# The Impact of Unemployment Insurance Receipt on Nonemployment Duration and Subsequent Job Quality: Evidence from the U.S. 

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#### Abstract

This paper examines nonemployment duration and subsequent job quality among UI benefit recipients and non-recipients in the U.S. using four panels of household survey data together covering most of 1995 to 2013. It does not find strong evidence of a negative relationship between receiving unemployment insurance benefits and subsequent job quality once relevant characteristics are controlled for, and finds suggestive evidence indicating that it may not be differences in potential duration that are driving observed differences in nonemployment duration.


## 1. Introduction

The U.S. unemployment insurance (UI) system provides weekly payments to qualifying workers who have lost their jobs. In 2016, 32 billion dollars in unemployment insurance benefits were paid to 6.2 million beneficiaries in the US (U.S. Dep't of Labor). Roles served by the UI system from an economic theory perspective include facilitating efficient search, smoothing consumption, and potentially serving as an automatic stabilizer during recessions. If benefits result in job quality improvement, there are also potential productivity gains. From individual quality of life and social perspectives, UI benefits potentially play a hugely important role in protecting cash-strapped individuals from the whims of industry shocks and reallocations. The major concern surrounding UI benefits, is that by paying individuals while they remain out of work, the system creates incentives for individuals to remain out of work longer, resulting in resource underutilization. This is a moral hazard concern. Benefit availability could also increase individual's willingness to accept more risky employment, cause individuals to put less effort into retaining employment, and crowd out forms of self-insurance (such as private savings, and spousal employment).

Theoretically, UI benefits are expected to increase unemployment durations, although not necessarily through a moral hazard effect. The impact on job quality is theoretically ambiguous. Empirical evidence supports the view of UI benefits as increasing unemployment durations, in terms of both benefit level (Landais 2015), and benefit duration (Card, Chetty, and Weber 2007b). Results on job quality are mixed, though tend to indicate negative or no impacts (Schmieder, von Wachter, and Bender 2016; Le Barbanchon 2016; Caliendo,

[^0]Kunn, and Uhlendorff 2016; van Ours and Vodopivec 2008; Lalive 2007). Nekoei and Weber (2017) recently argue that the impact is positive after taking into account negative duration dependence. Some U.S. studies have found positive impacts, although none have recently looked the question.

This paper looks at nonemployment duration and subsequent job quality among UI benefit recipients and non-recipients using four panels of U.S. survey data together covering most of 1995 to 2013. The term 'nonemployment' is used broadly herein to refer to the time until an individual finds employment following separation. Section 2 reviews related literature. Section 3 discusses the institutional background. Section 4 describes the data. Section 5 describes the empirical approach. Section 6 presents the results and Section 7 concludes.

## 2. Literature Review

This paper contributes to two areas of research. First, is that on how UI program features impact related durations. Second, is that on how UI program features impact subsequent job quality.

Early empirical work found evidence of large spikes in unemployment exit rates at around the time of and right before UI benefit exhaustion, suggesting that individuals were waiting to return to work until their UI benefits ran out (Meyer 1990; Katz and Meyer 1988). For individuals being recalled to a prior job, the impact was greater (Katz and Meyer 1988; 1990). More recent work indicates some of those effects were a consequence of how spells were being measured, but that benefits still do have an impact on duration even when measured differently (Card, Chetty, and Weber 2007b). Some of the increase in duration likely reflects greater search intensity and fewer transitions out of the labor market, rather than a pure moral hazard effect (Chetty 2008; Farber, Rothstein, and Valletta 2015).

Recent empirical studies on UI program parameters and subsequent job outcomes have mostly find negative or no impact on quality, most commonly measured by either earnings or job tenure. ${ }^{2}$ These estimates have primarily been for European countries. Using Austrian data, Lalive (2007) and Card, Chetty, and Weber (2007a) find that severance pay and extended benefit duration eligibility increase nonemployment durations, but have no effect on subsequent job match quality (RDD). On the other hand, and also using Austrian data, Nekoei and Weber (2017) find positive match quality effects. They argue that select other

[^1]studies are consistent with their findings once negative duration dependence is taken into account and that in fact positive impacts associated with UI benefits may offset some of the impact from negative duration dependence. The role of negative duration dependence is an interesting and important point.

