Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects*

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Abstract

We exploit policy discontinuity at U.S. state borders to identify the effects of unemployment insurance policies on unemployment. We find large effects of unemployment benefit extensions on unemployment. In fact, the estimates imply that most of the persistent increase in unemployment during the Great Recession can be accounted for by the unprecedented extensions of unemployment benefit eligibility. In contrast to the existing literature that mainly focused on estimating the effects of benefit duration on job search and acceptance strategies of the unemployed – the micro effect – we focus on measuring the general equilibrium macro effect that operates primarily through the response of the job creation to unemployment benefit extensions. We find that it is the latter effect that is very important quantitatively.

Keywords: unemployment insurance, unemployment

JEL codes: E24, J63, J64, J65

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1 Introduction

Unemployment in the U.S. rose dramatically during the Great Recession and has remained at an unusually high level for a long time. The search for explanations has identified the unprecedented extension of unemployment benefits during and following the recession as a possible culprit. This explanation has been largely dismissed, however, based on the results from a number of empirical studies that have shown that benefit extensions have only a small impact on the search activities of unemployed workers. However, in the classic equilibrium search framework of Mortensen and Pissarides (1994), the primary analytical device used by economists to study the determination of unemployment, the response of unemployment to changes in benefits is primarily driven not by the impact on the workers job search and acceptance decision, but by the response of employers' decisions of whether and how many jobs to create. The objective of this paper is to assess the magnitude of the latter effect empirically.

Our empirical strategy exploits policy discontinuity at state borders to identify the effects of unemployment insurance policies on unemployment. While we discuss the institutional features of the U.S. unemployment insuranse system in detail below, its key property is that UI policies are determined at the state level and apply to all locations within a state. To assess the effects of these policies on unemployment, we compare the evolution of unemployment in counties that border each other but belong to different states.[1] Since locations separated by a state border are expected to have similar labor markets due to the same geography, climate, access to transportation, agglomeration benefits, access to specialized labor and supplies, ets., the key feature that separates them is the difference in policies on the the two sides of the border. This policy discontinuity allows to identify its labor market implications. A fundamentally similar identification strategy was used, among others, by Holmes (1998) to identify the impact of right-to-work laws on location of manufacturing industry and by Dube, Lester, and Reich (2010) to identify the effect of minimum wage laws on earnings and employment of low-wage workers.

We extend this successful empirical strategy to accommodate features of the policies that we are interested in evaluating. First, the decisions of firms to create jobs are forward looking. Thus, they might be affected not only by the existing policy but also by the expectation of possible future policy changes. We derive a quasi-difference estimator of the effect of UI policies on variables such as vacancies and unemployment that controls for

[1] A Map of U.S. state and county borders can be found in Appendix Figure A-1.

the effect of expectations. Among other things, this allows to generalize our findings and estimate of the effect of a permanent change in nationwide UI policy on unemployment - the effect of particular interest to macro economists. Second, our estimation is based on a panel of border counties over the period of the Great Recession. Numerous shocks and policy changes have affected the aggregate economy but their impact was likely heterogeneous across county pairs. For example, shocks to and changing regulations of the financial system, while aggregate in nature, might have had a particularly strong impact on the counties on the border of New York and New Jersey, while the auto bail out has likely affected relatively more counties surrounding the border between Michigan and Indiana or Ohio. To obtain consistent estimates of the UI policies we follow Bai (2009) and use a flexible model of multiple interactive effects.

Our empirical findings indicate that benefit extensions quantitatively account for much of the unemployment dynamics during and after the Great Recession.

