Does Unemployment Insurance discourage pre-emptive on-the-job search? New evidence from older American workers*

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March 31, 2011

Preliminary

Keywords: Probability of job loss, on-the-job search, unemployment insurance benefits, job displacement

Abstract

In this paper, I add evidence to an underdeveloped literature on how the Unemployment Insurance (UI) system can create incentives for workers to become unemployed. Specifically, UI may discourage workers who feel vulnerable to job loss from looking for other jobs while employed in order to experience a job-to-job transition instead of a job-to-unemployment transition (i.e. "preemptive on-the-job search"). In this way, higher UI benefits increase the inflow into unemployment and the overall unemployment in the economy in a different (and complementary) way to what has been extensively documented in the literature before. Only a few papers have looked at this mechanism previously: Light and Omori (2004) find a very small effect of UI benefits in discouraging job-to-job transitions. Using a rich dataset with information on expectations of job loss and on-the-job search, I present evidence that the effect of UI in discouraging preemptive on-the-job search among older Americans who feel at risk of displacement is actually substantial. However, the effect of more generous UI on experiencing a posterior job separation and a non-working spell is much smaller, which may be explained because on-the-job search effort does not necessarily lead to success in finding suitable offers.

*I thank Jeffrey Smith, Charlie Brown, Melvin Stephens, Brian McCall and all participants at the University of Michigan Labor Seminar for their helpful comments. I also thank Michael Nolte, Janet Keller and all the staff at the Health and Retirement Survey at the Institute for Social Research for their help and kind assistance through this project. This work has been supported (in part) by a grant from the National Poverty Center at the University of Michigan, which is supported by award #1 U01 AE000002-03 from the U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation. Any opinions expressed are those of the author(s) alone and should not be construed as representing the opinions or policy of any agency of the Federal Government.

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1 Introduction

Most of the literature on the effects of unemployment insurance (UI) systems on unemployment has focused either on analyzing how unemployment benefits (UB) affect the duration of unemployment spells or on studying how the way the UI system is financed in the US can affect the probability that workers become unemployed. For a survey on the literature of the effect of UB on unemployment duration see Meyer (1995) and Krueger and Meyer (2002). For the effects of the UI payroll tax on unemployment, see Feldstein (1976), Topel (1983), Topel (1984) , Anderson and Meyer (1993) and Card and Levine (1994).

In this paper I add evidence to an underdeveloped literature that departs from the two mainstreams described above. UB can actually encourage workers to become unemployed because it reduces the expected benefit of conducting preemptive on-the-job search (POJS). POJS is defined as the strategic on-the-job search performed by a worker who is at risk of job loss, in order to find a new job before displacement occurs and experience a job-to-job transition instead of a job-to-unemployment transition.

The idea that workers behave strategically upon the risk of job loss and start looking for a new job prior to being displaced has been discussed before in the literature. For example, Lengermann and Vilhuber (2002) and Pfann and Hamermesh (2001) discussed the composition of jobs and workers' flows before displacement in the context of plant closures. They studied the selection process of workers who decided to "leave the sinking ship" versus those who stayed until plant closure. For example, Lengermann and Vilhuber (2002) found that in the periods prior to closure, the data are consistent with both discouraged high-skilled workers leaving the firm and management actions to layoff low-skilled workers. Schwerdt (2011) also found evidence from the Austrian labor market that at least a high fraction of all separations happening up to two quarters before plant closure are directly related to "early leavers", or workers who decided to abandon the sinking ship. These early leavers are associated with significantly higher pre-closure earnings, even after controlling for observable characteristics. Thus, their evidence suggests that early leavers differ from ultimately displaced workers in terms of unobserved characteristics related to the productivity of workers. They also found that early leavers are mainly men and blue collar workers.

There are many institutional factors that can affect POJS and the type of workers who decide to leave a firm in economic distress earlier rather than later. As Schwerdt (2011) pointed out, one of those factors is unemployment insurance. UB reduce the cost of losing a job and might induce workers to stay longer in distressed firms (Schwerdt (2011)). However, so far only two studies have looked at the effect of UB on POJS. Burguess and Low (1992 and 1998) present evidence from displaced workers in Arizona. They found that male workers who received advanced notification of being laid off performed on-the-job search (i.e. before displacement) with a probability of 60.6%, whereas workers who did not received notification only did so with a probability of 38.9%. Moreover, they found that UB strongly discouraged on-the-job search for workers who received notification and did not expect a recall from their employers (Burgess and Low (1998)). For example, a $10 increase in weekly benefits above its mean reduced the likelihood of on-the-job search by 8 percentage points from 59.7% to 51.7% (an elasticity slightly above -1). Conversely, they found no statistical significant effect of UB on search behavior for non-notified workers or for notified workers who expected to be recalled (Burgess and Low (1992) and Burgess and Low (1998)). Thus, evidence from this study seems to suggest that workers behave strategically looking for a job when they know that they are going to be laid off and that the intensity of their search is reduced greatly by the generosity of the UI system. Despite the coherent results of this study, there are some limitations that can affect its validity as acknowledged by the authors. First, there is a sample selection issue because the study sample is comprised of workers with at least 5 weeks of unemployment and one would expect that workers who did perform POJS would be less likely to be part of the sample. And second, all workers in the sample are unemployed workers in Arizona in 1975-1976. Therefore, there is not exogenous variation in UB (either across states or within the state over time) that could be used to identify causal effects.

The second paper in the literature that addresses POJS is Light and Omori (2004). They formulated the mechanism more formally and looked for evidence by analyzing job-to-job (quits) and job-to-unemployment transitions using the 1979 National Longitudinal Survey of Youth (NLSY). If UB actually reduce incentives to perform POJS and encourages workers to become unemployed, then higher UB would be associated with a decline in job quits and an increase in job-to-unemployment transitions. They found that job quits decline as UI benefits increase, although the effect was very small: a one standard deviation increase above the mean in weekly UB reduce the job quit probability (for a worker with 30 weeks of tenure) from 0.047 to 0.045 (an elasticity of -0.09). Many factors may explain the small effects they found. For example, their paper lacks a good measure of job loss risk. As will be discussed later, UB only reduce the benefits of POJS if the worker feels vulnerable to job loss, and the effect would be greater for workers who feel at a greater risk of job loss. Without being able to control for the risk of job loss, the estimated coefficient would only capture the effect of UB for the average worker. That effect can be small if the average worker feels relatively secure. Another explanation for the small coefficients is that POJS would not necessarily lead to a job quit, since the search may not be successful in finding a competitive offer.

In this study I use the Health and Retirement Study (HRS), waves 1994 through 2004, to re-address the question of whether strategic POJS exists and whether it is discouraged by the generosity of UB. There are two main advantages of using the HRS. First, the HRS contains information on the subjective probability that workers give to the event of job loss, which allows for testing whether workers react pre-emptively by looking for another job. In contrast with previous studies, the sample of workers in the HRS is not restricted to workers from firms that are closing down or to workers who had received a layoff notification, so we can study POJS in a more general setting. Second, HRS contains information on on-the-job search (see for example Benitez-Silva and Ni (2010)) and I can also construct whether the worker experiences a job-to-unemployment (or not working) transition or a job-to-job transition. Therefore, I can observe both the behavior of interest (POJS) and the policy relevant outcome (transition into another job or into unemployment) and piece together the evidence suggested separately by Burguess and Low (1992 and 1998) on POJS and by Light and Omori (2004) on transitions.

The rest of the document is divided as follows: Section 2 describes the main theoretical predictions to be tested in the data; Section 3 describes the econometric strategy; Section 4 describes the data sets, outcomes of interest and main covariates; Section 5 describes the empirical results; and 6 concludes.

2 Theoretical model

Mortensen (1977) showed that in a fully dynamic setting the effect of UB on job search for unemployed workers is ambiguous. Increases in UB have two opposing effects: i) an increase of the value of being unemployed -let's call it "immediate effect" (IE)-, and ii) an increase of the value of future employment since better paying jobs come with better UB -let's call it "forward looking effect" (FLE). Mortensen (1977) showed that the first effect increases the length of the unemployment spell whereas the second one decreases it. He also showed that IE dominates at the beginning of the spell, whereas the FLE dominates when the worker is near the end of his benefit period.

UB has the same ambiguous effect on on-the-job search. On one hand, it reduces the cost of falling into unemployment (IE), but on the other hand it increases the payoff from getting a higher-paying job since it comes with a better unemployment insurance (FLE). Therefore, in theory, the effect of more generous UB on on-the-job search would be ambiguous. However, for my sample of analysis the second effect is less important for two reasons: First, the FLE becomes less important for a worker the fewer remaining working years he has. The HRS sample individuals who are 50 years or older and thus in my analysis the average male worker is 60 years old and the average expected working years until retirement is 6; second, each state sets a maximum level of weekly unemployment benefits. The FLE would not exist for workers whose calculated UB if they were displaced are above that maximum level (since there is no gain from the point of view of UB to move to a better paying job). Since earnings are usually positively correlated with experience and age, in my sample of male workers, 57% have earnings that would put their UB above their state's maximum level. For those workers UB should not have a FLE on on-the-job search. For these two reasons, I will work with a simple model that abstracts from the FLE and only considers the IE of UB. The most simple model is the two-period model proposed by Light and Omori (2004)[1]. I borrow that model in this section and expand their analysis in order to derive the main hypothesis that I will test in the empirical section.

