 10.5 times of unemployment benefit the weighted average of waiting time would increase from 12.99 weeks to 22.98 weeks. In other words, a 16% increase in application costs would increase the waiting time to apply for UI by 43.5%. Another counterfactual exercise is to set the the ratio $b(w)/c$ to be bigger than the original estimation. When $b(w)/c$ is increased from the original estimation 0.111 to 0.118, which means application cost c is decreased from 9 times of unemployment benefit to 8.5 times of unemployment benefits the weighted average of waiting time would decrease from 12.99 weeks to 5.21 weeks. In other words, a 5.2% decrease of application costs would decrease the waiting time to apply for UI by 60%. These results indicate that the direction of change of the application costs might have different size of effect on the waiting time to take up unemployment benefits. If the application costs increase by 1% the UI waiting time will increase by about 2.7%. However, if the application costs decrease by 1% the UI waiting time will decrease by 11.5%. The big difference in the direction of change of application cost c on the effect of UI waiting time indicate that the applicants of unemployment insurance are likely to be more responsive to decreases in application costs than increases. This finding has informative policy implications. Knowing unemployment applicants will be more responsive to the decrease of application costs in terms of their waiting time, the government can make use of this feature and decrease the application costs by a small amount in order to improve UI uptake.

On the other hand, it is likely less financially efficient to increase the application costs if the government is aiming to increase the unemployment waiting time. It is worth mentioning that the cost of UI application is hard to quantify in reality. However, there would still be different levels of measures the government can take in order to increase or decrease the application costs. For instance, the local department of workforce or department of labor can make the requirement of 'actively seeking full-time work' more or less strictly as a measure to increase or decrease the costs of application. Implementing the criteria of 'refuse an offer of suitable work' more or less strictly is another measure to increase or decrease the costs of application. Changing the extent of the strictness of the criteria or requirements in order to qualify or continually qualify for unemployment benefit can be used as one of the tools to increase or decrease the costs of applying for unemployment benefit.

The weighted average of time it takes to find a job (mix_jobT) remains the same as the original simulation as 25.04 weeks since the weighted average of job finding time will be determined only by initial belief of high state ϕ_0 and job finding rate λ.

Table 2.4. Counterfactual Result-When Application Costs Change

Variable	**Counterfactual I**	**Counterfactual II**
ϕ_0	0.1114	0.1114
b/c	0.096	0.118
c	4.89	4.00
mix_waitT	22.98	5.21
mix_jobT	25.08	25.08

In Table 2.5 I conduct another counterfactual exercise by keeping the application cost the same as in the original simulation and change the initial belief that the state is high and see how changes both the UI application wait time and the job finding time. Table 2.5 indicates that if the initial belief that the state is high decreases from 11% to 4.4% , the average UI waiting time will decrease from 12.99 weeks to 7.94 weeks. This means a 60% decrease of initial belief of that state is high will cause the UI waiting time to decrease by about 39%. On the other hand, if the initial belief of that the state is high is increased to 18% from the original value of 11%, the average of UI waiting time will increase from 12.99 weeks to 15.74 weeks. In other words, a 63% increase of initial belief that the state is high will increase the UI waiting time by about 21%. Table 2.5 demonstrates that the size of the effect of a change in beliefs varies with the direction of the change. The effect of initial belief on UI waiting time is twice as large when ϕ_0 is decreased, compared to if it is increased. Based on this counterfactual result, UI applicants are more responsive in terms of the waiting time before applying for unemployment benefits when their belief that the state is high decreases than when the belief of that the state is high increases. The policy implication is since UI applicants are more responsive decreases in their prior the government needs to be more aware of small economic downturn in terms of its effect on the unemployment seeking unemployment benefits. Also, considering a 60% increase of belief of the state is high will result in only 20% increase of waiting time relatively small changes in prior beliefs about economic circumstances will have only a mild effect on the decision to delay UI application. The average job finding time is close but not very different from the original value 25.04 weeks. The difference in the weighted average of job finding time is only caused by the difference of weight across the two states of the world (h and l) and so will only shift proportionally with the change in priors. .

Table 2.5. Counterfactual Result-When Initial Belief Changes

Variable	**Counterfactual III**	**Counterfactual IV**
c	4.22	4.22
b/c	0.111	0.111
ϕ_0	0.044	0.179
mix_waitT	7.94	15.74
mix_jobT	26.54	24.79

By comparing the result of Table 2.4 and Table 2.5, we can see that the unemployed workers seeking benefits are much more responsive to the change of application costs than the change of their initial belief of a high state. A 1% increase in application costs will increase UI waiting time by almost 3% while a 1% increase in the prior belief about the state being high will only increase the UI waiting time by about 0.3%. In the other direction, a 1% decrease of application costs will decrease UI waiting time by over 11% while a 1% decrease of initial belief of the high state will only decrease the UI waiting time by about 0.7%. Table 2.4 and Table 2.5 indicates that if the government is aiming to decrease the waiting time of applying for unemployment benefit for the unemployed workers, it will be more effective and financially efficient to take measures that will reduce the application cost.

2.4 Conclusion

Unemployment insurance (UI) is designed to provide temporary support and compensate for income losses for insured workers losing jobs through no fault of their own. The majority of optimal UI research focused on the level and length of unemployment insurance benefits and its effect on unemployment duration. The existing literature normally assumes that unemployed would apply for benefits immediately after job loss. Little research has explored whether this assumption is actually correct.

Chapter 1 and Chapter 2 address this issue head on. It first demonstrates that waiting to apply for UI is a significant problem among UI applicants (Chapter 1), and then explores the mechanisms behind the delay (Chapter 2).

To provide a mechanism that can explain the delay in applying for UI in this chapter I use a revised McCall job search model to model the transition between employment and unemployment. It has seems natural to assume that applying for unemployment benefit is time consuming and not effortless so there is a cost associated with UI application. The question is if the existence of application cost can explain applicants' 'waiting' behavior in the data and if so, what is the magnitude of application cost compared to benefits received. In the revised McCall search model, the state variable is the an individual's belief that the state is high. Each period the person update his belief of high state based on whether he finds or is separated from a job using Bayes' Rule. I use SMM(Simulated Method of Moments) to estimate the two key parameters of the model: the application cost, and the initial beliefs about the economy. I show that the estimated costs are large – 9 times the weekly value of unemployment benefits on average. I then conduct several counterfactual exercises to understand how changes in the environment will lead to changes in behavior. The first counterfactual exercise is to keep the prior beliefs about the economic state of the world fixed and change the application costs. The second counterfactual exercise keeps the application cost fixed and changes the initial beliefs about the economy. The counterfactual exercises indicates the UI applicants are much more responsive to a change in application costs compared to a change in their belief about health of the economy. More specifically, a 1% increase in application costs will increase UI waiting time by almost 3% while a 1% increase in the belief of the economy being in a good state will only increase the UI waiting time by about 0.3%. Finding from counterfactual exercises has informative policy implication as it will be more effective and financially efficient for the government to take measures that will reduce the application cost if the government aims to reduce the waiting time for the unemployment applicants.

In 2020 the average weekly unemployment benefits payments is about $387 nationwide. Using the estimated result of total application costs that are roughly 9 times of benefits received, the average total weekly application costs of UI is $3484. This seems like a huge number. How can we interpret the seemingly extremely high application costs of UI? As discussed earlier, the total application costs are composed of transaction or administrative costs, psychological costs or stigma associated with claiming UI as well as the potential procrastination tendency of the applicants. Even though we can not quantitatively identify what proportion of the total application costs should be contributed to transaction costs, psychological costs or procrastination respectively we can discuss the potential magnitude of these costs. In my opinion, the transaction costs and procrastination tendency are not the driving factors of the high estimated total application costs compared to stigma associated with claiming UI. With the convenience brought by modern technology it is reasonable to assume the transaction costs of UI application should not be very high compared to benefits received. Unemployment insurance program has gone through reform over the past years to make application process easier and more accessible to the applicants. Applicants can apply and get recertification through phone or internet without the need to file for benefits in person nowadays. The large extensive and intensive margin of 'waiting' found in Chapter 1 make procrastination very unlikely to be the major factor to drive UI applicants to wait. It is hard to imagine almost 90% of UI applicants will choose to delay because of their procrastination tendency and will wait almost 13 weeks mainly because of they procrastinate. Moreover, unemployment benefits are very likely the only source of income for a lot of claimants during the period of unemployment. Delaying benefits application while having no other source of income because of procrastination are unlikely to be the reason for the large proportion of individuals choosing to wait. On the contrary the stigma or psychological costs can be immensely large or even immeasurable. It is almost impossible to measure how big of the negative effect losing job and financial stability will have on a person's mental health. Tefft (2011) [38] studied the relation of unemployment, unemployment insurance and mental health. The author found a positive relationship between the unemployment rate and the depression search index. Moreover, the paper found continued UI claim is associated with a higher depression search index. The findings in my paper is consistent with the relation between unemployment insurance claim and depression and anxiety indexes found in previous papers. The high total applications costs are very likely to be driven by the high psychological costs, or the negative effect of claiming UI on mental health. Many people are possibility feel ashamed to claim unemployment benefits and the stigma of claiming benefits are added to the existed anxiety by losing job and becoming unemployed.

Chapter 1 and 2 have two major contributions compared to the existing literature. First, I documented that on the contrary to the common assumption of UI application, the majority of UI applicants wait at least one week before claiming benefits. This finding may have important policy implications. The phenomenon of 'waiting' before claiming UI indicates that current UI program is incomplete to insuring people. The barriers exist in UI application make UI applicants not making the optimal decision to apply for benefits. Second, I estimated that the total application costs are 9 times of the benefits received. Even though the total application costs consist of administration costs, procrastination tendency as well as stigma or psychological costs, the seemingly very large application costs are most likely to be driven by the psychological costs associated with UI application. This finding is consistent with previous paper's finding of a correlation between UI claims and depression and anxiety search indexes.

2.5 Appendix

2.5.1 Figure of Employment Exit Probability

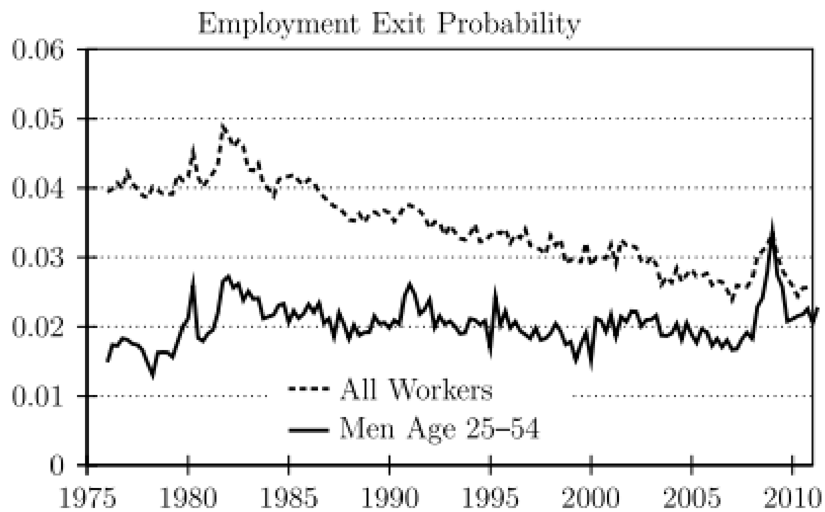


Figure 2.3. Employment Exit Probability (Shimer 2012)[35]

Figure 2.3 is the employment exit probability constructed in Shimer(2012) [35]. Employment exit probabilities from data using prime-age men and during period 1976Q1-2010Q4 and is quarterly average of monthly data. Employment, unemployment, and short term unemployment data are constructed by the BLS from the CPS and seasonally adjusted. Short term unemployment data are adjusted for the 1994 CPS redesign.