1.1 Related Literature

Economists have long been interested in estimating the effects of unemployment benefits on labor market outcomes. Consequently, there is an enormous literature devoted to this subject. This makes it impossible for us to mention all individual contributions. Instead, we summarize the key branches of this research agenda, organized around the following stylized illustrative decomposition:

$$\text{Job finding rate}_{it} \quad = \quad \underbrace{s_{it}}_{\text{search intensity}} \quad \times \quad \underbrace{f(\theta_t)}_{\text{finding rate per unit of } s}$$

In other words, the probability that an individual i finds a job in a given time period t depends on how hard that individual searches and how selective he is in his acceptance decisions, which is captured by the "search effort" component s_{it}. It also depends on the aggregate labor market conditions θ_t that determine how easy it is to locate jobs by expending a unit of search effort. To use an extreme example, if there are no job vacancies created by employers, $f(\theta_t) = 0$ and no amount of search effort by an unemployed worker would yield a positive probability of obtaining a job. Changes in unemployment benefit policies affect both the search intensity of unemployed workers and the aggregate job finding rate per unit of search effort driven by the general equilibrium effects. As is customary in the literature, we label the impact of benefits on the search intensity of an unemployed worker, holding aggregate conditions fixed, the "micro" effect. In contrast, the "macro" effect measures the effect of benefits on the job finding rate per unit of search effort.

1.1.1 Micro Effects

Two seminal contributions that spawned a large subsequent literature on measuring the *micro* elasticity of unemployment benefits are Moffitt (1985) and Meyer (1990) that examine how individual unemployment spells vary with the generosity of unemployment benefits. That is, these studies attempt to estimate how individual search efforts respond to changes in benefits holding labor market conditions constant. Krueger and Meyer (2002) provide an excellent survey of this literature. The general finding is that the micro elasticity of unemployment duration to unemployment benefits is relatively small, with the estimates implying that only a small fraction of the persistent increase in unemployment after the Great Recession can be attributed to a decline in worker search effort.

In recent, innovative work, Rothstein (2011) estimates the partial equilibrium effects of the unemployment benefits extensions on labor market outcomes during the Great recession. Using data from the Current Population Survey (CPS) on individual unemployment duration he exploits the variation in benefits available across states to identify how unemployment benefit durations impact individual search behavior. Importantly, Rothstein (2011) goes to great lengths to "absorb labor demand conditions" – that is, he controls for any changes in job creation to isolate solely the effect on worker search. For example, in one specification he uses unemployed workers who are ineligible for UI benefits as a control group. If unemployment benefits have a large effect on job creation, the job finding rate of all unemployed works would drop significantly, but comparing ineligible to eligible would only capture the behavioral response of search between workers, not the possibly much larger *macro* effect. The sampling methodology of the CPS does not allow for a representative study exploiting policy discontinuity at border counties.

In this paper, we aim to exploit the same heterogeneity in policy as in Rothstein (2011), but with the goal of identifying the labor demand or macro elasticity of unemployment benefits that is beyond the scope of his analysis. We see our work as highly complementary and helping provide the complete picture on the effect of benefit extensions.

Another recent paper, Schmieder, Von Wachter, and Bender (2012) estimates the disincentive effect of unemployment benefits over the business cycle. Using detailed administrative data from Germany they exploit a policy discontinuities based on the age of workers on the day they become unemployed. The months of unemployment benefits a worker is eligible changes discontinuously at two age cutoffs. Using a regression discontinuity design they are able to estimate the change in behavioral response due to increased benefit eligibility, and how this response varies with business cycle conditions. Schmieder, Von Wachter, and Bender (2012) find overall a small disincentive effect that does not vary much with business cycle conditions. However, it is important to note that they also hold constant any market-level factors, and identify only the micro elasticity.