Light and Omori (2004) proposed a two-period, discrete time model. In the first period, a worker is employed and earns w_1. His total endowment of time equals $\bar{l}+1$. Labor supply is indivisible and equal to 1 hour. The maximization problem of the worker is to decide how many hours to search on-the-job (s) and how

[1] In a two-period model, there is no FLE by definition since only the immediate future (period 2) matters for period 1 decision.

many hours of leisure he enjoys $(\bar{l}-s)$. The flow utility is given by $U(w_1,\bar{l}-s)$, where $U_j > 0$ and $U_{jj} < 0$ for $j = 1, 2$. If a worker searches, the probability of getting an offer in the second period equals $\alpha(s)$. As it is conventional, I assume that $\alpha'(s) > 0$ and $\alpha''(s) < 0$. Offers come from a known distribution $F(w)$ and at most one offer can be received. The worker faces a probability of layoff in period two equal to p. If he gets laid off he can collect UB equal to b. Since there is no on-the-job search in the second period (because the worker lives only for two periods), the reservation wage in period two, denoted by w_r, is such that the following equality holds: $U(w_r,\bar{l}) = U(b,\bar{l}+1)$.

In this setting, four different scenarios can occur in period two: i) with probability equal to $(1-\alpha(s))(1-p)$ the worker did not lose his job and did not find an offer; ii) with probability equal to $(1-\alpha(s))p$ the worker lost his job and did not find an offer; iii) with probability $\alpha(s)(1-p)$ the worker did not lose his job and found an offer; and iv) with probability $\alpha(s)p$ the worker lost his job and found an offer. Also I will define the probability of job separation $(P(E))$ as the probability that a worker is not at the same employer in the second period. This can happen if the worker has fallen into unemployment or if he has changed jobs.

Appendix A contains the solution to the worker's maximization problem. The worker chooses the optimal on-the-job search effort in period 1. In Appendix A I analyzed what happened to that optimal search effort level when the probability of job loss (p) and the level of UB (b) change and what the implications are for the probability of job separation $(P(E))$ and for the probability that given separation a worker has fallen into unemployment $(P(U|E))$. The main predictions are summarized in Table 1. The first result in column 1 indicates the POJS mechanism described earlier: if workers feel vulnerable to job loss, they will perform on-the-job search to increase the probability that they remain employed (probably at a different employer) in period two. The second result in column 1 indicates that an increase in UB lead to a lower search effort but only when workers feel at risk of job loss $(p > 0)$. This is because more generous UB diminish the marginal return to on-the-job search that comes from the scenario of an eventual job loss[2]. The third result from column 1 indicates that the impact of an increase in the probability of job loss on on-the-job search is smaller if the worker is entitled to more generous benefits $(\frac{\partial s}{\partial b \partial p} < 0)$ and that the effect of UB on on-the-job search gets more negative as the probability of job loss increases $(\frac{\partial s}{\partial p \partial b} < 0)$. The latter finding may seem odd but can be explained because, as mentioned before, greater UB reduce the marginal return to on-the-job search in the scenario where the worker is displaced and, as the probability of job loss increases, that scenario has a larger weight in determining the overall returns.

The second column in Table 1 indicates that the probability that the worker is separated from his job $(P(E))$ increases with the probability of job loss -as expected- but decreases with higher UB (as long as the probability of job loss is non-zero). The later result can be explained because, all else equal, workers

[2] If a worker feels completely safe at work $(p = 0)$, the scenario of a job loss does not exist and thus UB should not affect search behavior. As it will be described in Section 4.2 workers in general feel moderately confident about their permanence at their jobs. The median value for the expected probability of job loss in the next 12 months is 0% for respondents in the HRS (years 1994-2004 for workers aged 50 or older) and 5% in the Survey of Economic Expectations (years 1994-1998 for workers of all ages). This fact may explain the small effects found by Light and Omori (2004) in contrast with the large effects found by Burguess and Low (1992 and 1998).

Table 1: Main predictions from Theoretical Model

	On-the-job search s (1)	Probability of separation (E) $P(E)$ (2)	Probability of unemployment (U) given separation $P(U\|E)$ (3)
$\frac{\partial}{\partial p}$	> 0	> 0	$\gtrless 0$
$\frac{\partial}{\partial b}$	$= 0 \quad if \quad p = 0$ $< 0 \quad if \quad p > 0$	$= 0 \quad if \quad p = 0$ $< 0 \quad if \quad p > 0$	$= 0 \quad if \quad p = 0$ $> 0 \quad if \quad p > 0$
$\frac{\partial}{\partial b \partial p} = \frac{\partial}{\partial p \partial b}$	< 0	$\gtrless 0$	$\gtrless 0$

with higher UB will perform on-the-job search with less intensity, and thus the probability of getting an outside offer is lower. The last result in column two shows that the sign of the cross derivative of $P(E)$ with respect to the probability of job loss (p) and to UB is ambiguous. On one hand, an increase in UB reduces search effort and thus ameliorates one of the channels through which an increase in p leads to an increase in $P(E)$. However, on the other hand, the size of the impact of an increase of p on $P(E)$ gets larger the less on-the-job search the workers are exerting. Since both effects go in opposite directions, more generous UB can either increase or ameliorate the effect of an increase of the probability of job loss on the probability that in period two the worker is separated from his current employer.

Finally, the third column of Table 1 shows that once separation has taken place, the probability of job loss has an ambiguous sign in discriminating whether such separation happened because the worker found another job or because he fell into unemployment. In contrast, higher UB are associated with a greater probability that separation has occurred because the worker fell into unemployment. The last result indicates that the sign of the cross-derivatives is again ambiguous, which is not surprising given the ambiguity of the effect of the probability of job loss.

To summarize, the following conclusions can be drawn from the model:

1. Higher (subjective) probability of job loss leads to more on-the-job search effort and higher separation rates.
2. Higher UB lead to lower on-the-job search effort and lower probability of separation (at least for workers who feel at risk of job loss).
3. The effect of UB on on-the-job search gets unambiguously larger (more negative) the more at risk of job loss workers feel.
4. Given separation, larger UB are associated with a larger probability that separation occurred because the worker fell into unemployment.

In the next section I set up the econometric strategy to test for these effects in the data.

3 Econometric strategy

3.1 Model specification

The general regression specification is as follows:

$$y_{ijt} = \alpha + \beta_1 p_{ijt} + \beta_2 UB_{ijt} + X_{ijt}\beta + \phi_t + \gamma_j + \epsilon_{ijt} \quad (1)$$

where i indexes for individual, j for state and t for time. I will test empirically the role of the probability of job loss and unemployment benefits on three outcomes of interest represented by y_{ijt} in equation 1: 1) whether the worker is performing on-the-job search (dichotomous variable), 2) the probability that the worker ended his job (separation) between the current interview and the next one (i.e. in a two year window), and 3) given that the worker ended his job, the probability that he ended it by falling into a non-working spell (instead of moving to another job).

The variable p_{ijt} measures the individuals subjective probability of job loss and the variable UB_{ijt} measures the weekly unemployment benefits the individual would collect if he is displaced from his job. In alternative specifications I will use the replacement rate RR_{ijt} -i.e. the percentage of earning that the individual can recover through UI- instead of weekly unemployment benefits. The vector X_{ijt} contains additional covariates such as age and a dummy for being older than 62 years[3], wealth, educational attainment (dummies), partnered status (dummy) and self-reported health status. It also includes several characteristics of the current job: tenure, stress and physical effort conditions, employer-provided health insurance, employer pension plans and whether the individual has received and early retirement incentive offer. X_{ijt} also includes the average annual unemployment rate for the worker's state of residence. As an additional control for local labor market characteristics I included the worker's subjective probability of finding a similar job if they lose their jobs[4]. ϕ_t is a year effect and is captured by introducing year-specific dummies. γ_j is a geographic-specific effect captured either by census-region dummies or by state dummies.

We can see from the first column in Table 1 that when the outcome of interest is on-the-job search, the generosity of UB should only matter if the worker feels at risk of job displacement ($p > 0$) and its effect gets larger the more vulnerable to job loss the worker feels. In order to test for these predictions I re-write equation 1 as follows:

[3] Workers who are 62 years or older are eligible to start collecting social security pensions and thus, this institutional factor may affect their on-the-job search behavior.

[4] In the Health and Retirement Survey (HRS) currently employed workers are asked the following question: *"Suppose you were to lose your job this month. What do you think are the chances that you could find an equally good job in the same line of work within the next few months?"* The response to this question was included to control for workers and job unobserved characteristics that may encourage or discourage on-the-job search, beyond the aggregate measure of unemployment rates. It can be shown from the model presented in Section 2 that an increase in the probability of finding a suitable offer (at every level of search effort) will increase the marginal benefits of search and thus increase the optimal intensity of search effort exerted by the worker.

$$y_{ijt} = \delta + \theta_1 p_{ijt} + \theta_2 UB_{ijt} + \theta_3 (p_{ijt} * UB_{ijt}) + X_{ijt}\theta + \tau_t + \lambda_j + \nu_{ijt} \quad (2)$$

Testing that UB should have a larger discouragement effect on POJS for workers who feel more vulnerable to job loss implies testing that $\theta_3 < 0$. When the outcomes of interest are the probability of job separation or the probability that workers ended their job by moving to another job instead of falling into unemployment, the sign of θ_3 is ambiguous.

3.2 Instrumental variables approach

Unemployment benefits (UB_{ijt}) and the replacement rate (RR_{ijt}) depend on current and previous earnings and state policies. Earnings may be correlated with other unobserved factors that may affect on-the-job search. For example, high paying-jobs may also come with other desirable unobserved attributes. Thus, high wage workers (after controlling for observables) may have less incentives to perform on-the-job search. Since higher wages are correlated positively with UB_{ijt} and negatively with RR_{ijt} (because of the maximum level on weekly unemployment benefits set by each state), we would expect the ordinary-least squares (OLS) coefficients of UB_{ijt} to be potentially biased downwards and OLS coefficients for RR_{ijt} to be potentially biased upwards.