2.5.2 Simulation Algorithm

- Part 1: Find threshold belief under different cost c
  - Discretize initial belief ϕ_0 and application cost c
  - Write out the three value functions: V_e, V_b and V_0. Update next period's belief ϕ' using Bayes' rule.
  - Use value function iteration to find the policy functions. i.e. the threshold belief under different values of cost c.

- Part 2: Use SMM to estimate Initial Belief ϕ_0 and and Application Cost c by matching two moments: Job finding Time and UI waiting time
  - Assume 1000 people and each person is in the labor force for a length of $T = 1000$. Simulate $1000x1000$ random numbers N_{sim}. For each person, at the beginning of time assume the person is employed.
  - For each person, by comparing the simulated random numbers with job destruction rate and job finding rate and updated belief with threshold belief, find the time the person is fired each time T_{fire}; the time finding job T_{job}; and the time applying for UI each time T_{uiapp} after each time of job separation.
  - Record the beliefs ϕ_{fire} when separated from jobs, i.e. T_{fire}.
  - Update ϕ_{fire} using $phi' = phi_{uu}$. ϕ' will decrease until it reaches the threshold ϕ^*. Record the time it takes from ϕ_{fire} to reach ϕ^*. This is the simulated 'waiting time' to apply for UI after job loss.
  - Take average of 'waiting time' across all job loss and over 1000 people. This is the simulated average 'waiting time'.
  - Find the time difference between the time separated from jobs T_{fire} and the time find jobs T_{job} again. This is the 'job finding time'. Take average across all job loss and over 1000 people. This is the simulated average 'job finding time'.
  - Estimate initial belief of high state ϕ_0 so that the average of job finding time in low and high state is equal to job finding time in the data.
  - Using the estimated ϕ_0 to estimate benefit to cost ratio $b(w)/c$ such that the estimated $b(w)/c$ will corresponds to the average 'waiting time' in high and low state to be the UI 'waiting time' in data.
  - Run 20 simulations and take the expectation of $b(w)/c$ to generate $\mathbb{E}b(w)/c$

2.5.3 Complete Table of Simulation under different ϕ and c

Table 2.6. Waiting Time Simulation

$b/c\phi_0$	0.010	0.044	0.078	0.111	0.145	0.179	0.213	0.247	0.280	0.314	0.348	0.382	0.416	0.449	0.483
0.119	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.118	1.50	2.98	4.21	5.26	6.15	7.12	7.98	8.82	9.63	10.35	11.23	11.98	12.86	13.55	14.26
0.116	2.06	4.47	6.25	7.85	9.22	10.36	11.48	12.65	13.63	14.52	15.39	16.28	17.30	18.28	19.24
0.115	2.51	5.68	7.98	9.81	11.37	12.84	13.99	15.10	16.11	17.29	18.40	19.46	20.37	21.44	22.37
0.113	2.91	6.79	9.47	11.45	13.27	14.60	15.78	17.22	18.47	19.61	20.69	21.78	22.69	23.51	24.48
0.111	3.35	7.79	10.56	12.90	14.60	16.00	17.55	18.95	20.25	21.47	22.50	23.32	24.26	25.14	25.80
0.110	3.76	8.74	11.68	14.02	15.72	17.53	19.08	20.48	21.84	22.81	23.70	24.62	25.57	26.39	27.26
0.109	4.17	9.60	12.82	15.05	17.03	18.88	20.36	21.84	22.80	23.94	24.91	25.56	26.76	27.75	28.78
0.107	4.53	10.22	13.73	15.92	18.22	20.05	21.61	22.82	23.95	24.94	25.68	26.87	28.00	29.09	29.68
0.106	4.88	11.03	14.51	17.02	19.23	21.08	22.58	23.75	24.81	25.57	26.85	28.05	29.16	29.67	30.32
0.105	5.31	11.68	15.26	17.96	20.23	22.06	23.30	24.69	25.59	26.70	27.89	29.06	29.69	30.28	31.39
0.103	5.66	12.49	15.91	18.88	21.12	22.81	24.09	25.37	26.33	27.45	28.72	29.64	30.27	31.24	32.31
0.102	5.96	13.19	16.70	19.66	21.91	23.46	24.80	25.87	27.06	28.60	29.37	30.10	31.14	32.15	33.28
0.101	6.36	13.75	17.52	20.41	22.63	24.16	25.51	26.76	28.20	29.24	29.93	30.98	31.84	33.09	34.32
0.100	6.78	14.30	18.34	21.26	23.19	24.80	25.95	27.39	28.86	29.70	30.51	31.53	32.97	34.09	35.20
0.098	7.19	14.88	19.02	21.99	23.84	25.46	26.86	28.29	29.42	30.20	31.22	32.40	33.68	34.92	35.77
0.097	7.58	15.39	19.70	22.58	24.52	25.85	27.39	29.09	29.76	30.97	31.87	33.19	34.48	35.68	36.15
0.096	7.92	15.88	20.32	23.04	25.00	26.55	28.32	29.39	30.23	31.54	32.81	34.10	35.25	35.93	36.67
0.095	8.36	16.50	21.06	23.70	25.60	27.13	28.93	29.85	31.08	32.16	33.48	34.93	35.79	36.55	37.34
0.094	8.76	17.23	21.68	24.26	25.99	27.95	29.34	30.23	31.52	33.02	34.32	35.52	36.10	37.02	38.00
0.093	9.14	17.85	22.28	24.70	26.72	28.49	29.73	31.09	32.25	33.74	35.09	35.86	36.70	37.69	37.90
0.092	9.56	18.48	22.78	25.39	27.15	29.21	30.20	31.55	33.05	34.47	35.75	36.36	37.18	38.04	38.46
0.091	9.87	19.07	23.28	25.55	28.03	29.62	30.90	32.17	33.83	35.18	35.97	36.84	37.84	38.22	38.53
0.090	10.23	19.63	23.76	26.09	28.56	29.96	31.30	33.11	34.47	35.69	36.53	37.39	38.09	38.46	39.08
0.089	10.69	20.25	24.35	26.93	29.18	30.33	31.90	33.66	35.18	36.14	36.99	38.00	38.21	38.68	39.74
0.088	11.13	20.83	24.83	27.36	29.57	31.14	32.83	34.41	35.71	36.52	37.53	38.05	38.43	39.43	40.36
0.087	11.57	21.52	25.41	28.24	29.94	31.50	33.36	35.08	36.15	37.03	38.01	38.47	38.96	39.95	41.43
0.086	12.03	22.14	25.63	28.72	30.30	32.20	34.27	35.67	36.50	37.70	38.01	38.44	39.68	40.76	42.29
0.085	12.59	22.66	26.25	29.28	31.10	33.03	34.93	36.02	37.10	37.97	38.43	39.07	40.35	41.94	42.91
0.085	13.12	23.03	27.05	29.72	31.52	33.74	35.58	36.54	37.72	38.16	38.70	39.89	41.02	42.46	43.54
0.084	13.56	23.62	27.46	30.10	32.19	34.47	35.90	37.04	38.00	38.47	39.31	40.35	42.09	43.16	44.07
0.083	13.97	24.20	28.29	30.65	33.05	35.22	36.42	37.71	38.29	38.74	39.92	41.47	42.84	43.76	44.67
0.082	14.54	24.68	29.09	31.25	33.89	35.73	36.91	37.91	38.49	39.59	40.89	42.42	43.50	44.39	45.11
0.081	15.05	25.37	29.42	31.89	34.62	36.12	37.57	38.25	38.94	40.30	41.95	43.05	44.00	44.99	45.88
0.081	15.56	25.70	29.91	32.95	35.35	36.68	38.02	38.44	39.80	41.15	42.78	43.77	44.74	45.56	46.61
0.080	16.17	26.51	30.36	33.58	35.82	37.34	38.24	39.01	40.34	42.22	43.44	44.42	45.21	46.07	47.55
0.079	16.98	27.15	31.25	34.61	36.53	38.04	38.46	39.77	41.74	43.00	44.13	45.01	46.01	47.37	48.78
0.078	17.76	28.25	31.94	35.43	37.14	38.30	39.24	41.03	42.67	43.73	44.82	45.80	46.99	48.51	50.15
0.078	18.57	28.97	33.05	35.99	37.95	38.47	40.07	42.14	43.51	44.59	45.47	46.62	48.06	49.82	51.38
0.077	19.48	29.66	34.16	36.64	38.16	39.46	41.41	43.09	44.34	45.35	46.37	47.85	49.65	51.22	52.82
0.076	20.38	30.26	35.18	37.55	38.45	40.39	42.64	43.91	45.04	46.08	47.70	49.51	51.15	52.70	54.28
0.075	21.51	31.32	35.97	38.06	39.70	42.08	43.75	45.01	46.07	47.59	49.46	51.18	52.78	54.29	55.95
0.075	22.62	32.56	36.92	38.48	41.14	43.40	44.75	46.00	47.60	49.58	51.36	53.05	54.60	56.22	57.73
0.074	23.68	34.13	38.14	39.95	42.84	44.56	45.94	47.60	49.71	51.62	53.42	54.95	56.58	58.03	59.41
0.073	24.92	35.83	38.58	42.04	44.21	45.81	47.69	50.04	52.16	54.08	55.70	57.29	58.52	60.14	61.92
0.073	26.29	37.01	40.22	43.81	45.87	48.10	50.69	52.85	54.85	56.68	58.23	59.77	61.54	63.36	65.20
0.072	28.74	38.60	43.24	45.90	48.85	51.86	54.29	56.40	58.23	60.06	61.97	63.66	65.74	67.56	69.51
0.072	31.43	41.97	46.32	50.68	54.23	56.89	59.05	61.32	63.53	65.84	67.95	69.92	72.18	74.18	76.16
0.071	37.06	47.27	54.32	58.63	62.03	65.34	68.32	70.99	73.61	76.04	78.33	80.31	82.44	84.60	86.61
0.070	97.34	119.56	129.32	136.09	141.04	145.17	148.84	152.10	155.21	158.11	160.73	163.39	165.94	168.45	170.95