1.1.2 Macro Effects

The evidence on the magnitude of the macro effect is predominantly based on the estimation of structural models.[2] Clearly, the firm's vacancy creation decision is based on comparing the cost of creating a job to the profits the firm expects to obtain from hiring the worker. The profit is the difference between worker's productivity and the wage. Hagedorn and Manovskii (2008) have shown that the fluctuations in productivity of the magnitude observed in the data can account for the observed business cycle fluctuations of the aggregate unemployment and vacancies using the Mortensen and Pissarides (1994) model. This implies that the amount of job vacancies is highly responsive to the relatively small business cycle frequency changes in productivity. They note that the flip side of this argument is that changes in unemployment benefit policies that affect wages can have a similar impact on profits also implying a large response of vacancies, and, as a consequence, of unemployment. This insight was extended in Mitman and Rabinovich (2013) who have shown that automatic benefit extensions in the recent recessions have substantially amplified the response of unemployment and served as the root cause of the widely documented phenomenon of the jobless recoveries (benefit extensions are triggered when unemployment reached a sufficiently high level so that they effectively kick in after the productivity is already recovering, inducing a delayed recovery of employment).[3] The persuasiveness of these arguments depends, however, on whether one agrees with the parameter values estimated by these authors. Key among them is the flow utility obtained by unemployed workers. This parameter is difficult to measure directly but its value is crucial for the amount of amplification delivered by the search model. Moreover, the answer based on estimating a particular model depends on a large number of theoretical assumptions and modeling choices. Thus, it is desirable to obtain a more direct empirical evidence on the impact of unemployment benefits on vacancies and unemployment. This is our objective in this paper.

[2] One line of research, reviewed in e.g., Costain and Reiter (2008), has studied the effects of unemployment benefits on unemployment using cross-country regressions. While this literature typically finds much larger effects than those implied by the micro studies, these estimates are relatively hard to interpret given the endogeneity problems and heterogeneity across countries that is difficult to control for.

[3] See also Nakajima (2012).

2 Empirical Methodology

In this section we develop our empirical methodology.

2.1 Basic Identification via Border Counties

In its most basic form, the identification of policy effects on the sample of contiguous counties on the two sides of a state border is based on the following specification:

$$\Delta x_{p,i,t} = \alpha_p + a\Delta b_{p,i,t} + \Delta\epsilon_{p,i,t}, \tag{1}$$

where $x_{p,i,t}$ is the labor market outcome of interest in logs (unemployment rate, vacancy rate, or the ratio of vacancy to unemployment rates, commonly referred to as labor market tightness), α_p is a pair-specific fixed effect that captures permanent differences in unemployment across border counties caused by, e.g., permanent differences in tax policies across states they belong to, $b_{p,i,t}$ is the logarithm of number of weeks of benefits available, and $\epsilon_{p,i,t}$ is the error term. The subscript p denotes the county pair, i is the index for county, and t denotes time. Δ denotes the difference operator over counties in the same pair. More specifically, if counties i and j are in the same county-pair p, then $\Delta x_{p,i,t} = x_{p,i,t} - x_{p,j,t}$.

To make this specification operational, we need to develop a way to control for the anticipation effects of policy changes and specify the structure of the error term. This is the subject of the following two subsections.

2.2 Controlling for Expectations

Since vacancy posting decisions by employers are forward looking, they are affected by the expectations of future changes in benefits. Moreover, the expectations of the future path of benefits might depend on the benefit level today. For example, suppose raising benefit levels leads to a a rise in unemployment. If benefit level and duration is increasing in state unemployment, an increase in benefits today makes it then more likely that benefits would be increased further in the future. Since vacancy creation and consequently unemployment respond to this change in expectations, it is clear that the coefficient a in regression (1) will be a biased estimator of the effect of current benefit structure on the current variable of interest, such as unemployment. Obviously, this issue cannot be resolved by including future values of benefits into the regression because they represent a realized path and will bias all the coefficients due to their correlation with today's expectation error. In this section we develop a methodology that allows to obtain an unbiased estimate of the coefficient a despite a forward looking nature of the job creation decisions.