In order to control for the endogeneity of unemployment benefits and the replacement rate I instrumented them using the average weekly dollar benefit and the average replacement rate that an employed worker aged 50 years or older in the same state and year would received if he lost his job. This approach is similar to the simulated instruments approach used in Currie and Gruber (1996) with the difference that I do not calculate the instruments for each state using a national representative sample but using a representative sample for each state. The reason for doing this is that I want to capture how generous the UI benefit rules in each state are for the average older worker who lives (and make his earnings) in that state. Using a national sample would not necessarily measure that generosity. The calculated instruments should not correlate with a worker's and his job's specific unobserved characteristics. However, they may correlate with some state's unobserved characteristics. That's another reason for controlling for local market conditions as explained in Section 3.1. I also controlled for region dummies or state dummies. However, as it will be described in Section 4 most of the variation in the simulated instruments comes from differences between states rather than variation within states over time and thus including state dummies reduces the statistical power to detect significant effects.

The subjective probability of job loss is also an endogenous variable. Although I control for observed variables that can affect the subjective probability of job loss such as health status (see for example Smith (1999)) and job tenure, there may be other factors that may affect both the probability of job loss and on-the-job search effort. For example, Figure 1 in Appendix B plots the average probability of job loss and the average rates of job separation. It can be seen, as it was reported by Stephens (2003), that workers who feel safe (i.e. that stated $p = 0$) still separate from their jobs with a probability of 0.3 in the following two years (of course, some of these separations are due to retirement) and workers who feel at a relatively high risk of separation do not actually experience on average separation rates as high as their beliefs. One possible explanation could be a factor of optimism or pessimism, which would also matter for job search behavior. Workers with low subjective probability of job loss may be the of the "optimistic type" and workers with high subjective probability of job loss may be of the "pessimistic type". In fact, although it is only suggestive evidence of this explanation, on average, workers who feel more vulnerable are also less optimistic of being able to find a job if they are displaced, after controlling for all observable characteristics described in Section 3.1.

We need an exogenous shifter that affects the subjective probability of job loss and that is unrelated to other workers' unobservable characteristics. I use as an instrument whether the employer has experienced a reduction in employment (in at least the last two years)[5]. About 20% of workers report their employers have experienced a downsizing in labor force. The exclusion restriction could be violated if downsizing firms may change unobserved working conditions (i.e. beyond the job characteristics described in Section 3.1) that can also affect on-the-job search behavior for reasons other than the probability of a job loss. HRS allows further investigation of this issue. HRS asks workers who got separated from their jobs whether there were some changes in employment conditions that encouraged them to leave. I found no statistical significant differences for workers who were in downsizing firms versus workers who were not in terms of working environment (i.e. supervisor or coworkers encouraging departures), nor in terms of wages or other working conditions (schedules, hours, duties, locations and health insurance). The only factor that was statistically associated with downsizing firms was the probability of being offered an early retirement incentive offer, which I control for in my regressions. So, this is indicative evidence that downsizing affects on-the-job search through the probability of job displacement rather than through changes in other working conditions[6].

4 Data

4.1 Data sources

There are three data sources for this study. The main source of information is the Health and Retirement Study (HRS), which consists of a nationally representative sample of adults over the age of 50. More

[5] The HRS question is *"Has your employer experienced a permanent reduction in employment since you started working there / last interview? (Permanent employment reductions are sometimes called 'downsizing'; 'layoffs' can be permanent or temporary)"*

[6] Even if there were some unobservable job characteristic correlated with downsizing, it is more likely that workers in downsizing firms would be more willing to leave. These would bias my coefficient of interest (β_2 in equation 1 and θ_2 and θ_3 in equation 2) against finding the hypothesized results.

than 22,000 Americans have been interviewed every two years since the study was launched in 1992. The study collects information about income, work, assets, pension plans, health insurance, disability, physical health and functioning, cognitive functioning, and health care expenditures. I use the following waves: 1994, 1996, 1998, 2000, 2002 and 2004. The relevant information from HRS for this study includes labor force participation, reason for leaving last employer, employment dates and employment history, expected probability of job loss, self-reported earnings, wealth, demographic characteristics, health status, and information about current jobs: health insurance, pension plans, level of physical effort and stress and incentives for early retirement. I will also use information about the state of residency.

The second source of information is the Current Population Survey (CPS). The CPS is the primary source of information on the labor force characteristics of the U.S. population. It contains information on employment, unemployment, earnings, hours of work, and other indicators. I specifically use the CPS March Supplement, which has detailed information on earnings over the past year, to calculate the state's average replacement rate and weekly unemployment benefits that could be collected by employed workers if they were to lose their jobs. I use supplements for the following years: 1995, 1997, 1999, 2001, 2003 and, 2005.

The third source of information is a database on unemployment insurance rules by year and state for the years 1994-2004. Information includes the replacement rate formula, the minimum and maximum amount of weekly UB, and the requirements to qualify for UB. This dataset was provided by Professor Brian McCall and corroborated with the "Comparison of State Unemployment Insurance Laws" reports, which are published annually by the United States Department of Labor.

4.2 Description of outcomes of interest and main covariates

For this paper I focus on male workers only. Table 2 shows the sample means of the outcomes of interest and main covariates. On average 8% of employed workers (aged 50 years or older) perform on-the job search; and this average is relatively stable over the period of analysis. Burgess and Low (1992) also reported that 8% of workers in the same age group who did not received advanced notification of displacement were searching on-the-job[7].

In each wave of the HRS survey (every two years) we have information on the labor force status and whether the worker is still working at the previous wave employer. Those who are not working at their previous employer can be working at at different employer, be self-employed, unemployed (and seeking employment) or out of the labor force. In this paper, I will define separation as a termination of an employment relationship. Thus, termination may occur because of changing jobs (including self-employment), falling into unemployment or leaving the labor force (retirement being an important factor for this demographic group). I include leaving the labor force as part of the termination process because I only observe labor force

[7] In contrast, 31% of workers aged 50 years and older who received advanced notification of displacement performed on-the-job search (Burgess and Low (1992 and 1998)).

Table 2: Sample Means 1/

Variable	Mean	SD
A. Outcomes		
S = on-the-job search {0,1} 1/	0.088	0.283
E = Separation {0,1} 2/	0.328	?
B. Covariates 1/		
p = Subjective probability of job loss [0,1]	0.153	0.247
F = Subjective probability of finding a job [0,1]	0.477	0.376
UB = Potential weekly UI benefits (2006 $)	287.110	106.541
RR = Replacement rate [0,1]	0.392	0.137
w = Weekly wage (2006 $)	978.996	1243.029
t = Current tenure length (years)	13.401	12.104
a = Age (years)	59.418	5.792

1/Sample means for the sample used in the analysis of POJS
2/Sample mean for the sample used in the analysis of $P(E)$

status every two years and many workers who claim to be out of the labor force may have been previously unemployed in-between survey waves. According to Chan and Stevens (2001) "it is likely that individuals [in the HRS] will move from being unemployed and searching for work to being out of the labor force or retired over the course of a non-employment spell". Also, Peracchi and Welch (1994) argue that unemployment status is among the strongest predictors of exiting the labor force and thus question whether the distinction between unemployment and being out of the labor force is meaningful for older workers. Therefore in my empirical analysis I will work with non-working spells rather than unemployment spells. Table 2 shows that the separation rate for our sample of analysis from one wave to another (i.e. in a two year window) is on average 0.33.

I am not only interested in the probability of separation, but also in the probability that separation has occurred with or without a non-working spell. Workers who report to be working at a different employer at any wave may have had an intervening non-working spell. In fact, using the HRS Chan and Stevens (2001) found that a "representative displaced worker in his or her 50s has a 70%-75% chance of returning to work within 2 years of a job loss. Return rates for displaced workers in their 60s are substantially lower". Thus, in order to account for non-working spells, I differentiate workers who started their new work immediately after ending their previous jobs and workers who experienced a working gap between both employments[8]. Table 3 registers the average employment status transition rates, from one wave to another in the HRS (i.e. in a two-year window), conditional on being currently employed. As described before, on average, 33%

[8] The HRS asks about the ending date of the previous employment and the starting date of the new employment. I categorized those workers with a new employer who had a gap in their working history of a month or more as "Different employer with intervening non-working spell" and those with a gap less of a month as "Different employer without an intervening non-working spell". However, this reclassification could not be done in all cases. Specifically, for workers who returned to a previous employer, these calculations cannot be performed because the date of the first employment (ever) was recorded. I recorded those cases as moving to another employer without a gap.

Table 3: Average employment status transition rates (in a two year window)

Transition into:	# of cases	**Average rate**
Same employer	6,903	67.18
Different employer without an intervening non-working spell	506	4.92
Different employer with intervening non-working spell	569	5.54
Self-employment	308	3.00
Not working (includes unemployment and out of labor force)	1,990	19.37
Total	**10,276**	**100.00**

of workers separate from their current employers from one wave to another. And around 10% moved to a different employer with a little over half of them with an intervening non-working spell.

The HRS elicit the subjective probability of job loss through the following question: "*Sometimes people are permanently laid off from jobs that they want to keep. On the same scale from 0 to 100 where 0 equals Absolutely no chance and 100 equals Absolutely certain, what are the chances that you will lose your job during the next year?*". The median of the responses is 0, which indicates that this group of workers feels relatively safe in their jobs and the mean value is 0.15[9]. The distribution of the responses is similar to the one observed in the The Survey of Economic Expectations (SEE)[10] for male workers aged 50 years or older (years 1994-1998), although the average expected probability of job loss is slightly smaller in SEE than in HRS[11]. The histogram of the responses in HRS is shown in Figure 2.

As discussed in Section 3.2, firm labor force downsizing is a shifter of the subjective probability of job loss. In fact, among male workers whose firms experienced a permanent reduction in employment in the last two years, the mean expected probability of job loss is 20.5%, whereas among male workers whose firms did not experience a permanent reduction in employment the average expected probability is 14%.