The latest to look at job quality using U.S. data appear to be Centeno and Novo (2006), Centeno (2004), and McCall and Chi (2008). All three use NLSY data collectively covering 1979-2002 and find that more generous UI benefits have positive impacts on subsequent job quality. ${ }^{3}$ Consistent with those results, in Canada, Belzil (2001) finds that maximum benefit duration has a positive impact on subsequent job duration.

Using German data, Caliendo, Tatsiramos, and Uhlendorff (2013), and Schmieder, von Wachter, and Bender (2014; 2016) find that potential benefit durations have no or negative job quality impacts (RDD). Using French data and focusing on "low employability workers," Le Barbanchon (2016) finds similar results. Using Slovenian data, van Ours and Vodopivec (2008) find that reducing potential benefit duration had no impact on subsequent wages or job duration, or on the probability of finding a permanent as opposed to temporary job. Using Portuguese data, Centeno and Novo (2009) is sometimes portrayed as finding positive quality impacts, however, they find more evidence of negative than positive impacts. ${ }^{4}$

## 3. Institutional Background

In the U.S., many features of the UI system are set at the state level. Different states have different rules created within federal program parameters. To start a period of benefit receipt, a worker must first establish eligibility. This is done by looking at earnings during a base period. The standard base period used is the first four of the last five completed calendar quarters preceding the date of application for benefits. Many states allow alternative and modified base periods for individuals unable to establish eligibility based on the regular base period. The idea behind these eligibility requirements is to ensure sufficient attachment to

[^2]the labor force among benefit recipients. Particular standards vary, but can be grouped into a number of types, all requiring sufficient earnings during the base period. Another typical requirement is that separation from employment have been involuntary, although there are exceptions. In some states, even a worker who has not fully separated from employment can establish benefit eligibility through short time compensation programs.

Once eligibility is established, base period earnings are again used to determine an individuals benefit amount and maximum potential benefit duration. Particulars vary here as well.

## 4. Data

This study uses data from the 1996, 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. The panels range from 36 to 64 months long, and start with samples ranging from approximately 90,000 to approximately 105,000 individuals. Interviews are conducted every four months, although most variables are recorded on a monthly basis. Employment status is reported weekly. The data includes a rich set of information on surveyed individuals. Other papers using SIPP data in the unemployment context include Chetty (2008), Kroft and Notowidigdo (2016), and Rothstein and Valletta (2017), Fujita and Moscarini (2017).

### 4.1. Sample and Spell Construction

Following recommendations from the SIPP User's Guide, I only use observations which are assigned strictly positive longitudinal weights and do not use observations with either of the Type Z imputations. Fujita and Moscarini (2017) use the same restriction. This restricts the sample to individuals who participate in the entire panel and eliminates observations for which all labor force characteristics are imputed. The same longitudinal weights are used throughout much of the analysis.

I transform the individual-month level SIPP data into individual-spell level data based on weekly employment status. Following common practice in the literature, individuals are classified as either having a job (employed) or not having a job (nonemployed). ${ }^{5}$ Status definition details are provided below. Initial spells begin with each individual's first observation

[^3]in the panel (and are all left censored). Subsequent spells begin each time an individual is observed changing status (from employment to nonemployement, or from nonemployment to employment). In particular, new spells begin in the week that a new status is first observed.

The spell-based data is restricted to nonemployment spells for which data on pre and post spell employment are available. This is necessary for comparing job attributes before and after the spell. It also eliminates left censored nonemployment spells. Further, nonemployment spells are restricted to those with at least three months of preceding employment (Kroft and Notowidigdo 2016 and others impose this or similar restrictions). NU spells lasting longer than two years are dropped (following Nekoei and Weber (2017)). I also eliminate NU spells that do not last at least two weeks. Two weeks corresponds to the waiting and filing time period needed to apply for UI benefits (Addison and Blackburn 2000). I also drop individuals who transition between employed and nonemployed more than once in a single month.