To estimate the macroeconomic effects of unemployment insurance on a variable x_t such as vacancies or unemployment, we first estimate the effect on labor market tightness, θ_t, defined as the ratio of vacancies to unemployment, and therefore look at firms' job creation rate decision. Firm profits from employing a worker are given by:

$$\log(\pi_t) = \alpha \log(z_t) - \gamma \log(b_t), \tag{2}$$

where z_t is worker's productivity and b_t are benefits, and α and γ are unknown coefficients, so that the value of a filled job for the firm is:

$$J_t = \pi_t + \beta(1-\delta)E_t J_{t+1}, \tag{3}$$

where β is the discount factor, δ is the probability that the job ends and E_t is the expectation using information at time t. Free entry into vacancy posting implies that the expected cost of posting a vacancy is equal to the value of a filled job. The job creation decision is then

$$\frac{1}{q(\theta_t)} = \kappa J_t, \tag{4}$$

where $q(\theta_t)$ is the probability to fill a vacancy and κ is the inverse of the cost of maintaining a vacancy. This approximately yields

$$\log(\theta_t) = \tilde{\kappa} \log(J_t). \tag{5}$$

We now approximate $\log(J_t)$ as a function of $\log(\pi_t)$, $\log(J_{t+1})$ and an expectational error $\log(\epsilon_t)$ around the steady state with a constant $\pi^* = J^*(1-\beta(1-\delta))$, so that the previous equation reads

$$\log(\theta_t) = \tilde{\kappa}\frac{\pi^*}{J^*}\log(\pi_t) + \tilde{\kappa}\beta(1-\delta)\log(J_{t+1}) + \log(\epsilon_t). \tag{6}$$

Using $\pi^*/J^* = (1-\beta(1-\delta))$ and the job creation decision for $t+1$, $\log(\theta_{t+1}) = \tilde{\kappa}\log(J_{t+1})$, yields

$$\log(\theta_t) = \tilde{\kappa}(1-\beta(1-\delta))\log(\pi_t) + \beta(1-\delta)\log(\theta_{t+1}) + \log(\epsilon_t). \tag{7}$$

In quarterly data variables such as unemployment are well approximated a linear function of $\log(\theta)$:[4]

$$\log(x_t) = \lambda_x \log(\theta_t), \tag{8}$$

[4]See, e.g., Hall (2005), Shimer (2007)

so that we obtain the quasi-difference

$$\tilde{x}_t := \log(x_t) - \beta(1-\delta)\log(x_{t+1}) = \tilde{\kappa}\lambda_x(1-\beta(1-\delta))\log(\pi_t) + \lambda_x \log(\epsilon_t) \tag{9}$$

Thus, taking into account the effects of expectations, the empirical specification in Equation (1) is modified as follows:

$$\Delta\tilde{x}_{p,i,t} = \alpha_p + a\Delta b_{p,i,t} + \Delta\epsilon_{p,i,t}, \tag{10}$$

The coefficient a equals

$$\gamma\lambda_x\tilde{\kappa}(1-\beta(1-\delta)), \tag{11}$$

which is related to the permanent percentage change of a variable x of a permanent one percentage change in the policy variable b, $\gamma\lambda_x\tilde{\kappa}$ by a measurable factor $(1-\beta(1-\delta))$.

In order to ascertain the accuracy of our specification, In Appendix I we compare the predicted permanent effect estimated using the proposed method to the actual permanent effect in a calibrated Mortensen and Pissarides (1994) model. We find that our empirical specification is very accurate in model generated data.

2.3 Allowing for the Interactive Fixed Effects

As we mentioned in the introduction, various shocks have affected the aggregate economy during the Great Recession. But the same aggregate shocks are likely to have a heterogeneous impact on different border county pairs. In this case, estimating the panel regression in Equations (1) or (10), perhaps with the set of county pair and time fixed effects, might be problematic for inference (see Andrews (2005) for the discussion of this problem in a cross-sectional regression). Fortunately, Bai (2009) has shown that consistency and proper inference can be obtained in a panel data context, such as ours, through the use of the interactive-effects estimator. In particular, decomposing the error term in Equation (10) as

$$\Delta\epsilon_{p,i,t} = \lambda_{p,i}' F_t + \nu_{p,i,t}, \tag{12}$$

where λ_i $(r \times 1)$ is a vector of factor loadings and F_t $(r \times 1)$ is a vector of common factors, our baseline specification can be written as

$$\Delta\tilde{x}_{i,t} = a\Delta b_{i,t} + \lambda_i' F_t + \nu_{i,t}. \tag{13}$$