Finally, table 4 shows the variation in four variables related to UI generosity. The first two variables are the nominal replacement formula and the maximum level for weekly UB (in 2006 dollars) set by each state. On average, the replacement formula in the data (over the period 1994-2004) is 0.53, with the more generous state being Kentucky in year 2004 and the least generous state being California in year 1994. And the average maximum weekly benefits (in 2006 dollars) is 347. Most of the variation in these two

[9] There is also some bunching of responses at 10% and 50%, and to less extent around 90%, which is indicative that responses may be rounded around some focal points. In fact, Manski and Molinari (2010) found strong evidence of rounding responses for subjective probability questions in the HRS, with the extent of rounding differing across respondents. They proposed the use of a person's response pattern across different subjective probability questions to infer his rounding pattern and establish a credible interval for his responses, which can be used in estimations. In this paper I am going to abstract from the effect of rounding practices, although that would be an interesting avenue for further research on this topic.

[10] Dominitz, Jeff, and Charles F. Manski. The Survey of Economic Expectations – Waves 1-8, with data from the UW Survey Center's National Survey [computer file]. 1st ed. Madison, WI.: John D. Straub, University of Wisconsin-Madison [producer], 2000. Madison, WI: Data and Program Library Service [distributor], 2000; <http://dpls.dacc.wisc.edu/econexpect/index.html>; (10 March 2011).

[11] In the SEE, the average value of the subjective probability of job loss in the next 12 months is 11.2% for male workers aged 50 years or older and 13.8% for all male workers.

Table 4: Variation in UI generosity

	Mean	Sd	Min	Max	Between-Group Variace/ Within-Group Variance
Replacement Formula	0.53	0.05	0.39	0.68	64.91
Max weekly benefits	347.05	74.39	218.78	573.76	39.76
Average potential replacement rate	0.38	0.04	0.26	0.49	26.95
Average potential weekly benefits	296.84	54.90	195.73	474.13	7.82

variables is across states rather than within states over time: for example, the between-states variance in the replacement rate is 65 times the within-states variance; in the case of the maximum weekly benefits that ratio is 39.76.

The last two variables in Table 4 are the average potential replacement rate and the average potential weekly benefits that an employed male worker aged 50 years or older would be entitled to if he lost his job. As explained in Section 3.2, these variables are calculated from the CPS March Supplement by workers earnings interacting with the replacement formulas and the maximum weekly UB in each state. These variables are the instruments I use for the workers' own potential replacement rate and weekly UB. The ratio of cross-state variance to within-state variance is significantly lower for these two variables although it is still large. Therefore, it is expected that including state dummies in the regression will absorb up much of the variation in the instruments and will make it harder for the estimated coefficients to achieve statistical significance.

4.3 Sample

In the HRS sample there are a total of 6,267 employed male workers aged 50 years or older for the period of analysis[12]. Each worker contributes on average with 3.2 observations, for a total of 19,928 initial observations. After controlling for non-missing information on on-the-job search activities, subjective probabilities, wages, firm downsizing and other covariates, the final sample size is around 8,700 observations for on-the-job search analysis and 8,250 observations for the probability of job separation analysis (see Table 5 for more details)[13]. Finally, there is a total of 10,283 job separations in the sample. After controlling for non-missing information on covariates, the final sample size is 3,373 as shown in Table 3.

[12] In this paper I focus only on male workers aged 50 years or older

[13] In some specifications I do not instrument for the subjective probability of job loss with whether the firm has downsized labor force in the last two years. In those cases the sample sizes are around 10,800 for on-the-job search analysis and 10,270 for the probability of job separations.

Table 5: Sample for on-the-job search

Conditioning on	Sample size
Working	19,928
Working & non-missing info on on-the-job search	17,060
Working & non-missing info on on-the-job search and on expectations on job loss	12,694
Working & non-missing info on on-the-job search, expectations of job loss and probability of finding a job.	12,558
Working & non-missing info on on-the-job search, probability of job loss, probability of finding a job and wages	11,556
Working & non-missing info on on-the-job search, expectations of job loss, probability of finding a job, wages and firm labor downsizing	9,351
Final sample sizes:	
For on-the-job search analysis	8,712
For probability of separation analysis	8,255

5 Empirical results

5.1 UI and POJS

Tables 6 and 7 show the results for estimating equations 1 and 2 when the outcome of interest is on-the-job search. All regressions are estimated with regional dummies and controlling for all the covariates described in Section 3.1. Although our outcome of interest is dichotomous, estimations are done using linear probability models (LPM) and two-stage least squares (2SLS) for two practical reasons: i) the linear specification facilitates the interpretation of the estimated parameters when there are interaction terms[14]; and ii) the linear specification facilitates the calculation of standard errors clustered by state[15]. Even though the causal relationships I want to estimate are more likely non-linear (unless I used a fully saturated model), LPM and 2SLS procedures are still useful for estimating casual effects on conditional means (Angrist (2001)).

Columns 1 and 4 of Table 6 show the linear coefficients using the endogenous regressors for p_{ijt} and UB_{ijt}, columns 2 and 5 show the linear coefficients when I instrument for UB_{ijt} only and columns 3 and 6 show the linear coefficients when I instrument for both UB_{ijt} and p_{ijt}, as described in Section 3.2. The lower panel of the table depicts the marginal effects on the probability of job search evaluated at the mean values of the covariates[16].

In general, the results from Table 6 support the theoretical predictions in column 1 of Table 1. In particular

[14] See Ai and Norton (2003) for a discussion on interaction terms in non-linear models such as probits and logits.

[15] I cluster standard errors by state in order to account for intra-state correlation in the error term (either cross sectional or over time).

[16] For example, in column 5 we have that $\frac{\partial P(S)}{\partial UB}|_{\overline{x}} = \theta_2 + \theta_3 * \overline{p} = -0.0002$. The marginal effects when I estimate main effects only are equal to the estimated coefficients, so I do not repeat those in the table.

we can draw the following conclusions:

1. Workers who feel at risk of job loss are more likely to perform on-the-job search. Back-of-the-envelope calculations using the results from column 3 (main effects only) show that an increase in the subjective probability of job loss of 25 percentage points (one standard deviation) above its mean leads to an increases the probability of performing on-the-job search by 16 percentage points (from 0.08 to 0.024). The estimated elasticity at mean values is 1.16.

2. Higher UB discourage on-the-job search efforts and that effect gets larger for workers who feel more at risk of job displacement. For example, using the results from column 6 and back-of-the-envelope calculations at the mean value for the expected probability of job loss (0.15), an increase in the weekly UB of $107 (one standard deviation) decreases the probability of job search in 2 percentage points, from 0.07 to 0.05 or an implied elasticity of -0.7. In contrast, at a value for the expected probability of job loss of 0.5, the same increase in weekly UB leads to a decrease in the probability of search of 32 percentage points, from a predicted value of 0.42 to 0.10, or an implied elasticity of -2.1

Appendix B shows the first-stage regressions. The F-statistic for all regressions are large. The effect of other covariates on search behavior is also as one would expect: workers with longer tenure, with employer-provided health insurance and pension benefits and in less stressful jobs are less likely to perform on-the-job search. Conversely, younger workers, more educated workers, and workers who feel more confident about the probability of finding a job are more likely to perform on-the-job search[17]. Most of the variation of the instruments for UI generosity is across states, not within-state over time. Thus, after controlling for state many of the estimated coefficients of interest do not achieve statistical significance although the point estimates are relatively similar. The results are also presented in Appendix B.

Table 7 presents the results for the impact on POJS when the UI generosity is measured by the replacement rate (RR_{ijt}) instead of the weekly unemployment benefits (UB_{ijt}). Again, all regressions are estimated with regional dummies and controlling for the same covariates as before. The conclusions that can be drawn from these results are similar to the previous ones: workers entitled to larger replacement rates of their wages in case of displacement are discouraged from POJS and that effect gets larger for workers who feel more at risk of displacement.

5.2 UI and Job Separations

The theoretical model in Section 2 pointed out that the probability of job separation increases with the (subjective) probability of job loss and decreases with more generous UB (at least for workers with a positive probability of job loss). Table 8 shows the results for regressing an indicator variable of whether

[17] The full estimation results are not reported here but are available from the author upon request.

Table 6: Estimation results for on-the-job search (using weekly benefits and regional dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1282	0.1278	0.6417	0.1431	0.2329	3.2921
	[0.0157]***	[0.0156]***	[0.1148]***	[0.0377]***	[0.0644]***	[1.1009]***
UB_{ijt} (2006 $)	-0.0003	-0.0002	-0.0002	-0.0003	-0.0001	0.001
	[0.0000]***	[0.0001]**	[0.0001]*	[0.0000]***	[0.0001]	[0.0005]**
$p_{ijt} * UB_{ijt}$	—	—	—	-0.0001	-0.0004	-0.008
	—	—	—	[0.0001]	[0.0002]*	[0.0032]**
# Obs.	10812	10812	8712	10812	10812	8712
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1277	0.1244	0.9989
	—	—	—	[.01570] ***	[.01413]***	[0.2265]***
UB_{ijt}	—	—	—	-0.0003	-0.0002	-0.0002
	—	—	—	[0.0000]***	[.0001]**	[.0001]**

1/ Marginal effects at covariates mean values

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Estimation results for on-the-job search (using replacement rate and regional dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1267	0.1287	0.6221	0.1700	0.2801	5.796
	[0.0154]***	[0.0153]***	[0.1203]***	[0.0575]***	[0.0927]***	[3.0901]*
RR_{ijt} (2006 $)	0.0784	-0.1904	-0.1568	0.0939	-0.1302	1.9543
	[0.0379]**	[0.1113]*	[0.1017]	[0.0370]**	[0.1063]	[1.1418]*
$p_{ijt} * RR_{ijt}$	—	—	—	-0.1048	-0.3661	-13.6013
	—	—	—	[0.1252]	[0.2309]	[8.0710]*
# Obs.	10812	10812	8712	10812	10812	8712
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1289	0.1366	0.4263
	—	—	—	[0.0162]***	[0.0147]***	[0.2146]*
RR_{ijt}	—	—	—	0.0778	-0.1863	-0.1384
	—	—	—	[0.0381]**	[0.1110]*	[0.2236]

1/ Marginal effects at covariates mean values

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

the worker separated from his current employer between two contiguous HRS waves (wave *m* and *n*) on the set of regressors defined in Section 3.1 and regional dummies[18]. Thus, the dependent variable (called SEPARATION) takes the value of 1 if the person was separated and of 0 otherwise. As specified in Section 4.2, I define separation as termination of the employment relationship for any reason, including displacement, quitting and taking another job or leaving the labor force. As before, all regressions were estimated using LPM and 2SLS and the covariates are measured as of wave *m*.