Further, I drop spells for which the individual is less than 18 or greater than 70 years old as of the first month of the spell. Similar or more restrictive age restrictions are commonly imposed in related literature. ${ }^{6}$ I also drop spells during which an individual reports being retired, or for which average weekly household income during the spell is less than 1 or greater than 10,000. Additional restrictions, discussed further below, will be based on the reported reason for job separation.

### 4.2. Variable Construction

Labor Force Status. Nonemployment duration is measured as the number of weeks that a nonemployment spell lasts. Employed status includes: (1) people who are working, and (2) people who are absent without pay but not on layoff. Nonemployed status includes: unemployed and not in the labor force. Unemployed status includes: (1) people on layoff absent without pay, and (2) people with no job who are looking or on layoff. Not in the labor force includes: (1) people with no job and not looking. These categories are mutually exclusive.

Earnings. Individual earnings are reported monthly for up to two concurrent jobs. For months in which more than one is reported, I use the sum of both. During months in which an individual transitions from employment to nonemployment or vice versa, all earnings are attributed to the portion of the month associated with employment. Number of weeks

[^4]employed are used for the purpose of computing weekly averages. All dollar amounts are reported in November 2013 dollars. ${ }^{7}$ The difference in earnings before and after a nonemployment spell is used as a measure of job quality. The more earnings increase (or the less they decrease), the more likely the job is of higher quality. All else constant, individuals should prefer higher wages. To measure the change in earnings, I use the difference in log average weekly earnings. ${ }^{8}$ Note, I use monthly earnings as reported rather than using a reporting month earnings, such as in Ham and Shore-Sheppard (2005), because of the panel and spell construction structures. ${ }^{9}$

UI Program Participation. I distinguish between individuals who report receiving UI benefits and those who do not (non-recipients). This self-reported information is subject to measurement error and imprecision. In some cases, reported benefit receipt does not align well with reported employment status.

Resources and Constraints. Household income is measured using the household in which the individual was a member during the first month of a given nonemployment spell as the reference household. It includes all types of income received by all members of a household. The ratio of an individual's earnings to the household income, measures the individual's level of contribution from employment. The higher the contribution, the more impact might be expected from job loss.

Individual and Household Characteristics. Unless otherwise noted, demographic and household characteristics are as of the first month of a spell. They include: age, gender, race, highest grade completed, school enrollment status, marital status, children under 18, household income, and home ownership status. I construct indicators for changes in highest level of education, marital status, children under 18, and home ownership status occurring during spells.

State Policy Variables. State UI programs vary along multiple important dimensions. Variables used here are the average weekly benefit and average maximum potential duration. State benefit data on average maximum potential duration is obtained from Department of Labor Table AR218. Observations with average maximum potential duration less than 15

[^5]weeks are dropped. ${ }^{10}$ Durations afforded under extended benefit programs are not included. ${ }^{11}$ Potential durations offer largely exogenous variation. The average maximum potential duration is based upon realizations, but still offers some exogenous variation. It is used as a control variable for job quality (wage) regressions, and to split the sample into high benefit and low benefit states in looking at nonemployment duration. Average weekly benefit duration is from the Department of Labor Monthly Program and Financial Data.

State-Level Business Cycle / Economic Conditions. Following others, I use the monthly unemployment rate during the first month of a spell to control for business cycle conditions (see e.g., Centeno and Novo 2006a). State-month unemployment rate data is from the BLS.

## 5. Empirical Framework

The two outcomes are nonemployment duration and job quality. Nonemployment duration is analyzed graphically using Kaplan-Meier survival curves to compare recipients and nonrecipients. It is important to note that assignment into those statuses is not random. As a means of generating separation, I also analyze high and low benefit states separately. State-year observations in the sample are split into high and low benefit state groups based on the average maximum potential durations (PDs) recorded for each state-year. PDs above median are used to define the high benefit state group. PDs at or below median are used to define the low benefit state group. A similar approach is used in Chetty (2008). Spells are assigned to groups based on their initial state and year. In each group, I compare recipients and non-recipients. Non-recipients are not expected to respond to PD and should have similar survival curves in both high and low PD states. If recipients are responding to benefit levels, then their response is expected to be greater in high benefit states. I estimate a Cox Proportional Hazard model to assess the significance of observed survival curve differences. ${ }^{12}$