As is shown in Bai (2009), this model incorporates additive time and county pair fixed effects as special cases. It is, however, much more general and allows for a very flexible model of the heterogeneous time trends at the county pair level. The key to estimate a consistently is to treat the unobserved factors and factor loadings as parameters to be estimated.[5] Our implementation is based on an iterative two-stage estimator. The following is a brief description of the algorithm.

1. Start with a guess for a, say a_1.
2. At each iteration j, do the following:
   (a) given a_j, for each i and p, construct $\upsilon_{p,i,t} = \Delta x_{p,i,t} - \beta(1-\delta)\Delta x_{p,i,t-1} - a_j \Delta b_{p,i,t}$. Then, $\upsilon_{p,i,t} = \lambda'_{p,i} F_t$ is a pure factor model and can be estimated consistently using principal components.[6]
   (b) Given the estimates for λ and F, estimate equation (**??**) via OLS and update the guess to obtain a_{j+1}.
3. Repeat 2 until a_j converges.[7]

We compute bootstrap estimate of the standard errors.

2.3.1 Estimating the Number of Factors

To implement this estimator, we need to specify the number of factors. Bai and Ng (2002) have shown that the number of factors in pure factor models can be consistently estimated based on the information criterion approach. Bai (2009) shows that their argument can be modified to the panel data model with interactive fixed effects. Thus, we define:

$$CP(k) = \hat{\sigma}^2(k) + \hat{\sigma}^2(\bar{k})\left[k(N+T) - k^2\right]\frac{\log(NT)}{NT},$$

where $\bar{k} \geq r$ and $\hat{\sigma}^2(k)$ is mean squared error, defined as

$$\hat{\sigma}^2(k) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\Delta\tilde{x}_{i,t} - a\Delta b_{i,t} - \lambda'_i(k)F_t(k)\right)^2$$

and $F_t(k)$ and $\lambda'_i(k)$ are the estimated factors and their loadings, respectively, when k factors are estimated. We set $\bar{k}$ to $T-1$. Our estimator for the number of factors is then given by

$$\hat{k} = \arg\min_{k \leq \bar{k}} CP(k).$$

[5] As in all factor models, some normalizations are needed in order to identify the factors and their loadings. We use the same normalizations as in Bai (2009).

[6] The exposition of the estimator assumes that there are no missing observations. We use the generalized procedure described in Bai (2009) and allow for missing observations.

[7] We have conducted a number of Monte Carlo simulations with sample sizes similar to our sample. The estimator described here is found to converge to the true parameter. Results are available upon request.

3 Data

To implement the empirical strategy, we use data at the county level on unemployment rate, labor force, vacancies, and separations, as well as data on unemployment benefit durations at the state level. County unemployment rates and labor force are obtained from the Local Area Unemployment Statistics (LAUS) provided by the Bureau of Labor Statistics.[8] We obtain vacancy data from the Help Wanted OnLine (HWOL) dataset provided by The Conference Board (TCB). This dataset is a monthly series that covers the universe of vacancies advertised on around 16,000 online job boards and online newspaper editions. The HWOL database started in May 2005 and replaced the Help-Wanted Advertising Index of print advertising also collected by TCB.[9] We have access to the data over the period May 2005 through April 2012. For a more detailed description of the data, some of the measurement issues, and a comparison with the well-known JOLTS data, see Sahin, Song, Topa, and Violante (2012).