The results in Table 8 suggest that the subjective probability of job displacement collected in HRS is a good predictor of separations, even after controlling for all the set of observable worker and job characteristics defined above. This fact has been previously documented by Stephens (2003). Back-of-the envelope calculations using estimation results from column 3 suggests that a in increase in the subjective probability of job separation above its mean of 25 percentage points leads to an increase in the probability of separation of 12 percentage points, from 0.33 to 0.45, or an implied elasticity of 0.21.

The coefficients for UB in columns 2 and 3 are negative (reversing the OLS sign) as predicted by theory although they are not statistically significant. This is likely a problem of small statistical power since the reduced form coefficients (i.e. regressing the outcome on the instruments) are negative and statistically significant (at least at a 10% confidence level). Using the results from column 3, back-of-the envelope calculations suggests that an increase is weekly UB of $107 (one standard deviation) decreases the probability of separation for the average worker by 2 percentage points, from 0.33 to 0.31, or an implied elasticity of 0.17. As discussed in Section 2, there is an ambiguity in whether this effect should get larger or smaller for individuals who feel more at risk of displacement. In my results, the evidence presented in column 5 and 6 of table 8 shows that the interaction effect is not statistically significant (and has a very high p-value).

Table 9 presents the results using the earnings replacement rate (RR_{ijt}) as a measure of UI generosity. Again, the probability of job loss stands out as a strong predictor of job separations, even after controlling for all other covariates. As with UB, the coefficients on RR_{ijt} are negative and not significant although the reduced form coefficients are negative and significant (at the 10% confidence level). Also, as before, the interaction effect is not significant either.

5.3 UI and transition into Non-working

Given that a worker was separated from his current employer, I ask what is the probability that he fell into a non-working spell and how that probability is affected by UI generosity. For workers who experience a job separation from wave *m* to wave *n*, I constructed the variable *NOWORK* that equals 1 if the worker is not working in wave *j*[19] or if he is working at a different employer but had a period of not working in between

[18] Appendix B shows the first stage results and the estimation results using state dummies.

[19] Following the discussion in Section 4.2 I group together workers who claimed to be out of the labor force (mostly retired) and workers who claim to be unemployed (not working but looking for job).

Table 8: Estimation results for Probability of Job Separation (using weekly benefits and regional dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1878	0.1884	0.4645	0.1674	0.2471	-0.3082
	[0.0202]***	[0.0201]***	[0.1976]**	[0.0473]***	[0.1315]*	[1.7638]
UB_{ijt} (2006 $)	0.0001	-0.0001	-0.0002	0.0001	-0.0001	-0.0005
	[0.0001]*	[0.0001]	[0.0001]	[0.0001]	[0.0002]	[0.0008]
$p_{ijt} * UB_{ijt}$	—	—	—	0.0001	-0.0002	0.0023
	—	—	—	[0.0001]	[0.0005]	[0.0052]
# Obs.	10276	10276	8255	10276	10276	8255
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1885	0.1862	0.3592
	—	—	—	[0.0199]***	[0.0218]***	[0.3204]
UB_{ijt}	—	—	—	0.0001	-0.0001	-0.0002
	—	—	—	[0.0001]*	[0.0001]	[0.0001]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Estimation results for the Probability of Job Separation (using replacement rate and regional dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1885	0.189	0.4453	0.2723	0.3081	-1.7695
	[0.0201]***	[0.0200]***	[0.1919]**	[0.0633]***	[0.2040]	[4.2364]
RR_{ijt} (2006 $)	-0.0576	-0.1264	-0.1841	-0.0276	-0.0772	-1.1106
	[0.0393]	[0.1175]	[0.1288]	[0.0506]	[0.1691]	[1.7960]
$p_{ijt} * RR_{ijt}$	—	—	—	-0.2031	-0.2887	5.7725
	—	—	—	[0.1637]	[0.5007]	[10.9376]
# Obs.	10276	10276	8255	10276	10276	8255
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1929	0.1951	0.5012
	—	—	—	[0.0187]***	[0.0206]***	[0.2708]*
RR_{ijt}	—	—	—	-0.0586	-0.1213	-0.2266
	—	—	—	[0.0390]	[0.1216]	[0.1750]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

(see Table 3); and it takes the value of 0 if the worker is at a different employer in wave *j* and joined his new employer without a non-working spell. Table 10 shows the results of regressing *NOWORK* on the same covariates as before (measured as of wave *m*) and regional dummies[20]. Estimation was again done using LPM and 2SLS procedures.

The following conclusions can be drawn from Table 10:

1. The effect of the subjective probability of job loss is very small and insignificant as expected according to the theoretical discussion in Section 2: once separation has occurred the probability of job displacement has an ambiguous sign in discriminating whether that separation was due to a transition into unemployment or into a different job.

2. UB increase the probability that separation occurred because of a non-employment spell[21]. Using results from column 3, back-of-the-envelope calculations suggest that an increase in the weekly UB of $107 (one standard deviation) increases the probability that separation occurred because of non-employment in 7 percentage points, from 0.85 to 0.91, or an implied elasticity of 0.20.

3. The interaction effect turns out insignificant (and with a very high p-value), which is not surprising given the ambiguity of its sign in the theoretical model.

Table 11 presents the results using the earnings replacement rate (RR_{ijt}) instead of UB as a measure of UI generosity. Columns 2 and 3 show that higher replacement rates are associated with higher probability of falling into a non-working spell given separation. Moreover, in this case, the interaction effect in column 5 is positive and significant. It would indicate that for workers who separated from their previous employer and had the same expectations on job loss, those with larger replacement rates were more likely to fall into non-working spells. The statistical significance of this effect even remains after controlling for state dummies.

6 Conclusions

In this paper I find compelling evidence that workers react pre-emptively by looking for another job when they feel at risk of displacement (i.e. pre-emptive on-the-job search or POJS). The estimated effect is significantly high and complements the evidence presented in paper on advanced notification of layoff and papers that analyze the flow of workers in closing firms. I also found that UI discourage workers to perform POJS and that effect gets larger when workers feel more at risk of displacement. In fact, the estimated elasticity of POJS with respect to weekly unemployment benefits (UB) for workers with a

[20] Appendix B shows the first stage results and the estimation results using state dummies.

[21] Again, the significance of the coefficients disappear after I control for state dummies as it was expected (although the point estimates remain relatively similar).

Table 10: Estimation results for Probability of No Working Spell (using weekly benefits and regional dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	-0.0013	-0.0041	-0.2552	0.0038	-0.1419	0.1742
	[0.0215]	[0.0221]	[0.2076]	[0.0587]	[0.1035]	[2.5331]
UB_{ijt} (2006 $)	0.0002	0.0005	0.0006	0.0002	0.0004	0.0009
	[0.0001]***	[0.0002]**	[0.0002]***	[0.0001]**	[0.0002]**	[0.0017]
$p_{ijt} * UB_{ijt}$	—	—	—	0	0.0005	-0.0014
	—	—	—	[0.0002]	[0.0004]	[0.0080]
# Obs.	3373	3373	2751	3373	3373	2751
Marg. Effects 1/						
p_{ijt}	—	—	—	-0.0014	-.0025	-0.1991
	—	—	—	[0.0214]	[0.0205]	[0.4044]
UB_{ijt}	—	—	—	0.0002	.0005	0.0006
	—	—	—	[0.0001]***	[0.0002]**	[0.0003]**

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11: Estimation results for Probability of No Working Spell (using replacement rate and regional dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	-0.0001	0.0024	-0.208	0.0035	-0.3618	-2.6945
	[0.0213]	[0.0219]	[0.2060]	[0.0465]	[0.1288]***	[2.1172]
RR_{ijt} (2006 $)	-0.0862	0.2915	0.3908	-0.0845	0.1047	-0.8518
	[0.0621]	[0.1645]*	[0.1836]**	[0.0719]	[0.1558]	[1.1539]
$p_{ijt} * RR_{ijt}$	—	—	—	-0.0086	0.879	6.4975
	—	—	—	[0.1144]	[0.3200]***	[5.7236]
# Obs.	3373	3373	2751	3373	3373	2751
Marg. Effects 1/						
p_{ijt}	—	—	—	0.0000	-0.0052	-.0352
	—	—	—	[0.0210]	[0.0235]	[0.3330]
RR_{ijt}	—	—	—	-0.0861	0.2731	0.3840
	—	—	—	[0.0621]	[0.1671]	[0.2660]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

subjective probability of displacement of 0.15 (sample mean) is -0.7, whereas for workers with a subjective probability of displacement of 0.5 it is -2.1.

There is no statistically significant evidence that UI affects the probability of job separation. However, evidence suggests that given a separation has occurred, more generous UB (or larger replacement rates) are associated with a higher probability that the separation occurred because the worker fell into a non-working spell. The estimated elasticity of the probability of experiencing a non-working spell (given separation) with respect to weekly UB is 0.2 for the average worker. This elasticity is much smaller than the one estimated for POJS and may reflect that not all on-the-job search leads necessarily to a successful job offer. In fact, only around 48% of workers think that they would be able to find a equally good offer if they lost their jobs. Also, there is only mixed evidence (as suggested by theory) that the effect of UI on the probability of falling into a non-working spell gets larger for workers who feel more at risk of displacement.