I then estimate change in job quality using an OLS model. The approach is similar to that in Addison and Blackburn (2001). I control for state policy related variables, which vary over time and across states. I also include specifications that control for earnings, which is
${ }^{10}$ Illinois 2003-2004, Maryland 1998, Maine 2011, Utah 2003, Tennessee 2009.
${ }^{11}$ Future work could do this.
${ }^{12}$ The hazard model is specified as follows: (risk of finding a job at time $t$ )

$$
h_{i}(t)=h_{0}(t) \exp \left(\beta_{k} X_{i k}\right),
$$

where the baseline hazard function, $\alpha(t)=\log \left(h_{0}(t)\right)$, is unspecified, $X_{i k}$ are covariates, and $t$ is the survival time (time remaining in nonemployed status).
believed to be strongly correlated with significant job attributes such as occupation.

## 6. Empirical Results

Figure 1 presents Kaplan-Meier survival curves for the full sample of nonemployment spells (including those that are right censored). The survival curves show the time until reemployment for each group. The graph shows a clear gap between recipients and nonrecipients. Figure 2 shows the same graph split into high and low potential duration states. Both groups exhibit a similar notable gap between recipients and non-recipients.

Figure 3 shows the same graphs in Figure 2 but plots recipients with recipients and non-recipients with non-recipients. In panel (b) there is as expected almost no difference between non-recipients. In panel (a) there is a slight difference but in the opposite direction as expected. This is surprising and suggests that individuals are remaining out of work longer in lower potential duration states. Estimating a hazard model for the sample of recipients with an indicator for high potential duration states suggests the difference is significant at a five percent level, although with a positive coefficient (coef $=0.04916, p=.0372) .{ }^{13}$

Results for the wage equation regressions can be found in Tables 2 and 3. Table 3 is the same as Table 2 but includes spell duration as an independent variable. Results are mixed. While the for receiving UI benefits is mostly negative, it is mostly not significant. This suggests that there is not a significant difference in subsequent job quality, as measured by wage difference, between recipients and non-recipients.

## 7. Conclusion

This study does not find strong evidence of a negative relationship between receiving unemployment insurance benefits and subsequent job quality once relevant characteristics are controlled for. It finds suggestive evidence indicating that it may not be differences in potential duration that are driving observed differences in nonemployment duration, at least not entirely.

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## 9. Tables and Figures

Table 1: All Panel NU Spell Sample Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Max |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Duration (weeks) | 17,462 | 18.61 | 19.27 | 2 | 104 |
| Recieve UI | 17,462 | 0.32 | 0.47 | 0 | 1 |
| Find Job | 17,462 | 1 | 0 | 1 | 1 |
| Age | 17,462 | 37.87 | 11.99 | 19 | 69 |
| Sex |  |  |  |  |  |
| Female | 17,462 | 0.52 | 0.5 | 0 | 1 |
| Male | 17,462 | 0.48 | 0.5 | 0 | 1 |
| Race |  |  |  |  |  |
| White | 17,462 | 0.83 | 0.37 | 0 | 1 |
| Black | 17,462 | 0.11 | 0.32 | 0 | 1 |
| Asian | 17,462 | 0.02 | 0.14 | 0 | 1 |
| Other | 17,462 | 0.04 | 0.18 | 0 | 1 |
| Latino | 17,462 | 0.07 | 0.26 | 0 | 1 |
| Marital |  |  |  |  |  |
| Married | 17,462 | 0.50 | 0.50 | 0 | 1 |
| Not Married | 17,462 | 0.30 | 0.46 | 0 | 1 |
| Marg Attach | 17,462 | 0.18 | 0.38 | 0 | 1 |
| Top Educ |  |  |  |  |  |
| Less HS | 17,462 | 0.14 | 0.35 | 0 | 1 |
| HS | 17,462 | 0.30 | 0.46 | 0 | 1 |
| Some Coll | 17,462 | 0.36 | 0.48 | 0 | 1 |
| Bach Plus | 17,462 | 0.20 | 0.40 | 0 | 1 |
| Enroll | 17,462 | 0.10 | 0.30 | 0 | 1 |
| Living |  |  |  |  |  |
| Own | 17,462 | 0.61 | 0.49 | 0 | 1 |
| Rent | 17,462 | 0.36 | 0.48 | 0 | 1 |
| Occupy | 17,462 | 0.03 | 0.17 | 0 | 1 |
| Avg HH Inc (week) | 17,462 | 1,363 | 1,341 | 1.03 | 9,951 |

Source: SIPP 1994-2008 panels and author calculation. See text for detail.