Data on separations are obtained from the Quarterly Workforce Indicators (QWI).[10] QWI is derived from the Local Employment Dynamics, which is a partnership between state labor market information agencies and the Census Bureau. QWI supplies measures of employment, new hires, and separations for all counties except those in Massachusetts. These data are available starting in 1990 through 2011 Q4.[11]

To obtain data on unemployment benefit durations, we use trigger reports provided by the Department of Labor. These reports contain detailed information for each of the states regarding the eligibility and adoption of the two unemployment insurance programs over our sample period: Extended Benefits program (EB) and Emergency Unemployment Compensation (EUC08).[12]

EB program allows for 13 or 20 weeks of extra benefits in states with elevated unemployment rates. Essentially, participation in EB is optional. States can choose specific triggers in state unemployment rates that will activate extra benefits. At the onset of the recent recession, the costs were split between the state and the federal government. As a result, many states chose to opt out of the program or set high triggers. The American Recovery and Reinvestment Act of 2009 turned this into a federally funded program. Following this

[8]See ftp://ftp.bls.gov/pub/time.series/la/.

[9]Data collection is handled by Wanted Technologies for TCB. For detailed information on survey methodology, coverage, and concepts see the Technical Notes at http://www.conference-board.org/data/helpwantedonline.cfm.

[10]http://lehd.ces.census.gov/datatools/qwiapp.html

[11]Start dates for the data varies across states between 1990Q1 and 2001Q1.

[12]See http://ows.doleta.gov/unemploy/trigger/ for trigger reports on the EB program and http://ows.doleta.gov/unemploy/euc_trigger/ for reports on the EUC program.

act, many states joined the program and those with stringent triggers adopted lower triggers.

The EUC08 program enacted in June 2008, on the other hand, has been a federal program since its onset. The program started by allowing for an extra 13 weeks of benefits to all states and was gradually expanded to have 4 tiers, providing potentially 53 weeks of federally financed additional benefits. The availability of each tier is dependent on state unemployment rates.[13] The trigger reports contain the specifics of when each state was eligible for the EB program and for the different tiers of the EUC program. We have constructed the data starting in 2002 through December 2012.

There is a substantial heterogeneity in the actual unemployment benefit durations across time and the U.S. states. Appendix Figure A-2 presents some snapshots that illustrate the extent of this heterogeneity.

Finally, to identify the role of unemployment benefit extensions on labor market outcomes, we focus our analysis on a sample of county pairs that are in different states and share a border. There are 1,118 such pairs for which we have data on unemployment, vacancies, and labor force.[14]

4 Empirical Analysis

Data on unemployment rate, vacancies, and UI benefit durations are available at a monthly frequency. However, separations data are quarterly. Therefore, we aggregate monthly data to obtain quarterly measures of unemployment, vacancies, and UI benefit durations. We construct market tightness as the ratio of quarterly vacancies to quarterly unemployment. Logs are taken after aggregation. The next two subsections contain the estimates of the benchmark quasi-differenced specification that controls for the expectation effects obtained using the OLS and the interactive fixed effects estimator, respectively. When constructing the quasi-differences at the quarterly frequency, we set $\beta = 0.99$ and use the county pair and time specific job destruction rate $\delta_{p,t}$ observed in the data.

4.1 OLS Estimates

Table 1 contains the results of the estimation of the basic specification in Equation (10) using different dependent variables (unemployment rate, vacancy rate, or market tightness). We find that changes in unemployment benefits have large and statistically significant short-run effects on all three variables of interest: a 1% rise in benefit duration for only one

[13]This discussion is based on Rothstein (2011).

[14]Data on county pairs are provided by Arindrajit Dube and were used in Dube, Lester, and Reich (2010).