Table 2.7. Waiting Time Simulation Continued

$b/c\phi_0$	0.517	0.551	0.584	0.618	0.652	0.686	0.720	0.753	0.787	0.821	0.855	0.889	0.922	0.956	0.990
0.119	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.118	15.08	15.84	16.77	17.75	18.71	19.68	20.83	21.79	23.01	24.29	25.89	28.15	30.64	35.06	44.55
0.116	20.14	21.17	22.02	22.89	23.79	24.77	25.53	26.81	28.39	29.47	31.18	33.95	36.27	39.61	53.02
0.115	23.08	24.00	24.80	25.54	26.72	27.99	29.02	29.84	31.13	32.89	35.06	36.80	38.45	43.47	57.82
0.113	25.23	25.82	26.94	28.21	29.13	29.74	30.96	32.24	34.07	35.53	36.99	38.25	41.29	45.78	61.89
0.111	26.90	27.98	29.04	29.59	30.35	31.44	32.96	34.45	35.71	36.94	38.13	39.71	43.45	48.10	65.46
0.110	28.63	29.32	29.94	31.05	31.96	33.29	34.84	35.85	36.99	38.06	39.05	41.95	44.82	50.67	68.30
0.109	29.57	30.11	31.26	32.28	33.53	34.97	35.83	36.86	37.85	38.55	40.44	43.40	46.03	52.69	70.91
0.107	30.26	31.29	32.45	33.75	35.04	35.84	36.66	38.04	38.46	39.89	42.27	44.52	47.49	54.45	73.29
0.106	31.42	32.55	33.75	35.01	35.79	36.68	37.83	38.23	39.19	41.03	43.42	45.34	49.18	56.08	75.43
0.105	32.50	33.69	34.91	35.85	36.52	37.59	38.05	38.69	40.32	42.42	44.34	45.98	50.72	57.56	77.42
0.103	33.47	34.80	35.68	36.48	37.31	38.13	38.44	39.84	41.58	43.42	44.99	47.48	52.15	58.71	78.99
0.102	34.54	35.73	36.12	37.16	38.05	38.37	39.14	40.58	42.58	44.13	45.79	48.70	53.44	59.97	80.68
0.101	35.38	36.10	36.90	37.92	38.22	38.72	39.94	41.94	43.41	44.79	46.60	50.07	54.63	61.37	82.38
0.100	35.91	36.67	37.70	37.98	38.48	39.72	41.15	42.86	44.12	45.49	47.64	51.26	55.86	62.72	83.90
0.098	36.55	37.29	37.92	38.39	39.14	40.35	42.18	43.56	44.82	46.03	48.83	52.44	57.04	63.98	85.44
0.097	37.02	38.02	38.20	38.71	39.76	41.43	42.86	44.10	45.33	47.15	49.93	53.46	57.95	65.28	86.71
0.096	37.72	37.97	38.43	39.49	40.62	42.34	43.49	44.66	45.92	47.94	50.95	54.37	58.63	66.47	88.12
0.095	37.93	38.42	39.02	40.22	41.95	42.98	44.24	45.23	46.74	49.18	52.11	55.59	59.83	67.82	89.57
0.094	38.23	38.69	39.82	41.10	42.49	43.67	44.68	45.89	47.52	50.23	53.03	56.41	60.70	68.94	90.90
0.093	38.39	39.37	40.32	42.06	43.25	44.32	45.21	46.54	48.66	51.17	54.14	57.42	61.91	70.10	92.43
0.092	38.87	39.93	41.36	42.79	43.79	44.80	45.82	47.33	49.62	52.13	54.91	58.19	62.97	71.51	93.79
0.091	39.69	40.72	42.30	43.45	44.38	45.28	46.45	48.29	50.61	53.14	56.00	59.04	64.07	72.79	95.09
0.090	40.28	41.81	42.82	43.79	44.81	45.88	47.34	49.39	51.55	54.12	56.87	59.95	65.24	73.99	96.47
0.089	41.13	42.45	43.54	44.47	45.38	46.43	48.15	50.33	52.49	54.89	57.77	60.94	66.35	75.09	97.57
0.088	42.01	43.09	43.99	44.99	45.92	47.31	49.22	51.19	53.45	55.93	58.33	62.11	67.44	76.42	99.05
0.087	42.75	43.66	44.60	45.47	46.59	48.20	50.28	52.21	54.28	56.84	59.34	63.17	68.61	77.54	100.32
0.086	43.34	44.37	45.01	46.03	47.40	49.26	51.11	53.14	55.31	57.72	60.36	64.23	69.71	78.76	101.79
0.085	43.76	44.82	45.70	46.79	48.35	50.28	52.09	54.20	56.17	58.30	61.39	65.48	71.03	79.82	103.15
0.085	44.51	45.23	46.09	47.57	49.45	51.17	53.02	54.93	57.12	59.32	62.48	66.51	72.25	81.06	104.54
0.084	44.98	45.89	47.10	48.65	50.44	52.11	54.07	56.06	58.00	60.37	63.37	67.71	73.55	82.43	105.98
0.083	45.50	46.53	47.97	49.66	51.41	53.14	54.91	57.02	58.80	61.40	64.67	68.90	74.74	83.80	107.19
0.082	45.91	47.45	49.15	50.76	52.44	54.18	56.05	57.94	59.89	62.59	66.00	70.11	76.16	85.07	108.73
0.081	47.03	48.54	50.25	51.92	53.48	55.18	57.08	58.69	60.90	63.68	67.27	71.66	77.54	86.46	110.45
0.081	47.96	49.66	51.23	52.88	54.49	56.20	57.98	59.87	62.23	65.14	68.53	73.00	78.92	87.84	112.00
0.080	49.17	50.79	52.39	54.06	55.64	57.26	58.85	60.83	63.29	66.40	69.75	74.31	80.12	89.15	113.51
0.079	50.50	52.07	53.64	55.13	56.86	58.27	60.08	62.37	64.95	67.89	71.48	75.98	81.74	90.91	115.34
0.078	51.71	53.23	54.81	56.35	58.04	59.53	61.48	63.63	66.41	69.36	73.05	77.56	83.52	92.80	117.25
0.078	52.93	54.36	56.08	57.62	58.90	60.72	62.83	65.25	67.90	70.93	74.67	79.15	85.07	94.50	119.12
0.077	54.33	55.94	57.42	58.74	60.53	62.50	64.56	67.07	69.58	72.87	76.63	80.96	86.94	96.59	121.23
0.076	55.88	57.27	58.56	60.30	62.11	64.07	66.39	68.77	71.62	74.76	78.63	82.94	88.81	98.55	123.47
0.075	57.37	58.65	60.33	62.06	63.93	66.16	68.30	70.81	73.75	76.95	80.46	85.07	91.05	100.88	126.10
0.075	58.92	60.54	62.39	64.17	66.31	68.29	70.64	73.31	76.11	79.28	82.94	87.37	93.76	103.65	128.91
0.074	60.93	62.79	64.63	66.57	68.59	70.83	73.27	75.85	78.68	81.72	85.57	90.02	96.57	106.56	131.97
0.073	63.51	65.59	67.34	69.36	71.56	73.87	76.26	78.80	81.50	84.78	88.46	93.35	99.70	109.71	135.63
0.073	67.09	68.92	70.87	73.05	75.16	77.43	79.66	82.34	85.25	88.48	92.44	97.36	103.86	113.99	140.16
0.072	71.51	73.58	75.60	77.71	79.66	81.98	84.45	87.07	89.93	93.47	97.53	102.48	108.97	119.30	145.96
0.072	78.21	80.00	82.08	84.31	86.40	88.68	91.15	94.11	97.18	100.66	104.85	109.71	116.51	127.06	154.27
0.071	88.60	90.66	92.95	95.25	97.58	99.95	102.71	105.66	108.65	112.28	116.50	121.67	128.72	139.68	167.10
0.070	173.46	175.97	178.56	181.15	183.89	186.67	189.67	192.82	196.35	200.39	205.01	210.61	218.08	229.40	257.34

3. DELAY OF UI APPLICATION FOR DISABLED INDIVIDUALS

Abstract

This paper studies in more depth regarding the contributing factors for individuals who have reported disability to be more likely to delay and have longer delay before claiming UI. I extend the methodology build in previous chapters to study the effect of availability of other welfare programs such as Supplemental Security Income (SSI) on the application delay of UI for people who have reported disability. I find that for people who have reported disability, lower age, being female, lower total household income, being on SSI, high total household SSI amount received, facing good economic conditions, and fewer experienced number of job separations will make delay more likely and increase the length of delay. This finding shows the availability of SSI will increase the probability of waiting among people who have reported disability. Moreover, the higher the SSI amount received, the more likely the disabled individuals will wait and the longer they will wait. Simulation results show individuals who have reported disability have lower belief of high state and higher application costs of UI compared to the general population.

3.1 Introduction

In Chapter 1 I found that people with disability are more likely to wait and wait longer before taking up unemployment benefits compared to people without disability. More specifically, the probability of waiting for people with disability are 35.6% [1] higher compared to people report themselves to be healthy. The 'waiting time' before taking up UI is 18.2 [2] weeks longer for disabled individuals compared to people without disability. Moreover, Cox regression analysis shows disabled individuals have lower hazard (longer duration) of conditional UI than individuals without disability– conditional on idling without unemployment benefits, being disabled reduces the instantaneous probability of taking up unemployment benefits by 30.9% [3]. This paper study in more depth of this phenomenon and investigate the potential reason for disabled individuals' longer delay before taking up unemployment benefits.

As discussed previously a potential reason for the disabled individuals' longer delay of UI take-up is they may be eligible for other social insurance programs which provide higher replacement rate and longer program duration compared to state unemployment insurance. Therefore for people with disability that may be eligible for other benefit programs designed for people with disability they are likely to consider applying for those programs first before trying to take up unemployment insurance. The disability insurance programs including government provided programs such as SSDI (social security disability insurance) and SSI (supplement security income); employed sponsored disability insurance that are paid by employers of insured individuals; and commercial or private disability insurance that purchased by the individuals insured themselves.

Social Security Disability Insurance(SSDI): Social Security Disability Insurance benefits are federally funded and administered by the U.S. Social Security Administration (SSA). SSDI pays disability benefits to eligible individuals and certain family members have worked long enough and recently enough and paid Social Security taxes on earnings. The insured individuals also need to have a medical condition that prevents them from working for at least 12 months. More specifically, in order to be eligible for SSDI benefits one must be unable to work because of a medical condition and is expected to last at least one year or result in death. SSDI are paid monthly and will continue until the individual can work again on a regular basis. SSDI will automatically convert to retirement benefits if the eligible individuals reach full retirement age [4]. The SSA provides a strict definition of disability and is listed in detail in Appendix **??**. In addition to meeting the requirement of being disabled a person must also have worked long enough and recent enough

[1]↑Result in Table 1.4
[2]↑Result in Table 1.4
[3]↑Result in Table 1.5
[4]↑Full retirement age, also called 'normal retirement age', was 65 for many years. In 1983, Congress passed a law to gradually raise the age because people are living longer and are generally healthier in older age. The law raised the full retirement age beginning with people born in 1938 or later. The retirement age gradually increases by a few months for every birth year, until it reaches 67 for people born in 1960 and later [39]

under Social Security to qualify for disability benefits. Qualified individuals must have earned enough work credits which is based on total yearly wages. The number of work credits needed to qualify for SSDI depends on age and when disability begins. Generally a person need 40 credits and 20 of which were earned in the last 10 years [5] in order to qualify the work credits [6] requirement [39]. The amount of social security monthly benefits an individual will receive is computed using the person's average indexed monthly earnings (AIME), which is the average covered earnings over a period of time. SSA uses AIME in a formula to determine the person's primary insurance amount (PIA). PIA is the basic amount used to establish monthly benefits [7]. In 2022, the maximum social security benefit is $\$3345/month$. In January of 2022 the estimated average monthly benefits payable to disabled worker,spouse and/or children is $2383 [40].

Supplemental Security Income(SSI): Supplemental Security Income [8] is a Federal funded program designed to provide benefits to adults and children with disabilities whose income [9] and resources (things they own) [10] are below specific financial limits. SSI payments are also provided to people over 65 and older without disabilities and have limited income or resources. A key difference between SSI and SSDI is that SSI does not need the applicants to meet the work requirement. But the medical requirements for disability is the same for the two programs. The definition of disability in both SSDI and SSI programs means total disability. SSDI and SSI will not pay for partial disability or short-term disability. More specifically a person is considered to be disabled and qualify for SSI (SSDI) if all the following conditions are satisfied:

- The person cannot do work and engage in substantial gainful activity (SGA) [11] because of the medical condition.
- The person cannot work he did previously or adjust to other work because of the medical condition.
- The condition has lasted or is expected to last for one year or to result in death.

SSI is also paid monthly and require the applicants to have a medical condition expected to last at least a year or result in death [citeSSA]. Application of SSI can be online, by phone or in person and if approved the amount a person will receive depends on state, a person's other income and the total household income [12].