Finally, it is important to mention that the effects of UI on POJS and on the probability of experiencing a non-work spell (given a job separation) are consistently larger when I use the replacement rate as a measure of UI generosity rather than weekly UB. This finding is important because of two reasons. First, the standard practice in the analysis of the effect of UI on unemployment uses UB as a measure of generosity. And second, the replacement rate is in general larger for poor workers because of the cap on weekly benefits set by each state. Thus, the findings in this papers suggests that poor workers are particularly more likely to be discouraged to perform POJS because of the UI system, and thus more likely to fall into a non-working spell.

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A Appendix: Model solution and main predictions

As described in Section 2, I expand the analysis of the model two-period model proposed by Light and Omori (2004). In the first period, a worker is employed and earns w_1. His total endowment of time equals $\bar{l}+1$. Labor supply is indivisible and equal to 1 hour. The maximization problem of the worker is to decide how many hours to search on-the-job (s) and how many hours of leisure he enjoys ($\bar{l}-s$). The flow utility is given by $U(w_1, \bar{l}-s)$, where $U_j > 0$ and $U_{jj} < 0$ for $j = 1, 2$. If a worker searches, the probability of getting an offer in the second period equals $\alpha(s)$. As it is conventional, I assume that $\alpha'(s) > 0$ and $\alpha''(s) < 0$. Offers come from a known distribution $F(w)$ and at most one offer can be received. The worker faces a probability of layoff in period two equal to p. If he gets laid off he can collect UB equal to b. Since there is no on-the-job search in the second period (because the worker lives only for two periods), the reservation wage in period two, denoted by w_r, is such that the following equality holds: $U(w_r, \bar{l}) = U(b, \bar{l}+1)$. Four different scenarios can occur in period two: i) with probability equal to $(1-\alpha(s))(1-p)$ the worker did not lose his job and did not find an offer; ii) with probability equal to $(1-\alpha(s))p$ the worker lost his job and did not find an offer; iii) with probability $\alpha(s)(1-p)$ the worker did not lose his job and found an offer; and iv) with probability $\alpha(s)p$ the worker lost his job and found an offer. Mathematically, the maximization problem of the workers can be written as:

$$\begin{aligned} \underset{s}{Max}\, V &= U(w_1, \bar{l}-s) + (1-\alpha(s))(1-p)U(w_1, \bar{l}) + (1-\alpha(s))pU(b, \bar{l}+1) \\ &+\alpha(s)(1-p)\left[\int_{w_1}^{\infty} U(w, \bar{l})f(w)dw + \int_0^{w_1} U(w_1, \bar{l})f(w)dw\right] \\ &+\alpha(s)(p)\left[\int_{w_r}^{\infty} U(w, \bar{l})f(w)dw + \int_0^{w_r} U(b, \bar{l}+1)f(w)dw\right] \end{aligned} \tag{3}$$

The first-order condition is:

$$\begin{aligned} U_2(w_1, \bar{l}-s) &= \alpha'(s)(1-p)\left[\int_{w_1}^{\infty}\left[U(w, \bar{l}) - U(w_1, \bar{l})\right] f(w)dw\right] \\ &+\alpha'(s)p\left[\int_{w_r}^{\infty}\left[U(w, \bar{l}) - U(b, \bar{l}+1)\right] f(w)dw\right] \end{aligned} \tag{4}$$

We can write equation 4 as:

$$U_2(w_1, \bar{l} - s) = \alpha'(s)\left[(1-p)V^E + pV^U\right] \tag{5}$$

The left-hand side of equation 5 is the marginal cost of on-the-job search, whereas the right-hand-side is the marginal benefit. Note that V^E is the expected value of performing on-the-job search under the scenario where the worker does not lose his job in the second period and equals $\int_{w_1}^{\infty}\left[U(w,\bar{l}) - U(w_1,\bar{l})\right] f(w)dw$. Similarly, V^U is the expected value of performing on-the-job search under the scenario where the worker loses his job in the second period and equals $\int_{w_r}^{\infty}\left[U(w,\bar{l}) - U(b,\bar{l}+1)\right] f(w)dw$.

Using the Implicit Function Theorem, the following derivatives can be calculated:

$$\frac{\partial s}{\partial p} = -\left[\frac{\alpha'(s)[V^U - V^E]}{U_{22}(w_1,\bar{l}-s) + \alpha''(s)\left[(1-p)V^E + pV^U\right]}\right] > 0 \tag{6}$$

$$\frac{\partial s}{\partial b} = -\left[\frac{-\alpha'(s)p[1-F(w_r)]}{U_{22}(w_1,\bar{l}-s) + \alpha''(s)\left[(1-p)V^E + pV^U\right]}\right] \Rightarrow \frac{\partial s}{\partial b} = \begin{cases} = 0 & if\ p = 0 \\ < 0 & if\ p > 0 \end{cases} \tag{7}$$

$$\frac{\partial s}{\partial b \partial p} = \frac{\partial s}{\partial p \partial b} = \frac{U_1(.)[1-F(w_r)]\alpha'(s)\left(U_{22}(.) + \alpha''(s) * V^U\right)}{\left[U_{22}(w_1,\bar{l}-s) + \alpha''(s)\left[(1-p)V^E + pV^U\right]\right]^2} < 0 \tag{8}$$

Equation 6 indicates that workers with higher probability of job loss will perform on-the-job search with higher intensity. Equation 7 indicates that UB should not affect on-the-job search behavior if workers do not feel at risk of job loss. For workers who have a positive probability of job loss ($p > 0$), those entitled to higher UB will perform on-the-job search with lower intensity. Finally equation 8 indicates that the impact of job loss on on-the-job search is lower for workers entitled to higher UB.

Now, in our framework, in the second period the worker can continue to be employed at the same job (let's call this event C), he can be working at a different employer (let's call this event Q) or he can be unemployed (let's call this event U). Let's also define the event of separation from current job, denoted by E, as $E = \{Q, U\}$. The following probabilities can be calculated from the model:

$$P(Q) = \alpha(s)\left[(1-p)\int_{w_1}^{\infty} f(w)dw + p\int_{w_r}^{\infty} f(w)dw\right] \tag{9}$$

$$P(U) = p\left[1 - \alpha(s)\left(\int_{w_r}^{\infty} f(w)dw\right)\right] \tag{10}$$

$$P(E) = P(Q) + P(U) = p + (1-p)\alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right) \tag{11}$$

Using equation (11) we can calculate:

$$\frac{\partial P(E)}{\partial s} = \alpha'(s)(1-p)\left(\int_{w_1}^{\infty} f(w)dw\right) > 0 \tag{12}$$

Holding on-the-job search (s) constant, we have:

$$\frac{\partial P(E)}{\partial p}|_{\overline{s}} = 1 - \alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right) > 0 \tag{13}$$

The total derivative of $P(E)$ with respect to the probability of job loss (p) would also include its effect through on-the-job search (s):

$$\frac{\partial P(E)}{\partial p} = \left[1 - \alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right)\right] + \alpha'(s)\left(\frac{\partial s}{\partial p}\right)(1-p)\left(\int_{w_1}^{\infty} f(w)dw\right) > 0 \tag{14}$$

The total derivative of $P(E)$ with respect to UB (b) is:

$$\frac{\partial P(E)}{\partial b} = \left(\frac{\partial s}{\partial b}\right)\left[(1-p)\alpha'(s)\left(\int_{w_1}^{\infty} f(w)dw\right)\right] \Rightarrow \frac{\partial P(E)}{\partial b} = \begin{cases} = 0 & if\ p = 0 \\ < 0 & if\ p > 0 \end{cases} \tag{15}$$

And finally we can show that:

$$\frac{\partial P(E)}{\partial b \partial p} = \frac{\partial P(E)}{\partial p \partial b} = \left\{-\alpha'(s)\left(\frac{\partial s}{\partial b}\right) + (1-p)\left[\alpha''(s)\left(\frac{\partial s}{\partial b}\right)\left(\frac{\partial s}{\partial p}\right) + \alpha'(s)\left(\frac{\partial s}{\partial b \partial p}\right)\right]\right\}\left(\int_{w_1}^{\infty} f(w)dw\right) \gtrless 0 \tag{16}$$

Equations 13 and 14 show that the probability that the worker is separated from his job in the second period increases with the probability of job loss. Equation 15 shows that, all else equal, the probability that the workers is separated from his work in the second period decreases with higher UB, as long as the probability of job loss is non-zero. This result can be explained because, all else equal, workers with higher UB will perform on-the-job search with less intensity, and thus the probability of getting an outside offer is lower. Equation (16) shows that the sign of the cross derivative of $P(E)$ with respect to the probability of job loss (p) and to UB is ambiguous. On one hand, an increase in UB reduces search effort, thus ameliorating one of the channels through which an increase in p leads to an increase in $P(E)$. On the other hand, the size of the impact of an increase of p on $P(E)$ gets larger the less on-the-job search effort the workers are exerting. Since both effects go in opposite directions, more generous UB can either increase or ameliorate the effect of an increase of the probability of job loss on the probability that in period two the worker is separated from his current job.