Table 1: OLS Estimates

VARIABLES	Unemployment	Vacancies	Tightness
Weeks of Benefits	0.0700***	-0.1059**	-0.1770***
	(0.000)	(0.013)	(0.000)
Constant	0.0493**	-0.2541**	-0.2049***
	(0.021)	(0.020)	(0.000)
Observations	24,306	23,984	23,984
R-squared	0.184	0.198	0.209

Note: p-values (in parentheses) calculated via bootstrap.
*** p<0.01, ** p<0.05, * p<0.1

quarter increases unemployment rate by 7.0 log points, reduces the vacancy rate by 10.6 log points, and reduces market tightness by 17.7 log points. The formula derived in the previous section helps us extrapolate these effects and estimate the effect of a permanent increase in benefit durations. Using a quarterly separation rate of 10%, we find that the effect of permanently increasing benefits from 26 to 99 weeks is quite sizable: The effect on unemployment is 136%, meaning that such a permanent increase would increase the long-run average of unemployment from 5% to 11.8%. During the Great Recession, unemployment benefits have been on average at 88 weeks for approximately 16 quarters. This would imply that the effect of this particular extension on unemployment is

$$0.07 \times \frac{1-(\beta(1-\delta))^{16}}{1-\beta(1-\delta)} \times (\log(88) - \log(26)) = 0.6595 logpoints,$$

a rise of about 93%. Translating this to levels, this would predict a rise in unemployment from 5% to 9.67%.

4.2 Estimates with the Factor Model

We now extend our specification to allow for a more general form of heterogeneity. In particular, we allow for interactive fixed effects as in Equation (13) and use the estimator discussed in the previous section.

Table 2 shows the results of the estimation using the three dependent variables of interest. Our estimates suggest that changes in unemployment benefits have large effects on all variables of interest: a 1% rise in benefit duration for only one quarter increases unemployment rate by 8.4 log points, reduces the vacancy rate by 6.8 log points, and reduces market tightness by 14.2 log points. The permanent effect of increasing benefits from 26 to 99 weeks

Table 2: Factor Model Estimates

VARIABLES	Unemployment	Vacancies	Tightness
Weeks of Benefits	0.0839**	-0.0676**	-0.1415***
	(0.020)	(0.048)	(0.003)
Constant	0.018***	0.0241	-0.0039
	(0.000)	(0.260)	(0.480)
N. factors	6	6	6
Observations	24,306	23,984	23,984
R-squared	0.7285	0.5371	0.5459

Note: p-values (in parentheses) calculated via bootstrap.
*** p<0.01, ** p<0.05, * p<0.1

then results in a rise in unemployment of 180%, i.e. a rise from 5% to 14%. Similarly, the effect of extending benefits from 26 to 99 week for 16 quarters is a rise of 120%, which translates into a rise from 5% to 11%.

4.3 Testing for Endogeneity

Unemployment benefit extensions are determined at the state level and thus depend on state's economic conditions. Thus, a state-level shock can cause unemployment to go up and vacancies to go down in all the counties in the state and simultaneously lead to an extension of benefits. In this case, our estimation would suffer from the endogeneity bias. To test for this type of endogeneity, we add to our specification, the difference between labor productivities of the states the border counties belong to. If our empirical methodology suffers from this bias, we would expect the coefficient on benefit duration to change drastically and lose its statistical significance. (We do expect to see some impact on the estimate as there is at least some correlation between the productivities in the county and the state it belongs to.) We define state productivity as real gross state product (gsp) per worker, which is available at an annual frequency. Consequently, when estimating the specification including the state productivity, we first aggregate other variables and obtain their annual counterparts. These specifications are estimated via OLS as well as the interactive fixed-effects estimator. The results are provided in Tables 3 and 4, respetively. Note that including the difference in state productivity has almost no effect on the estimate for the effect on benefit duration. These results provide clear evidence that our findings are not driven by a mechanical relationship between the economic conditions at the state level and the duration of unemployment benefits.