[5]↑A person can earn up to 4 credits each year.
[6]↑The amount needed for a work credit changes over time. In 2022 one credit is equivalent to $1510 of wages or income and $6040 is the amount needed to earn the full four credit for the year.
[7]↑How the monthly benefits are computed using PIA is explained in more detail in Appendix 3.6.2
[8]↑Income includes earning through wages or self-employment; unearned income such as Social Security benefits, unemployment benefits, interest or dividends; in-kind income (food and shelter) and deemed income which is income from spouse, parents or sponsor.
[9]↑Spouse's income and resources is a factor when determining whether an individual is qualified. If the applicants is under 18 then parents' income and resources is a factor when determining whether an individual is qualified.
[10]↑Resources include real estate, bank accounts, cash, stocks and bonds. The requirement for resources is if a person's resources is worth $2000 or less and a couple's resources is worth $3000 or less.
[11]↑In 2022, the threshold of SGA is set to be $1350 for non-blind individuals and $2260 for blind individuals.
[12]↑Whether there is other family member in the household that has income.

The amount of Federal SSI benefit changes over time. In 2022 the Federal benefit rate (maximum Federal amount) is \$841 for an individual and \$1261 for a couple. Most states supplement the Federal SSI benefit with additional payments and make the total SSI benefit levels higher [13]. The SSI Federal benefit is calculated by subtracting the countable income [14] from SSI Federal benefit rate.

Difference between Unemployment Insurance and Disability Insurance: In order to study the potential reasons for disabled individuals' longer delay before taking up unemployment benefits it is necessary to discuss the difference between UI and DI programs. State unemployment insurance and SSDI or SSI are all government funded welfare programs but serve different purposes. State unemployment insurance is designed to provide the insured workers with temporary financial assistance in order to smooth consumption and maintain certain quality of life after they lost jobs. UI requires applicants to be physically and mentally available to work and actively seeking for work. UI applicants also are required to have worked long enough and recent enough in order to be eligible for UI. SSDI provides financial support to insured workers who can no longer work due to their disability. Having severe and long-term medical conditions that prevent them from working is the requirement for an individual to be eligible for SSDI. SSDI also require the claimants to be covered by social security, meaning they must have worked long enough and recent enough and have paid Social Security taxes on earnings. SSDI is designed to provide long-time support to eligible applicants since the disability status is expected to last at least a year on order to qualify for SSDI in the first place. Contrary to UI benefits which is temporary and will not last more than 26 weeks under normal economic condition, SSDI benefits will last as long as the person's medical condition does not improve. The SSI program is designed to provide financial support for people with severe disability [15] and have income and resources below certain financial limits. Similar as SSDI there is no 'expiration date' or maximum benefit duration for SSI benefits. A person can continue to claim for SSI as long as his/her current medical condition does not improve. The major difference between SSDI and SSI is that SSI does not require the claimants to have enough or recent work history. SSI is a means-tested program and the amount of benefit received is not related to a person's past earnings but the state the person is living and the amount of income and resources the person has. The amount of benefits payable differ for the three programs. For instance, in 2022, UI pays $\$1896/month$ $(4 \times \$474)$ [5] on average nationwide; SSDI pays on average $\$2383/month$[40] nationwide; SSI pays an average $\$841/month$ to individual and \$1261 to couple [40] nationwide. Comparing the average monthly benefit amount in the three programs we can see the amount of SSI benefits is significantly less than both SSDI and UI. Considering the fact that UI can only last a maximum of about 4 to 5 months normally and SSDI can last potentially a life-time a person who is on SSDI will receive significant more amount of

[13] ↑There are 6 states that do not pay a supplement. They 6 states are Arizona, Arkansas, Mississippi, North Dakota, Tennessee and West Virginia.
[14] ↑Countable income is the remaining amount after subtracting the income that do not count from total gross income.
[15] ↑And people age 65 and order without disability.

benefits comparing to if he is on UI.

Studies of Disability Insurance and Unemployment Insurance: Some papers studying the insurance and disincentive effect of disability insurance. Kitao (2014) [41]developed a life-cycle model in which individuals face uncertainty including employment, health status and medical expenditures. The paper focused on studying disability insurance system that include both cash and in-kind medical benefits. The author showed that not only the cash benefits but also the Medicare benefits are important to account for the level of DI coverage. DI coverage could drop significantly if its Medicare benefits were eliminated. Low and Pistaferri (2015) [42] studied the insurance and disincentive effects of disability benefits and how policy reforms impact behavior and welfare. The authors found that the government provided disability insurance against the work-limiting health risk that individuals face is incomplete and there are substantial false rejections for those in need. Simulation from the paper's model showed that the number of moderately disabled individuals receiving DI is particularly sensitive to the policy parameters, and the number of severely disabled is less sensitive. The paper concluded that despite the disincentive effect, welfare increases if the threshold for acceptance of disability insurance is lower, disability payments are higher, reassessment less frequent, and food stamp payments more generous. The paper also pointed out the allowing for partial disability and partial DI payments may be a way to reduce the incentive cost of DI. Some papers study the interaction of disability insurance and unemployment insurance. Daniel van and Pierre (2010) [43] estimated the degree of substitution between enrollment into disability insurance and unemployment insurance in Netherlands. The paper studied the interaction of UI and DI in two directions: whether reducing DI enrollment will lead to reduction in hidden unemployment in DI; and whether reducing DI enrollment will lead to increase of hidden disability in UI. The authors found that about one quarter of the DI enrollments in their data was in fact hidden unemployment, suggesting there is strong substitution of UI into DI scheme. The paper found no evidence that there is significant amount of disabled persons in UI, suggesting there does not exists reverse substitution of DI into UI scheme. Rutledge (2012) [44] studied the effect of UI benefit duration extensions on disability insurance application. The paper found people who are on extended UI benefits are significantly less likely to apply to disability insurance and those who have exhausted their UI benefits are significantly more likely to apply when UI is exhausted. Moreover, healthier potential applicants are more likely to delay in claiming disability insurance after UI extension. Since the extension of UI make applicants more likely to delay in applying for DI, the paper's finding suggested that the benefits of UI extensions may be understated. Lindner (2016) [45] examined whether Unemployment Insurance affect the decision to apply for Social Security Disability Insurance. The author found a negative association between UI benefits and DI applications at the aggregate level but the results are not robust at individual level. The paper's finding suggests the substitution effect of UI benefits on applications for DI may exist for some groups of workers but not for others. Further studying of the interaction of the two programs show that the substitution effect is economically significant. More specifically, a 1 dollar increase in UI benefits reduces DI expenditures by

15 cents. Since the cost savings of lowering DI expenditures could be substantial, when the interaction of UI and DI programs is present optimal UI benefits should be higher based on the optimal UI benefit calculations. The paper also found older workers' DI application decision is more sensitive to UI benefits as compared to younger workers. Mueller, Rothstein and Wachter (2016) [46] had somewhat different finding in the relationship between UI and SSDI. The paper examined the relationship between UI exhaustion and uptake of SSDI benefits and found no indication that expiration of UI benefits causes SSDI applications. The authors pointed out that due to the limitation of data a causal link between UI exhaustion and SSDI can not be conclusively ruled out.

In this paper, I also explore whether there is a potential link between unemployment and disability insurance programs. More specifically, I examine the question that whether the availability of other insurance programs designed for people with disability is a contributing factor of disabled people's higher likely to wait and longer waiting time before applying for unemployment benefits. The paper proceeds as follows: Section 3.2 describes data and findings from data. Section 3.3 explore the factors that have significant effect on the 'waiting time' and 'waiting likelihood' of people who have reported disability. Section 3.4 examines simulation results from model for people with disability. Section 3.5 Concludes.

3.2 Summary Statistics

3.2.1 Data Description

In this chapter I use the same data as Chapter 1 which is the 2008 panel of Survey of Income and Program Participation. As mentioned previously, 2008 panel covers from May 2008 to November 2012 with a duration of 4 and half years. The question studies in this paper is whether and how disability insurance will affect disabled individuals' 'waiting time' before getting on unemployment insurance. Therefore only people who have reported to be disabled should be selected in this study. Individuals who have always reported to be healthy during the survey period will not be in the sample for this paper. SIPP does not have a question directly ask the person whether he/she is disabled. But there is a variable where the question is asking 'Do you have a physical, mental, or other health condition that limits the kind or amount of work that you can do at a job or business'. This variable should be a good proxy for whether the person has work-limited disability in the current reference period [16]. I keep all individuals who have reported having work-limited disability at some point during survey period. SIPP does not have a variable that ask interviewed individuals about Social Security Disability Insurance (SSDI). However SIPP have questions regarding Supplemental Security Income. One variable is 'Receipt of State administered SSI' where the question is asking 'Did you receive a separate SSI payment from the State or local government'. One variable is 'Receipt of Federal SSI for self' where the question ask 'Did you receive any income from Supplement Security Income for yourself during

[16] ↑Reference period is a month.

the reference period'. Another variable is 'Receipt of Federal SSI for Children' where the questions asks 'Did you receive any Supplemental Security Income on behalf of children during the reference period'. I construct a variable 'OnSSI' where OnSSI is 1 if any of the above three variables is 1. The number of individuals who have reported to be on SSI is 4343.

Table 3.1. Main Variables Summary Statistics for People with Disability

Variable	Mean	Std.Dev	Median	Min	Max	N
HouseIncome	$4147.57	$3570.09	$3262.81	$-1845.46	$56855	12505
Age	44.19	14.21	47	18	65	16789
Education	19.40	3.06	19	7	30	16789
Unem Duration	72.94	85.31	35	1	279	27362
Individual	99.88	91.44	65	1	279	16789
UI Duration	49.37	30.07	35	4	99	2440
TotalHouseSSI	$120.30	$246.07	0	0	$5185	12505

Table 3.1 shows main variables summary statistics for people with disability. There are a total of 16789 people who have reported to have work-limited disability. Among these people 7727(46%) are male and 9062 (54%) are female. In this sample I keep the individuals whose age are between 18 and 65. The average age is 44.19 years old. The average education is 19.4 years which corresponds to high school graduates. $HouseIncome$ is average total household income. There are a total of 12505 number of household in the sample with an average total household income of $4147.57. $UnemDuration$ indicates how long unemployment spells last on average. There are a total of 27362 number of unemployment spells among the 16789 individuals since one person can have multiple unemployment spells. On average each person has 1.63 (27362/16789) times of job separations. The average length of unemployment spells across all unemployment spells (at individual/unemployment spells level) are 72.94 weeks. At individual level, the average length of unemployment spells are 99.88 weeks. $UIDuration$ shows for people with disability and have claimed unemployment benefits how long unemployment insurance benefits last. Table 3.1 shows there are 2440 people who have claimed unemployment benefits and the benefits lasts 49.37 weeks on average. $TotalHouseSSI$ is total household supplemental security income. The average total household SSI is $120.3.

Compare Summary Statistics for People with Disability (Table 3.1) and All individuals (Table 1.1): It will be informative to see some traits of people who have reported with disability by comparing the summary statistics in Table 1.1 that includes all individuals and in Table 15 that include only individuals with disability. We can see that the average age for people with disability is 7 years (44 years old compared to 37 years old) older than in sample including all individuals. In other words, on average people with disability on 7 years older than the general population. Average education for disabled people is smaller but close to the general population. But since 19 years is a cutoff for degree the average education for disabled people are 'high school graduates' whereas the average education for the general population is 'some college, but no degree'. Average total household income for disabled individuals are about $1072 ($4147.6 vs 5219.1) less compared to the general population indicates the average total household income for disabled individuals is about 20% less. On average the unemployment duration for disabled individuals are about 20.8 (72.9 vs 51.2) weeks longer than the general population at individual/unemployment level and 35 (99.88 vs 64.92) weeks longer at individual level. The average length of unemployment benefits for disabled individuals are 3.5 (49.37 vs 45.87) weeks longer.