Table 1, continued

| Statistic | N | Mean | St. Dev. | Min | Max |
| :--- | ---: | ---: | ---: | ---: | ---: |
| Prior Emp |  |  |  |  |  |
| $\quad$ Duration (weeks) | 17,462 | 54 | 47 | 6 | 267 |
| Avg Earn (week) | 17,462 | 550 | 563 | 0 | 9,921 |
| Avg Hours | 17,462 | 36.9 | 17.9 | 0 | 168 |
| Ever PT | 17,462 | 0.645 | 0.479 | 0 | 1 |
| Ever Multi-Job | 17,462 | 0.324 | 0.468 | 0 | 1 |
| Future Emp |  |  |  |  |  |
| $\quad$ Duration (weeks) | 17,461 | 52 | 52.1 | 1 | 265 |
| Avg Earn (week) | 17,461 | 543 | 591 | 0 | 14,291 |
| Avg Hours | 17,461 | 36.8 | 18.9 | 0 | 170 |
| Ever PT | 17,461 | 0.6 | 0.5 | 0 | 1 |
| $\quad$ Ever Multi-Job | 17,461 | 0.324 | 0.468 | 0 | 1 |
| Changes |  |  |  |  |  |
| $\triangle$ Wage | 17,461 | -1.6 | 72.7 | -266 | 254 |
| $\triangle$ Log Wage | 17,461 | -0.3 | 1.5 | -5.6 | 3.5 |
| $\triangle$ Educ | 17,462 | 0.013 | 0.114 | 0 | 1 |
| $\triangle$ Kid | 17,462 | 0.024 | 0.152 | 0 | 1 |
| $\triangle$ Marital | 17,462 | 0.015 | 0.121 | 0 | 1 |
| $\triangle$ Living | 17,462 | 0.038 | 0.191 | 0 | 1 |

Source: SIPP 1996-2008 panels and author calculation. See text for detail.

Figure 1: Kaplan Meier Survival Curves, Recipient vs Non-Recipient


Full sample of nonemployment spells.

Figure 2: Kaplan Meier Survival Curves, High vs Low Potential Duration States

(a) Low Potential Duration States

(b) High Potential Duration States

Figure 3: Kaplan Meier Survival Curves, High/Low, Recipient/Non-Recipient

(a) UI Recipients in High and Low Potential Duration States

(b) Non-Recipients in High and Low Potential Duration States

Table 2: Wage Difference Regression Results

|  | $(1)$ | $(2)$ | $(3)$ |
| :--- | ---: | ---: | ---: |
| Receive UI | -0.0436 | 0.0006 | -0.0044 |
|  | $(0.0281)$ | $(0.0308)$ | $(0.0310)$ |
| Log Prior Earn |  | 0.0150 | 0.0164 |
|  |  | $(0.0168)$ | $(0.0167)$ |
| Log Avg Week Ben |  | $-0.4691^{* * *}$ | $-0.9630^{* * *}$ |
|  |  | $(0.0579)$ | $(0.0892)$ |
| Avg Pot Dur | $0.0140^{* * *}$ | $0.0184^{* * *}$ |  |
|  | $(0.0047)$ | $(0.0064)$ |  |
| Female | -0.0322 | -0.0292 |  |
|  |  | $(0.0283)$ | $(0.0283)$ |
| Age | $-0.0233^{* * *}$ | $-0.0242^{* * *}$ |  |
|  | $(0.0080)$ | $(0.0080)$ |  |
| Age2 | 0.0002 | $0.0002^{*}$ |  |
|  |  | $(0.0001)$ | $(0.0001)$ |
| HS | -0.0211 | -0.0017 |  |
|  |  | $(0.0394)$ | $(0.0395)$ |
| Less HS | -0.0614 | -0.0397 |  |
|  |  | $(0.0473)$ | $(0.0479)$ |
| Some Coll | -0.0393 | -0.0227 |  |
|  |  | $(0.0384)$ | $(0.0384)$ |
| Married | 0.0180 | 0.0142 |  |
|  |  | $(0.0388)$ | $(0.0388)$ |
| Not Married | -0.0082 | -0.0099 |  |
|  | $(0.0466)$ | $(0.0465)$ |  |