Finally, let's define the probability that the worker falls into unemployment given that he was separated from his current job as:

$$P(U|E) = \frac{P(U)}{P(U) + P(Q)} = \frac{p\left[1 - \alpha(s)\left(\int_{w_r}^{\infty} f(w)dw\right)\right]}{p + (1-p)\alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right)} \tag{17}$$

It can be shown that:

$$\frac{\partial P(U|E)}{\partial p} = \frac{\alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right)\left[1-\alpha(s)\left(\int_{w_r}^{\infty} f(w)dw\right)\right] - p\alpha'(s)\left(\frac{\partial s}{\partial p}\right)\left[p\left(\int_{w_r}^{\infty} f(w)dw\right) + (1-p)\left(\int_{w_1}^{\infty} f(w)dw\right)\right]}{\left[p+(1-p)\alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right)\right]^2}$$

$$\frac{\partial P(U|E)}{\partial p} \gtrless 0 \tag{18}$$

$$\frac{\partial P(U|E)}{\partial b} = \frac{p\alpha(s)f(w_r)\frac{\partial w_r}{\partial b}}{p+(1-p)\alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right)} - \frac{p\alpha'(s)\frac{\partial s}{\partial b}\left[p\left(\int_{w_r}^{\infty} f(w)dw\right)+(1-p)\left(\int_{w_1}^{\infty} f(w)dw\right)\right]}{\left[p+(1-p)\alpha(s)\left(\int_{w_1}^{\infty} f(w)dw\right)\right]^2}$$

$$\frac{\partial P(U|E)}{\partial b} = \begin{cases} = 0 & if\ p = 0 \\ > 0 & if\ p > 0 \end{cases} \tag{19}$$

Equation 18 shows that once separation has taken place, the probability of job loss has an ambiguous sign in discriminating whether such separation happened because the worker found another job (Q) or became unemployed (U). In contrast, equation 19 tells us that higher UB are associated with a greater probability that separation has occurred because the worker fell into unemployment. It can be also shown that $\frac{\partial P(U|E)}{\partial p \partial b} = \frac{\partial P(U|E)}{\partial b \partial p} \gtrless 0$. The proof is omitted because the expression is long and not particularly illustrative. However, this result should not be surprising given the ambiguity of the sign in equation 18.

B Complementary Graphs and Tables

B.1 Graphs

Figure 1: Subjective probability of job loss and average separation rates

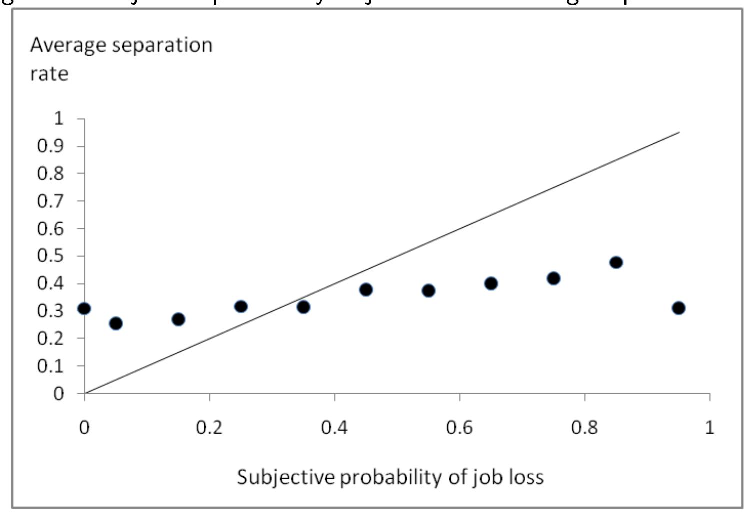
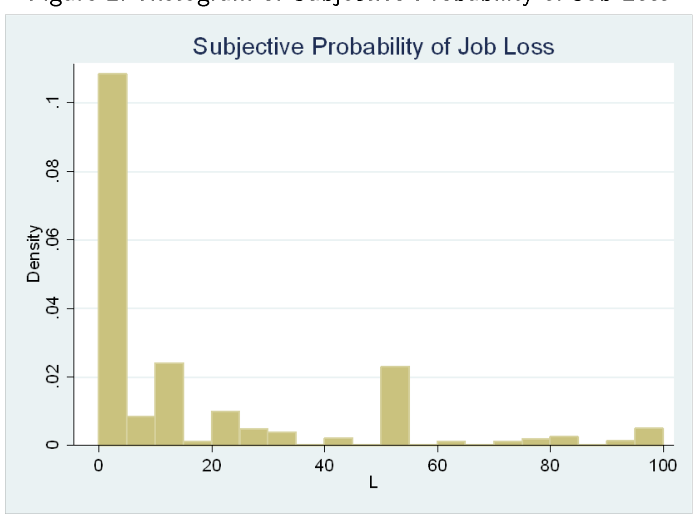


Figure 2: Histogram of Subjective Probability of Job Loss



B.2 First-stage Results

Table 12: First-stage regressions for on-the-job search (using weekly benefits and regional dummies)

	Endogenous regressors							
	Main effects only			Main and Interaction Effects				
	UB_{ijt} only	p_{ijt} and UB_{ijt}		UB_{ijt} only		p_{ijt} and UB_{ijt}		
Instruments	UB_{ijt}	p_{ijt}	UB_{ijt}	UB_{ijt}	$p_{ijt} * UB_{ijt}$	p_{ijt}	UB_{ijt}	$p_{ijt} * UB_{ijt}$
State mean benefits $(\overline{UB}_{jt})$	0.8410	0.0000	0.8146	0.8499	-0.0133	0.0000	0.7524	0.0920
	[0.0276]***	[0.0001]	[0.0307]***	[0.0335]***	[0.0082]	[0.0001]	[0.0342]***	[0.0281]***
Firm downsizing (D_{ijt})		0.0744	4.2095			0.0605	-78.1714	-10.9209
		[0.0088]***	[2.4533]*			[0.0390]	[16.4461]***	[12.9346]
$p_{ijt} * \overline{UB}_{jt}$				-0.0576	0.8910			
				[0.0781]	[0.0585]***			
$D_{ijt} * \overline{UB}_{jt}$						0.0000	0.2713	0.1189
						[0.0001]	[0.0568]***	[0.0453]**
# Obs.	10812	8712	8712	10812	10812	8712	8712	8712
F-Test:								
F-statistic	929.88	37.18	365.05	516.19	193.24	24.31	271.81	46.37

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 13: First-stage regressions for on-the-job search (using replacement rate and regional dummies)

	Endogenous regressors							
	Main effects only			Main and Interaction Effects				
	RR_{ijt} only	p_{ijt} and RR_{ijt}		RR_{ijt}only		p_{ijt} and RR_{ijt}		
Instruments	RR_{ijt}	p_{ijt}	RR_{ijt}	RR_{ijt}	$p_{ijt} * RR_{ijt}$	p_{ijt}	RR_{ijt}	$p_{ijt} * RR_{ijt}$
State mean rep. rate $(\overline{RR}_{jt})$	0.9105	-0.05	0.9022	0.907	-0.0061	-0.0761	0.8942	0.0991
	[0.0599]***	[0.0702]	[0.0674]***	[0.0558]***	[0.0102]	[0.0831]	[0.0742]***	[0.0397]**
Firm downsizing (D_{ijt})		0.0745	-0.003			0.0321	-0.016	-0.0077
		[0.0088]***	[0.0029]			[0.0651]	[0.0203]	[0.0238]
$p_{ijt} * \overline{RR}_{jt}$				0.0224	1.0035			
				[0.0840]	[0.1170]***			
$D_{ijt} * \overline{RR}_{jt}$						0.1138	0.0348	0.0954
						[0.1683]	[0.0574]	[0.0646]
# Obs.	10812	8712	8712	10812	10812	8712	8712	8712
F-Test:								
F-statistic	230.75	36.14	91.78	137.93	53.76	24.93	78.98	22.79

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 14: First-stage regressions for the Probability of Job Separation (using weekly benefits and regional dummies)

	Endogenous regressors							
	Main effects only			Main and Interaction Effects				
	UB_{ijt} only	p_{ijt} and UB_{ijt}		UB_{ijt} only		p_{ijt} and UB_{ijt}		
Instruments	UB_{ijt}	p_{ijt}	UB_{ijt}	UB_{ijt}	$p_{ijt} * UB_{ijt}$	p_{ijt}	UB_{ijt}	$p_{ijt} * UB_{ijt}$
State mean benefits $(\overline{UB}_{jt})$	0.8454	0	0.8185	0.8568	-0.0113	0	0.7574	0.0919
	[0.0266]***	[0.0001]	[0.0296]***	[0.0322]***	[0.0081]	[0.0001]	[0.0334]***	[0.0284]***
Firm downsizing (D_{ijt})		0.0747	3.6366			0.0601	-75.7389	-7.8564
		[0.0093]***	[2.5389]			[0.0367]	[16.7590]***	[12.1757]
$p_{ijt} * \overline{UB}_{jt}$				-0.0743	0.8721			
				[0.0742]	[0.0563]***			
$D_{ijt} * \overline{UB}_{jt}$						0	0.2613	0.1091
						[0.0001]	[0.0581]***	[0.0431]**
# Obs.	10276	8255	8255	10276	10276	8255	8255	8255
F-Test:								
F-statistic	1010.31	33.13	400.02	566.26	209.98	21.67	282.88	37.04

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 15: First-stage regressions for the Probability of Job Separation (using replacement rate and regional dummies)

	Endogenous regressors							
	Main effects only			Main and Interaction Effects				
	RR_{ijt} only	p_{ijt} and RR_{ijt}		RR_{ijt}only		p_{ijt} and RR_{ijt}		
Instruments	RR_{ijt}	p_{ijt}	RR_{ijt}	RR_{ijt}	$p_{ijt} * RR_{ijt}$	p_{ijt}	RR_{ijt}	$p_{ijt} * RR_{ijt}$
State mean rep. rate $(\overline{RR}_{jt})$	0.9104	-0.0469	0.9034	0.9026	-0.0062	-0.0804	0.8916	0.101
	[0.0615]***	[0.0713]	[0.0694]***	[0.0581]***	[0.0093]	[0.0835]	[0.0764]***	[0.0390]**
Firm downsizing (D_{ijt})		0.0747	-0.0028			0.0212	-0.0217	-0.0134
		[0.0093]***	[0.0031]			[0.0646]	[0.0204]	[0.0226]
$p_{ijt} * \overline{RR}_{jt}$				0.0499	1.0348			
				[0.0867]	[0.1115]***			
$D_{ijt} * \overline{RR}_{jt}$						0.1438	0.0508	0.1117
						[0.1651]	[0.0574]	[0.0603]*
# Obs.	10276	8255	8255	10276	10276	8255	8255	8255
F-Test:								
F-statistic	219.08	32.79	86.95	121.86	58.97	23.92	78.20	22.58