In summary, on average, compared to the general population, people who have reported disability are 7 years older, with total household income about 20% less, with unemployment duration about 20.8 weeks longer and having an average length of unemployment benefits about 4 weeks longer.

3.2.2 Findings from Data

Next I analyze the waiting time before taking on unemployment insurance for people who have reported disability in Table 3.2and Table 3.3. The difference between Table 3.2and Table 3.3 is in line with in Table 1.2 and Table 1.3. Table 3.2 calculates 'waiting time' as the time length from job separation to either finding jobs, or on UI or still unemployed before survey ends. In this case, any time period without UI after job loss is treated as 'waiting time'. People who are separated from jobs and never applied for UI can be interrupted as having an indefinite 'waiting time'. The 'waiting time' calculated in Table 3.2 should be the upper bound of the length of 'waiting time'. There are a few reasons for 'waiting time' calculated this way to be upper bound of the true 'waiting time'. First not all individuals in this sample will be eligible for UI, especially since the sample selected are people who have reported to be disabled. The requirement to be eligible for UI is to be able to work and actively searching for work, which will make some people with disability not eligible because of there health conditions. Others will not be eligible because they do not have enough work credit. Therefore some 'waiting time' observed are not people waiting but because they are not eligible to claim UI. The second reason is there should be a percentage of people who do not aware either the existence of UI or that they are eligible for UI simply because they are not familiar with the UI program. This reason may be particularly prominent in this sample since for people who have reported disability they may be deterred to apply for UI if they have concerns that their medical condition will make them ineligible. The third reason for 'waiting time' calculated in this way to be upper bound is there should be a percentage of people that are out of the labor force or and not searching for jobs and UI at all. Considering a portion of people in the sample may have severe disability and not looking to be in the labor force again they are not waiting to claim UI. A proportion of people will be on other insurance program such as SSDI that will provide benefits for as long as their medical conditions last. For the above reasons, the actual 'waiting time' should be smaller than the ‘waiting time’ calculated in Table 3.2. But Table 3.2 still provide insight on what is the upper bound ‘waiting time’ will look like. Table 3.3 calculate waiting time including only the unemployment spells that result in receiving unemployment insurance. The results show in Table 3.3 should be the lower bound of ‘waiting time’. In Table 3.3 ‘waiting time’ is calculated including unemployment spells after job separation that only end up as unemployment benefits take-up. More specifically ‘waiting time’ is calculated as the time gap between job separation and receiving UI. This calculation ruled out the possibility that some individuals are either ineligible of UI or do not aware of the existence of UI because they have already claimed it. So all people include in this sample are clearly aware of the existence of UI and are eligible for UI. In this sense in my opinion Table 3.3 reports the UI ‘waiting time’ that are more close to the true ‘waiting time’ of UI. In Table 3.3 I exclude cases that people are still waiting to claim UI before the survey ends and adjust the ‘waiting time’ to eliminate the potential administrative period a person has to wait before receiving UI[17]. Therefore the ‘waiting time’ reported in Table 3.3 should be the lower bound of true ‘waiting time’. Results of Table 3.2 are Table 3.3 are shown below.

> **Finding 1: (Extensive Margin) The proportion of people who will wait at least one wait are about 8% (lower bound) to 10% (upper bound) higher among those who have reported disability than that in the general population. (Intensive Margin): The average ‘waiting time’ is about 36% (lower bound) to 40% longer (upper bound) among people with disability compared to the general population. (Multiple Separations): People with disability also has the pattern that ‘waiting time’ decreases as number of job loss increases.**

Upper Bound of ‘Waiting Time’ and Waiting Behavior: The findings in this section is in line with the findings in Table 1.2 and Table 1.3. Table 3.2 reports the upper of ‘waiting time’ and waiting behavior. Table 3.2 shows people with disability on average have 1.4 (16713/22740) times of delaying before taking up unemployment benefits and the vast majority of disabled individuals [18] have delays before getting on unemployment insurance. In Table 3.2, which reports the upper bound of waiting time, at individual/waiting time level there are about 85% (22740/26658) have at least a week between job loss and unemployment benefits take-up. Over 91% (15224/16713) disabled people would wait at least one week before taking up unemployment benefits. Comparing results in Table 3.2 for people with disability with results in Table 1.2 for the general population the proportion that would wait at least one week are about the same at individ-

[17]↑Similar as described previously in Table 1.2 and Table 1.3, ‘Waiting time’ is recalculated in order to eliminate the potential time period of administration delay. Since it can take up to 3 weeks for a UI application to get processed and approved. ‘Waiting time’ is adjusted to subtracting 3 if the original ‘waiting time’ calculated is bigger than or equal to 3 and is assigned as 0 if smaller than 3.

[18]↑The disabled individuals refer to people who have ever reported to have work-limited disability during survey period. It does not mean they are disabled at the time that they claim UI. I refer to these people as disabled individuals for simplicity.

Table 3.2. Waiting Time Summary Statistics for People with Disability -Upper Bound

		AvgWaitT	MednWaiT	Min	Max	Number
All						
	Indivl/WaitTime	69.42(85.84)	28	0	279	26658
	Imm	0	0	0	0	3918
	NotImm	81.28(87.64)	39	1	279	22740
	Individual	94.65(92.84)	54	0	279	16713
	Imm	0	0	0	0	1489
	NotImm	102.21(94.39)	66	1	279	15224
FirstTime						
	All	93.49(94.73)	22	52	279	16600
	Imm	0	0	0	0	1455
	NotImm	102.43(94.46)	67	1	279	15145
SecondTime						
	All	39.04(54.57)	17	0	266	4772
	Imm	0	0	0	0	947
	NotImm	48.56(57.08)	22	1	266	3825
ThirdTime						
	All	20.31(32.62)	7	0	255	8303
	Imm	0	0	0	0	533
	NotImm	34.19(42.62)	17	1	252	1667
>ThirdTime						
	All	22.25(36.30)	8	1	263	2397
	Imm	0	0	0	0	519
	NotImm	28.21(38.96)	13	1	263	1878

Table 3.3. Waiting Time Summary Statistics for People with Disability - Lower Bound

		AvgWaitT	MednWaiT	min	max	N
All						
	Indivl/WaitTime	19.76(39.52)	3	0	262	5214
	Imm	0	0	0	0	2226
	NotImm	34.31(47.22)	17	1	262	2988
	Individual	25.68(46.32)	8.4	0	262	2364
	Imm	0	0	0	0	1489
	NotImm	44.33(57.99)	18	1	262	1283
FirstTime						
	All	23.22(47.02)	2	0	262	2251
	Imm	0	0	0	0	1047
	NotImm	43.31(57.16)	18	1	262	1204
SecondTime						
	All	19.25(37.51)	3	0	261	1291
	Imm	0	0	0	0	542
	NotImm	33.02(44.43)	17	1	261	749
ThirdTime						
	All	16.77(29.02)	4	0	200	691
	Imm	0	0	0	0	269
	NotImm	27.26(33.13)	17	1	200	422
>ThirdTime						
	All	16.59(28.65)	4	0	209	826
	Imm	0	0	0	0	266
	NotImm	24.28(32.05)	12	1	209	560

ual/waiting time level(85% in general population versus 87% for people with disability). The proportion of people who would wait is about 10% higher among disabled individuals compared to in general population (91% versus 81%). Comparing the upper bound of waiting time in Table 3.2 with that in Table 1.2, the average waiting time for people with disability is about 34.23 (94.65 in Table 3.2 versus 60.42 in Table 1.2) weeks longer than that in the general population. The median waiting time is 28 (54 weeks in Table 3.2 versus 26 weeks in Table 1.2) weeks longer among people with disability than in the general population. There is clearly still a pattern among people with disability that the 'waiting time' decreases as number of job loss increases. Moreover, the 'waiting times' are consistently longer among people with disability than in the general population for the first, second, third and more than three times job loss.

Lower Bound of 'Waiting Time' and Waiting Behavior: Table 3.3 shows the lower bound of 'waiting time' and waiting behavior. In Table 3.3 there are 54.6% (1283/2384) percent of disabled individuals wait at least one week before claiming UI. The proportion of disabled individuals that will wait is about 8% (46.6% in the general population versus 54.6% for people with disability) higher compared to the general population showed in Table 1.3. The lower bound of average waiting time is 25.86 weeks at individual level and 19.76 weeks at individual/waiting time level. Comparing results in Table 3.3 to results in Table 1.3 we can see the average waiting time for people with disability is about 10.44 (25.68 weeks for disabled individuals versus 15.24 weeks in general population) weeks longer than the general population. The median 'waiting time' is about 4.7 (8.4 weeks for people with disability versus 3.7 in general population) weeks longer for people with disability. Table 3.3 also shows the pattern that 'waiting time' decreases as number of job loss increases. Results in Table 3.2 and Table 3.3 consistently show that the proportion of people that wait at least one week before claiming UI are about 8% (lower bound) to 10% (upper bound) higher for people with disability than in the general population. Moreover, the average 'waiting time' is about 36% (lower bound) to 40% (upper bound) longer for people with disability than in the general population. The median 'waiting time' is about 52% (upper bound) to 56% (lower bound) longer for people with disability.

3.3 What Influences Application Delay for People with Disability?

Previous section shows the proportional of people waiting is high and the length of 'waiting time' is longer for people who have reported disability than the general population. In this section I study the observable that affect disabled individuals delay and find the factors that will affect the disabled individuals to be more likely to wait and wait longer. In section 3.3.1 I use Probit model to find what factors will have significant effect on the probability of waiting, i.e. the extensive decision to delay and Linear regression model to find what factors will have significant effect on the length of 'waiting time' or the intensive decision of delay for people with disability. I also discuss conditional application for disabled individuals in this section. Since the main purpose of this paper is to answer whether having the choice of disability insurance is a contributing factor for people with disability to be more likely to delay and delay longer before claiming UI, in section 53 I will study this question in more depth using kaplan-Merer Curve and see how being on SSI (treatment) will affect the conditional application of UI. I also run Cox regression to provide a more quantitative analysis about the hazard of claiming UI.

3.3.1 Probit and Linear Regression for People with Disability

In this section I first use Probit model to determine what variables will have significant effect on the probability of waiting for people with disability. The general independent variables I use are demographic characteristics including age, education, gender, marital status, total household income and rate. I also use monthly state unemployment rate as proxy for economic conditions and a variable indicating the number of times of job loss. The main variables of interest are a variable that indicate whether the person have been on SSI and the total household supplemental security amount. Specifically, the Probit regression I run is

$$Wait_{i,t} = \beta_0 + \beta_1 OnSSI_i + \beta_2 House\mathrm{e}SSIAmt_{i,t} + \beta_3 Unemploy Rate_t + \beta_4 JoblossT_{i,t} + \beta_5 X_{i,t} + \epsilon_{i,t} \quad (3.1)$$

In the above equation, dependant variable indicates whether the person have waited before applying for UI. I calculate 'waiting time' for each time of job loss and the 'waiting time' calculated is adjusted for the administrative period [19]. Define variable $Wait$ to be 0 if 'waiting time [20] is 0 and 1 if 'waiting time' is bigger than 0. $OnSSI$ is the variable that will be equal to 1 if the person have reported to have received state or federal administered SSI for self or children [21]. The most ideal situation would be to count only

[19]↑The period a UI applicants may need to wait before receiving UI after application

[20]↑'Waiting time' find the time gaps between losing job and finding jobs, or on UI or still unemployed before survey ends.

[21]↑There are three variables in SIPP that are relevant to receipt of SSI: 'Receipt of State Administered SSI', 'Receipt of Federal Administered SSI' and 'Receipt of Federal SSI for children'. I assign $OnSSI$ to be 1 if any of the above three variables is 1 in the data.