Table 2 continued

|  | $(1)$ | $(2)$ | $(3)$ |
| :--- | ---: | ---: | ---: |
| Black |  | 0.0620 | 0.0680 |
|  |  | $(0.0458)$ | $(0.0484)$ |
| Asian |  | -0.0205 | 0.0046 |
|  |  | $(0.0968)$ | $(0.0996)$ |
| Other Race |  | 0.0903 | $0.1239^{*}$ |
|  |  | $(0.0669)$ | $(0.0680)$ |
| Enroll |  | 0.0382 | 0.0261 |
|  |  | $0.0446)$ | $(0.0446)$ |
| Kids |  | 0.0395 | 0.0422 |
|  |  | $0.0303)$ | $(0.0303)$ |
| Own |  | $0.0702^{* *}$ | $0.0711^{* *}$ |
|  |  | $0.03885^{* * *}$ | $(0.0292)$ |
| Urate |  | $0.0677^{* * *}$ |  |
|  |  | $0.0068)$ | $(0.0084)$ |
| Constant | $(0.0164)$ | $(0.3646)$ | $(0.5199)$ |
| State FE |  |  |  |
| Observations | 16,920 | 16,912 | 16,912 |
| $R^{2}$ | 0.0002 | 0.0144 | 0.0243 |
| Adjusted R ${ }^{2}$ | 0.0001 | 0.0133 | 0.0204 |
| Residual Std. Error | 12.8840 | 12.8012 | 12.7551 |
| F Statistic | $3.1100^{*}$ | $12.9998^{* * *}$ | $6.1771^{* * *}$ |
| Note: | ${ }^{*} \mathrm{p}<0.1 ;$ |  |  |
|  | ${ }^{* *} \mathrm{p}<0.05 ;$ | ${ }^{* * *} \mathrm{p}<0.01$ |  |

Source: SIPP 1994-2008 panels. See text for detail.

Table 3: Wage Difference Regression Results

|  | $(1)$ | $(2)$ | $(3)$ |
| :--- | ---: | ---: | ---: |
| Receive UI | $-0.0565^{* *}$ | -0.0072 | -0.0117 |
|  | $(0.0284)$ | $(0.0312)$ | $(0.0314)$ |
| Duration (Weeks) | $0.0017^{* *}$ | 0.0010 | 0.0009 |
|  | $(0.0007)$ | $(0.0007)$ | $(0.0007)$ |
| Log Prior Earn |  | 0.0149 | 0.0164 |
|  | $(0.0168)$ | $(0.0167)$ |  |
| Log Avg Week Ben |  | $-0.4687^{* * *}$ | $-0.9645^{* * *}$ |
|  | $(0.0579)$ | $(0.0892)$ |  |
| Avg Pot Duration |  | $0.0140^{* * *}$ | $0.0183^{* * *}$ |
|  | $(0.0047)$ | $(0.0064)$ |  |
| Female | -0.0342 | -0.0310 |  |
|  |  | $(0.0283)$ | $(0.0283)$ |
| Age | $-0.0237^{* * *}$ | $-0.0245^{* * *}$ |  |
|  | $(0.0080)$ | $(0.0080)$ |  |
| Age2 | $0.0002^{*}$ | $0.0002^{*}$ |  |
|  |  | $(0.0001)$ | $(0.0001)$ |
| High School | -0.0234 | -0.0038 |  |
|  |  | $(0.0395)$ | $(0.0396)$ |
| Less High School |  | -0.0651 | -0.0429 |
| Some Coll | $(0.0474)$ | $(0.0480)$ |  |
|  |  | -0.0402 | -0.0235 |
| Married | $(0.0385)$ | $(0.0384)$ |  |
| Not Married | 0.0195 | 0.0154 |  |
|  | $(0.0387)$ | $(0.0387)$ |  |
|  | -0.0078 | -0.0096 |  |
|  |  | $(0.0466)$ | $(0.0465)$ |