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 16: First-stage regressions for the Probability of No Working Spell (using weekly benefits and regional dummies)

	Endogenous regressors							
	Main effects only			Main and Interaction Effects				
	UB_{ijt} only	p_{ijt} and UB_{ijt}		UB_{ijt} only		p_{ijt} and UB_{ijt}		
Instruments	UB_{ijt}	p_{ijt}	UB_{ijt}	UB_{ijt}	$p_{ijt} * UB_{ijt}$	p_{ijt}	UB_{ijt}	$p_{ijt} * UB_{ijt}$
State mean benefits $(\overline{UB}_{jt})$	0.7804	-0.0002	0.7503	0.7766	-0.0269	-0.0001	0.6691	0.0855
	[0.0303]***	[0.0001]	[0.0359]***	[0.0369]***	[0.0135]*	[0.0001]	[0.0413]***	[0.0350]**
Firm downsizing (D_{ijt})		0.0903	4.6386			0.1687	-100.5417	19.5262
		[0.0149]***	[4.2122]			[0.0717]**	[19.9964]***	[26.5512]
$p_{ijt} * \overline{UB}_{jt}$				0.0205	0.893			
				[0.0744]	[0.0677]***			
$D_{ijt} * \overline{UB}_{jt}$						-0.0003	0.3481	0.0315
						[0.0002]	[0.0703]***	[0.0936]
# Obs.	3373	2751	2751	3373	3373	2751	2751	2751
F-Test:								
F-statistic	663.53	24.88	229.52	363.86	151.30	17.54	171.36	12.07

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 17: First-stage regressions for the Probability of No Work Spell (using replacement rate and regional dummies)

	Endogenous regressors							
	Main effects only			Main and Interaction Effects				
	RR_{ijt} only	p_{ijt} and RR_{ijt}		RR_{ijt}only		p_{ijt} and RR_{ijt}		
Instruments	RR_{ijt}	p_{ijt}	RR_{ijt}	RR_{ijt}	$p_{ijt} * RR_{ijt}$	p_{ijt}	RR_{ijt}	$p_{ijt} * RR_{ijt}$
State mean rep. rate $(\overline{RR}_{jt})$	0.8615	-0.1488	0.8204	0.8762	-0.0045	-0.1585	0.8392	0.081
	[0.0666]***	[0.1372]	[0.0668]***	[0.0725]***	[0.0114]	[0.1359]	[0.0878]***	[0.0583]
Firm downsizing (D_{ijt})		0.0902	-0.0024			0.075	0.0269	0.0044
		[0.0150]***	[0.0042]			[0.0991]	[0.0401]	[0.0436]
$p_{ijt} * \overline{RR}_{jt}$				-0.0764	0.9737			
				[0.1133]	[0.0961]***			
$D_{ijt} * \overline{RR}_{jt}$						0.0411	-0.079	0.08
						[0.2712]	[0.1087]	[0.1233]
# Obs.	3373	2751	2751	3373	3373	2751	2751	2751
F-Test:								
F-statistic	167.22	25.78	77.25	83.88	61.54	17.07	98.16	9.42

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

B.3 Regression results with State Dummies

Table 18: Estimation results for on-the-job search (using weekly benefits and state dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1247	0.124	0.6122	0.1393	0.2218	3.1852
	[0.0156]***	[0.0154]***	[0.1123]***	[0.0375]***	[0.0653]***	[1.2974]**
UB_{ijt} (2006 $)	-0.0003	-0.0001	-0.0001	-0.0003	-0.0001	0.001
	[0.0000]***	[0.0002]	[0.0002]	[0.0000]***	[0.0002]	[0.0008]
$p_{ijt} * UB_{ijt}$	—	—	—	-0.0001	-0.0004	-0.0078
	—	—	—	[0.0001]	[0.0002]	[0.0038]**
# Obs.	10812	10812	8712	10812	10812	8712
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1242	0.1206	0.9601
	—	—	—	[0.0156]***	[0.0134] ***	[0.2438]***
UB_{ijt}	—	—	—	-0.0003	-0.0001	-0.0002
	—	—	—	[0.0000]***	[0.0002]	[0.0003]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 19: Estimation results for on-the-job search (using replacement rate and state dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1228	0.1238	0.6051	0.1591	0.2779	5.9527
	[0.0153]***	[0.0152]***	[0.1238]***	[0.0570]***	[0.0913]***	[3.4604]*
RR_{ijt} (2006 $)	0.1082	-0.0275	0.0295	0.1211	0.0571	3.2491
	[0.0366]***	[0.1829]	[0.2026]	[0.0357]***	[0.1651]	[2.0466]
$p_{ijt} * RR_{ijt}$	—	—	—	-0.0879	-0.3729	-13.9263
	—	—	—	[0.1241]	[0.2269]	[8.9677]
# Obs.	10812	10812	8712	10812	10812	8712
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1247	0.1316	0.4548
	—	—	—	[0.0161]***	[0.0148]***	[0.2164]**
RR_{ijt}	—	—	—	0.1076	0.0000	1.1064
	—	—	—	[0.0369]***	[0.1744]	[0.7520]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 20: Estimation results for Probability of Job Separation (using weekly benefits and state dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1899	0.1911	0.4878	0.1714	0.2453	-0.0811
	[0.0202]***	[0.0203]***	[0.2063]**	[0.0466]***	[0.1320]*	[1.7179]
UB_{ijt} (2006 $)	0.0002	-0.0002	-0.0002	0.0002	-0.0002	-0.0005
	[0.0001]**	[0.0004]	[0.0004]	[0.0001]**	[0.0004]	[0.0009]
$p_{ijt} * UB_{ijt}$	—	—	—	0.0001	-0.0002	0.0017
	—	—	—	[0.0001]	[0.0005]	[0.0051]
# Obs.	10276	10276	8255	10276	10276	8255
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1906	0.1890	0.4092
	—	—	—	[0.01991]***	[0.0219]***	[0.3103]
UB_{ijt}	—	—	—	0.0002	-0.0002	-0.0002
	—	—	—	[0.0001]**	[0.5250]	[0.0004]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 21: Estimation results for the Probability of Job Separation (using replacement rate and state dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.1908	0.1918	0.4726	0.2681	0.3054	-1.527
	[0.0200]***	[0.0208]***	[0.1893]**	[0.0641]***	[0.2052]	[4.6189]
RR_{ijt} (2006 $)	-0.0543	-0.1902	-0.065	-0.0269	-0.1253	-1.2999
	[0.0425]	[0.3562]	[0.4019]	[0.0540]	[0.4119]	[2.9690]
$p_{ijt} * RR_{ijt}$	—	—	—	-0.1873	-0.2757	5.1592
	—	—	—	[0.1659]	[0.5056]	[11.8347]
# Obs.	10276	10276	8255	10276	10276	8255
Marg. Effects 1/						
p_{ijt}	—	—	—	0.1948	0.1976	0.5029
	—	—	—	[0.0187]***	[0.0211]***	[0.2514]*
RR_{ijt}	—	—	—	-0.0555	-0.1674	-0.5098
	—	—	—	[0.0420]	[0.3720]	[1.1919]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 22: Estimation results for Probability of No Working Spell (using weekly benefits and state dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}	regressors	UB_{ijt} only	UB_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.0002	-0.0055	-0.2353	0.0054	-0.1446	0.7947
	[0.0217]	[0.0233]	[0.2032]	[0.0588]	[0.1047]	[6.5880]
UB_{ijt} (2006 $)	0.0002	0.0007	0.0007	0.0002	0.0006	0.0015
	[0.0001]**	[0.0005]	[0.0006]	[0.0001]*	[0.0005]	[0.0057]
$p_{ijt} * UB_{ijt}$	—	—	—	0	0.0005	-0.0033
	—	—	—	[0.0002]	[0.0004]	[0.0211]
# Obs.	3373	3373	2751	3373	3373	2751
Marg. Effects 1/						
p_{ijt}	—	—	—	0.0001	-0.0035	-0.0993
	—	—	—	[0.0216]	[0.0218]	[0.9124]
UB_{ijt}	—	—	—	0.0002	0.0007	0.0008
	—	—	—	[0.0001]**	[0.0005]	[0.0017]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 23: Estimation results for Probability of No Working Spell (using replacement rate and state dummies)

	Main Effects Only			Main and Interaction Effects		
	Endogenous	Instrumented results		Endogenous	Instrumented results	
	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}	regressors	RR_{ijt}only	RR_{ijt} & p_{ijt}
	(1)	(2)	(3)	(4)	(5)	(6)
p_{ijt} [0,1]	0.0009	0.004	-0.1854	-0.0062	-0.3973	-2.991
	[0.0214]	[0.0220]	[0.2211]	[0.0489]	[0.1431]***	[2.0592]
RR_{ijt} (2006 $)	-0.1221	0.3598	0.2966	-0.1254	0.077	-1.7095
	[0.0696]*	[0.4852]	[0.5549]	[0.0822]	[0.4653]	[1.6873]
$p_{ijt} * RR_{ijt}$	—	—	—	0.0171	0.9674	7.3964
	—	—	—	[0.1197]	[0.3520]***	[5.6805]
# Obs.	3373	3373	2751	3373	3373	2751
Marg. Effects 1/						
p_{ijt}	—	—	—	0.0007	-0.0048	0.0362
	—	—	—	[0.0212]	[0.0239]	[0.3877]
RR_{ijt}	—	—	—	-0.1222	0.2623	-0.3027
	—	—	—	[0.0697]*	[0.4837]	[0.8795]

1/ Marginal effects at covariates mean values.

Standad errors (in brackets) are clustered by state.

* significant at 10%; ** significant at 5%; *** significant at 1%