$OnSSI$ during the time after job loss and before claiming UI. However there are very few observations in the data that match this exact requirement. There are only 4343 individuals who have reported to receive SSI in the data. Table 3.3 shows there are only 2364 disabled individuals who have claimed UI. The number of cases that satisfy to have claimed SSI before UI are very few and not enough for analysis. Therefore I use an alternative way to define $OnSSI$ which is marking $OnSSI$ as 1 is a person has ever reported to claim SSI. With this definition we know that people who have claimed SSI are clearly aware of the existence of SSI, eligible for SSI and will likely choose SSI as a source for financial support when unemployed. Another variable of interest is the average total household SSI amount received $HouseSSIAmt$. SSI provides a variable that people report the total household SSI amount they receive in the reference period (month). I take an average of total household SSI amount for each individual and see how the amount of SSI received with affect the probability of waiting.

Next I run linear regression model to study the intensive margin of waiting for people with disability. The explanatory variables used in linear regression is the same as in Probit regression. The dependent variable in linear regression is the 'waiting time' which is the time gap between losing job and finding job again, on UI or remain unemployed until the end of survey. I add state and year fixed effect and cluster at industry level [22]. The main variables of interest in linear regression are also $OnSSI$ and $HouseSSIAmt$ which will help answer the question whether SSI will make people with disability to wait longer and how the amount of total household SSI received will affect the 'waiting time'.

The regression equation I used is,

$$WaitTime_{i,t} = \beta_0 + \beta_1 OnSSI + \beta_2 HouseSSIAmt + \beta_3 UnemployRate + \beta_4 JoblossT_i + \beta_5 X_{i,t} + \epsilon_{i,t} \tag{3.2}$$

Finding 2: For people who have reported disability, a lower age, being female, a lower total household income, being on SSI, higher total household SSI amount make delay more likely. Good economic conditions make delay more likely. Fewer experienced number of job separations makes delay more likely.

Table 3.4 reports the Probit and Linear regression results for people who have reported disability. As shown in Table 3.4, for people who have reported disability, a one year increase of age will decrease the probability of waiting by 0.84%; being female will increase the probability of waiting by 15.8% compared to male; increase of total household income will decrease the probability of waiting. As number of job loss increases the probability of waiting decreases. The likelihood of waiting increases when unemployment rate is low and the economic conditions are good. The sign of coefficients for the above variables reported in Table 3.4 are consistent with that reported in Table 1.4 for general population. The explanations for why these

[22]↑I tried cluster at individual level and household level as well. Different level of clustering will not affect the sign and significance of main results.

Table 3.4. Regression Results for People with Disability

	Probit If_Wait	Linear Wait_Time
Age	-0.00841***	0.126***
	(-6.32)	(3.88)
Education	0.00127	-0.854***
	(0.27)	(-4.74)
Gender	0.158***	5.958***
	(3.74)	(4.43)
Marital Status	0.0194	1.435
	(0.49)	(1.27)
White	-0.0344	-2.378*
	(-1.03)	(-2.21)
State Unemployment Rate	-0.0583***	-0.559
	(-4.65)	(-1.09)
Total Household Income	-0.0000302***	- 0.000413***
	(-9.58)	(-5.54)
OnSSI	0.123**	15.27***
	(2.77)	(11.91)
Total Household SSI Amount	0.000313**	0.00467**
	(3.13)	(3.13)
Number of Times Lost Jobs	-0.0727***	-2.614***
	(-7.31)	(-12.27)
year=2012	0.162**	13.81***
	(2.82)	(8.22)
Constant	1.845***	63.94***
	(10.62)	(8.24)
Observations	18584	18584

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

dependant variables will affect probability of waiting in those directions should be the same as described in Chapter 1 and are omitted here. One interesting observation we can see by comparing Table 3.4 and Table 1.3 is that age, gender, unemployment rate, number of times of job loss, and total household income have significant effect for both the general population and for people who have reported disability.

The coefficients of the most interest are variables 'OnSSI' and 'Total Household SSI Amount' where 'OnSSI' shows whether a person has reported to claim SSI during the period survey is conducted. From Table 3.4 shows both being on SSI and total household supplemental security amount received will have significant effect on the probability of waiting for people with disability. Having been on SSI will increase the probability of waiting by 12.3% for individuals who have reported disability and higher total household supplemental security amount received will increase the probability of waiting. The results above show having the option of SSI will increase the probability of waiting among people with disability. This finding provides evidence for the previous explanation that the option of disability insurance is a contributing factor for the disabled individuals to have a higher probability of waiting. The finding that total household SSI amount received also have significant effect on both the probability of waiting and length of waiting is worth noting. This shows the effect of other programs available to people with disability is a contributing factor for disabled individuals to be more likely to wait and wait longer not only on the extensive margin but also on the intensive margin. The higher the total household SSI amount received, the more likely the disabled individuals will wait and the longer they will wait and the results are significant at 5% significance level. The reason that a higher total household SSI amount received will increase the probability of waiting is in line with the explanation that the existence of other insurance available for people with disability is the reason for them to wait longer. The more disabled individuals receive from other insurance the longer they will wait before applying for UI.

> **Finding 3: For people who have reported disability a lower age, lower education level, being female, being on SSI and higher total household SSI amount and a lower total household income increase the length of delay. Good economic conditions increase the length of delay. Fewer experienced number of job separations increases the length of delay.**

The second column of Table 3.4 shows how the chosen dependant variables will affect the length of time waiting before taking up unemployment benefits after job loss for people who have reported disability. Table 3.4 shows for people with disability female will wait 5.9 weeks longer compared to male. Non-white individuals wait 2.38 weeks longer compared to white individuals. One year of education decreases 'waiting time' by 0.85 weeks. The 'waiting time' decreases as number of job loss increases. The sign of above variables are consistent with that reported in Table 1.3 for general population and the explanation for effect of these variables on 'waiting time' are consistent with that in Chapter 1 and is also omitted here. The above variables: gender, education, race, number of times lost jobs have significant effect on 'waiting time' for both the general population and people who have reported disability.

Table 3.4 shows among people with disability those with lower total household income wait longer. A possible explanation for this is people with lower total household income might want to get on disability insurance (SSDI) than UI since SSDI has a much higher replacement rate than UI and last a lot longer than UI. For people who have lower total household income SSDI is therefore a more 'attractive' option when they are unemployed and have disability. However, without data related to SSDI we are unable to verify this explanation.

A variable in Table 3.4 is particular interesting: age. The sign for effect of age on 'waiting time' are opposite in Table 3.4 and Table 1.3 indicating the effect of age on 'waiting time' are different for the general population and people with disability. More specifically, Table 3.4 shows one year increase of age will increase 'waiting time' by 0.126 weeks. On the contrary, results in Table 1.3 shows a one year increase of age will decrease 'waiting time'. The increase of 'waiting time' as age increases for people with disability may be more evidence that disabled individuals wait longer because of the availability of SSDI for them. Older individuals are more likely to have enough work credit and a medical condition to make them more likely to be eligible for SSDI.

Now we look at the main variables of interest in this paper:' OnSSI' [23] and 'Total Household SSI Amount' and see how these two factors will affect 'waiting time' for the disabled individuals. The second column of Table 3.4 shows having been on SSI will increase 'waiting time' by 15.27 weeks for disabled individuals. This is more evidence that other insurance available for people with disability is a contribution factor for them to wait longer before taking up UI. Increase of total household SSI amount received will increase 'waiting time' for UI. The effect of total household SSI amount received on waiting time is consistent with the finding in Probit model.

Conditional Application for Individuals with Disability

In this section I study conditional application for people with disability similar as in chapter 1. I first draw Kaplan-Meier Curves to demonstrate the proportion of population that survive at time $t+1$ conditional on survived at time t. Then I draw Kaplan-Meier curve for people with SSI and without SsI to compare the effect of SSI on conditional application. Then I run Cox proportional hazards regression to analyze the factors that have significant effect on survival time.

[23]↑'OnSSI' indicates whether an individual has been reported to claim SSI during survey period.

Keplan-Meier Curve

I first draw Kaplan-Meier curve for three circumstances: Conditional Idle– the proportion of idling [24] who are unemployed and without UI in week $t+1$ conditional on unemployed and without UI in week t. This can be treated as the baseline; Conditional UI– the proportional of idling who are unemployed and with UI in week $t+1$ conditional on unemployed and without UI in week t; Condition Job– the proportional of idling who are employed in week $t+1$ conditional on unemployed and without UI in week t. The results of the three circumstances are shown in the subfigures of Figure 3.1.

Subfigure 3.1a of Figure 3.1 shows the 'survival' probability for 'conditional idle': the proportion of idling [25] that remains unemployed and without UI in $t+1$ conditional on unemployed without and benefits in t. The vast majority of unemployment will remain unemployed and without UI (idling) in $t+1$. There are a total of 786458 'conditional idle events'. Subfigure 3.1a shows the vertical drop in each week is consistent and there is no big drop in any week indicating the change of proportion that remained idling in each week is largely the same and there is no big change of proportion that remained idling in each week. We can also see from subfigure 3.1a that the change of proportion that remained idling is gradually decreasing over time.

Subfigure 3.1b shows the 'survival' probability for 'conditional UI': the proportion of idling that transitioned into unemployed and with UI in $t+1$ conditional on unemployed and without UI in t. There are a total of 781 'conditional UI events' which is the number of unemployment spell that transitions into UI in $t+1$ conditional on idling in t [26]. From Subfigure 3.1b we can see the change of proportion that transitions into UI has big drop around the first 4 weeks, week 17,18 and week 35. The pattern of change shown in Subfigure 3.1b of Figure 3.1 is the same as in Figure 1.3 The analysis of the change should be in line with the analysis for Figure 1.3 and is omitted here.

Subfigure 3.1c shows the 'survival' probability for 'conditional job': the proportion of idling that transitioned into employment in $t+1$ conditional on unemployed and without UI in t. There are a total of 12043 number of 'conditional job events' [27].Results in subfigure 3.1c shows there is big change of proportion that transitions into employment around the first 4 weeks and week 17,18.This pattern of change is also consistent with the pattern in Figure 1.3 and the explanations are also omitted here.

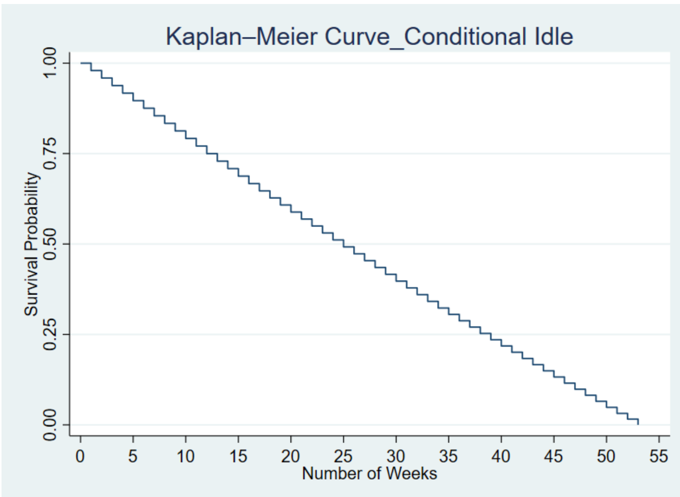
The Kaplen-Meier curves of conditional application in Figure 3.1 for people with disability are consistent with those in in Figure 1.3 for the general population. A question of interest to study the 'waiting' behavior

[24]↑I calculate the transitions of unemployment status not individuals. Since each individual can have multiple unemployment spells so I calculate the change at individual/unemployment spell level not at individual level. Therefore I call it idling here not individuals.