Table 3 continued

|  | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
| Black |  | 0.0594 | 0.0663 |
|  |  | (0.0459) | (0.0485) |
| Asian |  | -0.0235 | 0.0021 |
|  |  | (0.0968) | (0.0997) |
| Race Other |  | 0.0887 | 0.1226* |
|  |  | (0.0670) | (0.0681) |
| Enroll |  | 0.0225 | 0.0121 |
|  |  | (0.0462) | (0.0461) |
| Kids |  | 0.0393 | 0.0420 |
|  |  | (0.0303) | (0.0303) |
| Own |  | 0.0707** | $0.0716^{* *}$ |
|  |  | (0.0288) | (0.0291) |
| U Rate |  | $0.0316^{* * *}$ | $0.0669^{* *}$ |
|  |  | (0.0069) | (0.0084) |
| Constant | $-0.3264^{* * *}$ | 2.2463 *** | 4.3964** |
|  | (0.0203) | (0.3646) | (0.5197) |
| Other Controls |  |  | $\checkmark$ |
| State FE |  |  | $\checkmark$ |
| Observations | 16,920 | 16,912 | 16,912 |
| $\mathrm{R}^{2}$ | 0.0007 | 0.0146 | 0.0244 |
| Adjusted R ${ }^{2}$ | 0.0006 | 0.0134 | 0.0204 |
| Residual Std. Error | 12.8812 | 12.8006 | 12.7547 |
| F Statistic | $5.7387^{* * *}$ | $12.4730^{* *}$ | $6.1157^{* *}$ |
| Note: | ${ }^{*} \mathrm{p}<0$. | ${ }^{* *} \mathrm{p}<0.05$; | ${ }^{* *} \mathrm{p}<0.01$ |
| Source: SIPP 1994-200 | panels. See | ext for detail |  |


[^0]:    ${ }^{1}$ Email: jesmccloskey@gmail.com, Web: https://jesmccloskey.github.io.

[^1]:    ${ }^{2}$ Others considered include region, occupation, and industry changes, firm-specific attributes, and probabilities of full versus part-time, and of permanent versus temporary.

[^2]:    ${ }^{3}$ Centeno (2004) and Centeno and Novo (2006), using the NLSY male subsample covering 1979-1998, find positive impacts of UI generosity on starting wage and job tenure (proportional hazards model; quantile regression model). McCall and Chi (2008), use NLSY data extending to 2002, and find that weekly benefit amounts have a significant positive impact on re-employment wages, but that the impact dissipates with the length of the unemployment spell, reaching zero after about 34 weeks (hazards model).
    ${ }^{4}$ They consider heterogeneity along two dimensions, essentially splitting estimates into eight separate boxes. Two of those boxes were associated with positive impacts. Combined average effects would likely be negative.

[^3]:    ${ }^{5}$ See e.g., Nekoei and Weber (2017); Barbanchon (2016); Schneider, von Watcher, and Bender (2016); Lalive (2007); Chetty, Card, and Weber (2007a).

[^4]:    ${ }^{6}$ For example, Nekoei and Weber (2017) look at individuals age 30 to 50 (though use an age cutoff regression discontinuity design), Centeno and Novo (2006) look at individuals 16 or older (and not enrolled in school), Farber, Rothstein, and Valletta (2015) look at individuals age 18 to 69.

[^5]:    ${ }^{7}$ Adjusted using a monthly PCE price index. FRED, PCEPI. Nominal values are used in assessing UI eligibility and where comparison is drawn to nominal values from other sources.
    ${ }^{8}$ Similar measures are used in Lalive (2007), Nekoei and Weber (2017), as well as others.
    ${ }^{9}$ In particular, I use weekly earnings. Weeks per month vary, thus reference month earnings may not translate to weekly for all months.

[^6]:    ${ }^{13}$ Using the longitudinal weights the coefficient changes to 0.059751 and becomes more significant.