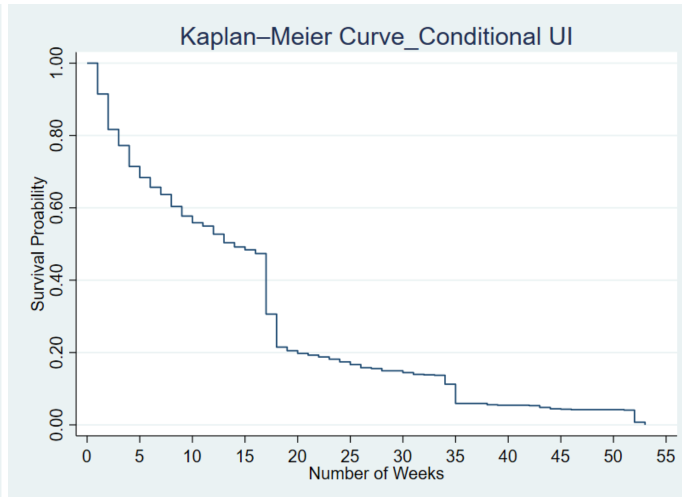
[25]↑The graphs draws transitions of unemployment not individuals.

[26]↑Since the number of unemployment spells that transitions into UI is not only 0.1% of idling. Subfigure 3.1b is drawn to show the transitions into UI based on the 781 'conditional UI events' not including all idling events.

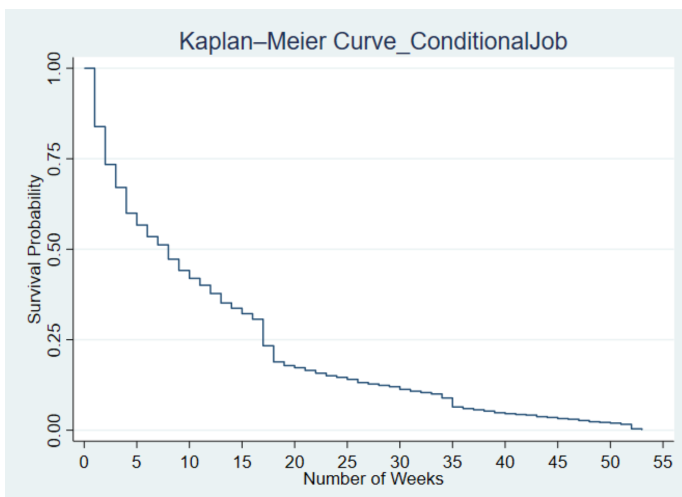
[27]↑This is only about 1% of idling events therefore Subfigure 3.1c also calculate transitions into employment based on 'conditional job events' not including all idling.



(a) Conditional Idle



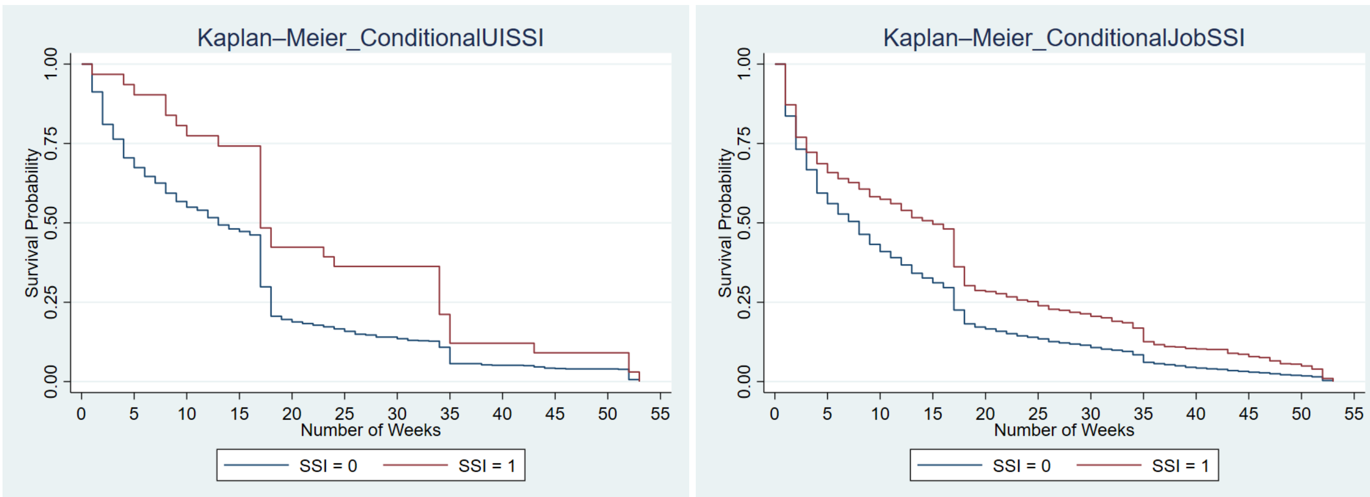
(b) Conditional UI



(c) Conditional Job

Figure 3.1. Kaplan-Meier Curve for People with Disability

for people who have reported disability is how the availability of SSI would effect the 'waiting time' before applying for UI. Kaplen-Meier Curves with 'OnSSI' as treatment will help to answer this question. Figure 3.2 shows the effect of 'survival time' with and without on SSI. In this case, I divide people who have reported disability into two groups: one group are those disabled individuals who have reported to claim SSI during the survey period and; the other group are those disabled individuals who have never reported SSI. I view the group who have been on SSI as the treatment group.



(a) Conditional UI

(b) Conditional Job

Figure 3.2. Kaplan-Meier Curve for People with Disability-SSI

Finding 4: Disabled individuals who have claimed SSI are more likely to wait without claiming UI in the next period if they are unemployed and without benefits in the current period.

Subfigure 3.2a of Figure 3.2 shows the transition of 'conditional UI' where 'conditional UI' still means the proportion of idling that transitioned into unemployed and with UI in $t+1$ conditional on unemployed and without UI in t. For simplicity I can this transition as 'conditional UI'. Subfigure 3.2a shows conditional on unemployed and without UI in t, the rate of transitions into UI in $t+1$ if slower for disabled individuals who have been on SSI than those who have never been on SSI. This is more evidence that the availability of SSI will increase the survival probability of 'waiting' and not claiming UI. 'Survival' means remaining unemployed and without benefits in this case. In other words, disabled individuals who have claimed SSI are more likely to wait without claiming UI in the next period if they are unemployed and without benefits in the current period.

Subfigure 3.2b of Figure 3.2 shows the transition of 'conditional Job' where 'conditional job' is the proportion of idling that transitioned into employment in $t+1$ conditional on unemployed and without UI in

t. Subfigure 3.2b shows the conditional on unemployed and without benefits in t, the rate of transitions into employment in $t+1$ is slower for disabled individuals who have claimed SSI. In other words, the probability of 'survival' is higher for people who claimed SSI compared to those who never it. Subfigure 3.2b shows the availability of SSI will make disabled individuals to take longer before getting employed in the next period given they are unemployed and without benefits in the current period.

Cox Regression Analysis

Next I run Cox regression to provide a quantitative analysis of conditional application for people with disability and to evaluate what variables will have significant effect on survival probability and how those variables will affect 'survival' [28]. The dependant variables I use are demographic characteristics including age, education, gender, race, total household income and marital status; number of job separations, $jobloss\_time$; state unemployment rate, $unem\_rate$; whether the week is in the seam month, $seam$; whether have reported being on SSI, $OnSSI$; and total household SSI amount received, $HouseSSIAmt$. I include year and state fixed effect and cluster at household level.

Below is the Cox regression I run for transitions into unemployed and with UI in $t+1$ given unemployed and without benefits in t among people who have reported disability,

$$\begin{aligned} Hazd_{UI}(t)_i = Hazd_{0,UI}(t)_i + \beta_1 OnSSI + \beta_2 HouseSSIAmt_{i,t} + \beta_3 jobloss\_time_{i,t} + \beta_4 unem\_rate_t \\ + \beta_5 seam_t + \beta_6 X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.3}$$

The setup of the above Cox regression is similar as equation (6) for the general population expect two variables added: Whether the person has reported to be on SSI during survey period, $OnSSI$ and the total household SSI amount received, $HouseSSIAmt$. The results of this regression are shown in Table 3.5.

> **Finding 5: Having received SSI, a lower education, being female, higher age, more previous job separation all decrease the hazard rate of transitions into UI. Being interviewed in seam month increases has the hazard rate of transitions into UI about 207 times compared to not being interviewed in the seam month. [29].**

As shown in Table 3.5, among people who have reported disability, being female decreases the hazard of transitions into UI from idling by 29.6% compared to being male; a one year increase of education increases the hazard of transitions into UI from idling by 7.5%; a one time increase of job separation increases the hazard of transitions into UI by 12.7%. Table 3.5 also shows being interviewed in seam month has a hazard rate of transitions into UI that is about 207 times of the hazard rate of transitions into UI not being interviewed in

[28]↑'Survival' still means remaining unemployed and without benefits.
[29]↑I focus only those variables that have coefficients significant at 5% or 10% level.

the seam month.The signs and magnitude of the above variables on the hazard rate of transitions into UI are consistent with that report in Table 1.6 for the general population.

There is one variable that is particular interesting: age. Table 3.5 shows a one year increase of age decrease the hazard of transitions into UI by 1.5%. The effect of age on hazard rate of transitions into UI is in the opposite direction in the general population and people with disability. For the general population, a one year increase of age increase the hazard of transitions into UI by 2.3% (Table 1.6) whereas for people who have reported disability a one year increase of age decrease the hazard of transitions into UI by 1.5%. The different direction of effect of age on conditional transitions into UI found in Cox regression model is consistent with the finding in linear regression model. The potential reason for age to have opposite effect on the general population and people with disability can be explained by the availability of disability insurance or SSI for disabled people. Since people with disability are potentially eligible for SSDI or SSI, the older the individuals are, the more likely that they will be eligible for SSDI or SSI [30]. Therefore an increasing of age will decrease the hazard of conditional transitions into UI among people with disability.

The main variable of interest in Table 3.5 is $OnSSI$ which is whether the person has claimed SSI during survey period. Table 3.5 shows having claimed SSI will decrease the hazard of conditional transitions into UI by 52.5%. This result is more evidence that the availability insurance designed for individuals with disability such as SSDI and SSI is the contributing factor to make disabled individuals to be less likely to claim UI.

Next just for completeness I run Cox regression for conditional transitions of employment to show what factors will affect the hazard of transitions of employment for people with disability.

Below is the Cox regression I run for transitions into employment in $t+1$ given unemployed and without benefits in t among people who have reported disability,

$$\begin{aligned} Hazd_{Job}(t)_i = Hazd_{0,Job}(t)_i + \beta_1 OnSSI + \beta_2 House\mathrm{e}SSIAmt_{i,t} + \beta_3 jobloss\_time\mathrm{e}_{i,t} + \beta_4 unem\_rate\mathrm{e}_t \\ + \beta_5 seam_t + \beta_6 X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.4}$$

The setup for equation 3.4 is similar to equation 3.3 expect the hazard refers to transitions into employment not unemployed and with benefits. The result is shown in Table 3.6. Table 3.6 shows being on SSI, lower education, being women, lower total household income and higher age all decrease the transitions into employment for people with disability. Being interviewed during seam month still increase hazard of transitions into employment reported. The effect of education, gender, total household income, age and being on seam on hazard rate reported in Table 3.6 are all consistent with that reported for the general population in Table 1.6. The explanations for the effect of these variables on transitions into employment are omitted here.

[30]↑Older individuals are more likely to have medical conditions that make them meet the medical requirement of SSDI or SSI.

Table 3.5. Cox Regression-Conditional UI for People with Disability

	(1) Coefficient	(2) Hazard Ratio
OnSSI	-0.745***	0.475***
	(-3.91)	(-3.91)
Total Household SSI Amount	-0.00057*	1.000*
	(-1.98)	(-1.98)
Education	0.073**	1.075**
	(3.16)	(3.16)
Gender	-0.351**	0.704**
	(-3.12)	(-3.12)
Marital Status	0.109	1.116
	(-0.51)	(-0.51)
White	-0.091	0.913
	(-0.68)	(-0.68)
State Unemployment Rate	0.136*	1.145 *
	(2.12)	(2.12)
Total Household Income	-0.00004*	1.000*
	(-2.05)	(-2.05)
Age	-0.0148***	0.985***
	(-3.91)	(-3.91)
Number of Times Lost Job	0.120 ***	1.127 ***
	(4.59)	(4.59)
Seam	5.354***	208.026 ***
	(7.31)	(7.31)
year=2012	0.638*	1.892*
	(2.35)	(2.35)
Observations	1656158	1656158

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The main variable of interest still $OnSSI$. Table 3.6 shows having claimed SSI will decrease the hazard of conditional transitions into employment. This result is consistent with the explanation for why people with disability have lower rate of transitions into UI. The availability of insurances designed for disabled individuals can make both claiming UI and finding employment less desirable. Especially if a person is with a medical condition that meet the requirement of disability in SSA and has enough work credit to be eligible for SSDI, the choice of claiming SSDI are likely to be a lot more desirable than claiming UI or finding employment. Therefore people who have reported disability have a lower hazard of conditional transitions into employment.

3.4 Model Simulation for People with Disability

In this section I use the model constructed in chapter 3 to estimate the application cost and initial belief for people with disability. The procedure of estimation is similar to that I did for the general population. I chose the same two moments: The number of weeks to find jobs again after job separation (job finding time) and the number of weeks between job loss and being on UI (UI waiting time). UI 'waiting time' is reported in Table 3.3 and it is 25.68 weeks. Job finding time is calculated among people who have reported disability to be 25.82 weeks. Compared to the general population, job finding time for people with disability is about 0.8 (25.82 vs 25.02) weeks longer; UI 'waiting time' for people with disability is about 12.69 (25.68 vs 12.99) weeks longer. The procedure of estimation is followed as described in previous chapter. The procedure of estimation is to first estimate initial belief of high state ϕ_0 by matching simulated moment to job finding time found in the data 25.82. Then I use estimated ϕ_0 to estimate benefit cost ratio $b(w)/c$ by matching simulated moment of 'waiting time' to that in the data 25.68. The results of estimation of $b(w)/c$ is shown in Table 3.8 [31]. The estimated results for ϕ_0 is 0.078 (Table 3.7) and the estimated results for $b(w)/c$ is 0.086 (Table 3.8). Table 3.7 shows estimation results by matching simulated job finding time to that in the data. I simulated job finding time in low and high states and the weighted average of job finding time in low and high state is equal to 25.82 (data). The simulated job finding time in low state is 4.15 weeks and in in high state is 27.65 weeks. The weight found is the belief of high state which is 0.078. I then simulate the 'waiting time' in low and high states and calculate the weighted average of 'waiting time' using 0.078 as weight. Then find the $b(w)/c$ that will make the simulated weighted average of UI 'waiting time' equal to 25.63 (data). Results in Table 3.8 shows when $b(w)/c$ is 0.086 the weighted average of UI 'waiting time' is 25.63.

Comparing simulation results for people with disability and general population. The estimated initial belief of high state ϕ_0 is 0.111 and the estimated benefit and cost ratio $b(w)/c$ is 0.111 for the general population. Comparing estimation results for people with disability and the general population it can be concluded that people who have reported disability has lower initial belief of high state. The initial belief

[31]↑The more detailed lists of estimated parameters are showed in Appendix 3.6.3.

Table 3.6. Cox Regression-Conditional Job for People with Disability

	(1) Coefficient	(2) Hazard Ratio
OnSSI	-0.319***	0.727***
	(-6.70)	(-6.70)
Total Household SSI Amount	-0.000035	1.000
	(-0.63)	(-0.63)
Education	0.031***	1.032***
	(5.08)	(5.08)
Gender	-0.136***	0.873***
	(-4.41)	(-4.41)
Marital Status	-0.049	0.952
	(-1.38)	(-1.38)
White	-0.100	0.990
	(-0.27)	(-0.27)
State Unemployment Rate	-0.036*	0.9649*
	(-1.97)	(-1.97)
Total Household Income	0.00002***	1.000***
	(4.53)	(4.53)
Age	-0.017***	0.983***
	(-14.36)	(-14.36)
Number of Times Lost Job	0.027	1.027
	(1.95)	(1.95)
Seam	1.396***	4.040***
	(42.10)	(42.10)
year=2012	-0.123	0.884
Observations	477,909	477,909

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of high state is about 70% compared to that in the general population. The benefit to cost ratio for people who have reported disability is also lower than the general population. The benefit to cost ratio is about 77% of the general population. Application cost is 11.64 times of benefits for disabled people and 9.01 times of benefits for the general population. This indicates compared to UI benefits received, the cost is higher for people who have reported disability than the general population. Estimation results for people who have reported disability and the general population shows that disabled people have a lower belief of high state. This can corresponds to people with disability are less likely to belief they are high skilled workers and will be competitive in the job market. Moreover, people with disability have higher cost compared to unemployment benefits received than the general population. In other words, it is more costly for people with disability to apply for UI and more specifically the cost of applying for UI is about 30% more than the general population. A higher cost of UI application can explain the behavior of higher likely to wait and longer 'waiting time' among people who have reported disability than the general population.

Table 3.7. Simulated Job finding Time for People with Disability

ϕ	**sim_jobH**	**sim_jobL**	**waited_avg**
0.078	4.15	27.65	25.82

3.5 Conclusion

In this paper I study whether and how the available of other insurance programs designed for people with disability can help explain disabled people's behavior of higher likely to wait and longer waiting time before apply for unemployment benefits. Since the only available variable in the data regarding disability insurance program is the receipt of Supplemental Security Income (SSI), I use the receipt of SSI to study the effect of availability of other insurance program on disabled individuals' UI 'waiting time'. First, I find he proportion of people who will wait at least one week are about 8% (lower bound) to 10% (upper bound) higher among those who have reported disability than that in the general population. The average 'waiting time' is about 36% (lower bound) to 40% longer (upper bound) among people with disability compared to the general population. People with disability also has the pattern that 'waiting time' decreases as number of job loss increases. Second, for people who have reported disability a lower age, being female, a lower total household income, being on SSI, higher total household SSI amount make delay more likely. Good economic conditions make delay more likely. Fewer experienced number of job separations makes delay more likely. Third, for people who have reported disability a lower age, lower education level, being female, being on SSI and higher total household SSI amount and a lower total household income increase the length of delay. Good economic conditions increase the length of delay. Fewer experienced number of job separations increases the length

Table 3.8. Simulation Result for People with Disability

c	b/c	mix_wait
3.94	0.119	1.00
4.00	0.118	4.21
4.05	0.116	6.25
4.11	0.115	7.98
4.16	0.113	9.47
4.22	0.111	10.56
4.28	0.110	11.68
4.33	0.109	12.82
4.39	0.107	13.73
4.44	0.106	14.51
4.50	0.105	15.26
4.56	0.103	15.91
4.61	0.102	16.70
4.67	0.101	17.52
4.72	0.100	18.34
4.78	0.098	19.02
4.84	0.097	19.70
4.89	0.096	20.32
4.95	0.095	21.06
5.00	0.094	21.68
5.06	0.093	22.28
5.12	0.092	22.78
5.17	0.091	23.28
5.23	0.090	23.76
5.28	0.089	24.35
5.34	0.088	24.83
5.40	0.087	25.41
5.45	**0.086**	**25.63**
5.51	0.085	26.25
5.56	0.085	27.05
5.62	0.084	27.46
5.68	0.083	28.29
5.73	0.082	29.09

of delay. Forth, disabled individuals who have claimed SSI are more likely to wait without claiming UI in the next period if they are unemployed and without benefits in the current period. Fifth, having received SSI, a lower education, being female, higher age, more previous job separation all decrease the hazard rate of transitions into UI. Being interviewed in seam month increases has the hazard rate of transitions into UI about 207 times compared to not being interviewed in the seam month. Simulation results show disabled individuals have lower belief of high state and have higher application cost of UI compared to the general population. The application cost is about 30% more for people who have reported disability than the general population. A higher application cost can explain why people with disability are more likely to wait and have longer 'waiting time' before applying for UI.

3.6 Appendix

3.6.1 Definition of Disability by Social Security Administration

The Social Security Administration use a five-step questions to determine if a person is qualified as being disabled. The five-step questions are as follows:

1. Are you working?
   If a person is currently working and earning more than $1350 a month the person is generally considered not qualify for being disabled.

2. Is the condition 'severe'?
   If the medical condition will not limit the person's basic work-related activities such as standing, walking, sitting for at lest 12 month the person's condition is considered not 'severe' thus not qualify as being disabled.

3. Is the condition found in the list of disabling conditions? The SSA has a list of medical conditions that they consider are severe enough. If the person's medical condition is on that list the person is considered qualify as being disabled. If the person's condition is not on the list then go to the next step.

4. Can you do the work you did previously? The SSA decide if the person's medical impairments will prevent him from performing any of the his past work. If it doesn't the person is considered not qualify for disability. If he does then go to step 5.

5. Can you do any other type of work? The SSA will decide whether the person is able to do other work with his current medical impairment considering factors such as age, education, past work experience and transferable skills. If he can't do other work the person will be determined as qualifying as being disabled.

3.6.2 How the Monthly Social Security Benefits are Computed

Step 1: Compute Average Indexed Monthly Earnings. First determine the number of years [32] of the worker's insured working period, then adjust (index) [33] his/her earnings to reflect the change of general wage level during those years of employment. Choose the years with the highest indexed earnings and divide the total amount by the total number of months in those years . The result is AIME.

Step 2: Use AIME amount to compute a person's PIA (primary insurance amount). PIA is the sum of three separate percentages of portions of average indexed monthly earnings [34].

Step 3: Monthly benefits amounts are derived from PIA. For SSDI recipients benefits may be reduced from PIA computed is the person is receiving other public disability benefits.

3.6.3 Simulation Result-Model Parameters for People with Disability

[32]↑Up to 35 years.

[33]↑The indexation of earning can ensure a worker's future benefits can reflect the general rise in the standard of living compared during his/her working time.

[34]↑In 2022, the three percentage and portions are 90%of the first 024 AIME; 32% of AIME between $1024 and $6172; and 15% of AIME over 6172. The $1024 and $6172 are called the 'bend points'.

Table 3.9. Simulation Result-Model Parameters

b/c	ϕ_0
0.119	0.010
0.118	0.044
0.116	**0.078**
0.115	0.111
0.113	0.145
0.111	0.179
0.110	0.213
0.109	0.247
0.107	0.280
0.106	0.314
0.105	0.348
0.103	0.382
0.102	0.416
0.101	0.449
0.100	0.483
0.098	0.517
0.097	0.551
0.096	0.584
0.095	0.618
0.094	0.652
0.093	0.686
0.092	0.720
0.091	0.753
0.090	0.787
0.089	0.821
0.088	0.855
0.087	0.889
0.086	0.922
0.085	0.956
0.085	0.990
0.084	
0.083	
0.082	
0.081	
0.081	
0.080	
0.079	
0.078	
0.078	
0.077	
0.076	
0.075	
0.075	
0.074	
0.073	
0.073	
0.072	
0.072	
0.071	
0.070	

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