Table 3: Testing for Endogeneity: State Productivity (OLS, Annual Data)

VARIABLES	Unemployment	Unemployment	Vacancies	Vacancies
Weeks of	0.0765***	0.0729***	-0.0924**	-0.0833**
Benefits	(0.000)	(0.000)	(0.035)	(0.041)
State GDP		-0.1231***		0.3173***
Per Worker		(0.000)		(0.000)
Constant	-0.0472***	-0.0630***	-0.2540***	-0.2134***
	(0.004)	(0.001)	(0.000)	(0.000)
Observations	7,369	7,369	7,341	7,341
R-squared	0.559	0.560	0.537	0.537

Note: Standard errors (in parentheses) and p-values calculated via bootstrap.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Testing for Endogeneity: State Productivity (Factor Model, Annual Data)

VARIABLES	Unemployment	Unemployment	Vacancies	Vacancies
Weeks of	0.0606**	0.0596*	-0.1230***	-0.1263***
Benefits	(0.020)	(0.060)	(0.004)	(0.004)
State GDP		-0.0138		0.1774
Per Worker		(0.440)		(0.160)
Constant	-0.0022	-0.0020	-0.0516***	-0.0549***
	(0.260)	(0.320)	(0.000)	(0.000)
N. factors	5	5	4	4
Observations	7,369	7,369	7,341	7,341
R-squared	0.559	0.560	0.537	0.537

Note: Standard errors (in parentheses) and p-values calculated via bootstrap.
*** p<0.01, ** p<0.05, * p<0.1

5 Migration in Response to Changes in Benefits

One potential concern is that households may live in different states than where they work. If the households systematically change their job search behavior in response to changes in unemployment benefits, this could bias our estimates. We address this concern in two ways.

First, we look for direct empirical evidence on where people work relative to where they live. We use data from the American Community Survey (ACS) from 2005-2011. The

Table 5: Regression Estimates of Out of State Employment

	Out of state work	
VARIABLES	Quasi-Difference	Diff-in-Diff
Weeks of Benefits	1.7057	1.028
	(2.322)	(1.572)
Constant	-0.1761**	-0.1880**
	(0.0775)	(0.0746)
Pair Fixed Effects	Yes	Yes
Observations	162	162
R-squared	0.6522	0.1091

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

ACS is an annual 1% survey of households in the United States conducted by the Census Bureau. The survey contains information on the county of residence of households and the state of employment. The survey is representative at the Public Use Micro Area level - a statistical area that has roughly 100,000 residents (and thus also for counties with more than 100,000 residents). We compute the share of households in border counties the work in the neighboring state. We can then examine how this share of border state workers responds to changes in benefits across states. We perform our analysis using the quasi-difference estimator derived in the empirical methodology section and using a difference-in-difference estimators:

$$\begin{aligned} \text{Quasi-difference:} \quad \Delta\tilde{e}_{p,i,t} &= \alpha_p + \beta\Delta b_{p,i,t} + \Delta\varepsilon_{p,i,t} \\ \text{Diff-in-diff:} \quad \Delta e_{p,i,t} &= \alpha_p + \beta\Delta b_{p,i,t} + \Delta\varepsilon_{p,i,t} \end{aligned}$$

where $e_{p,i,t}$ is the fraction of workers that live in county i that work in the state associated with county j also in pair p at time t. The results of the regressions are in Table 5. Using both the quasi-difference and difference-in-difference specification the coefficient on weeks of benefits available is insignificant. We interpret this as suggesting that worker search behavior does not respond significantly to changes in unemployment benefits.

This result is easily rationalized by the structure of the unemployment benefit system. Typically, the benefits that a worker is eligible for is determined by the earnings of the worker in the four quarters prior to the current quarter. A worker also needs to have sufficient earnings during the four quarter window in order to be eligible for benefits. Further, the benefits one is eligible for depends on the state of employment, not residence. However, imagine a worker that lived and worked in Pennsylvania was laid off. He would receive Pennsylvania state benefits. If he were to search for a job in New Jersey, he would not be eligible for New Jersey benefits until he had worked there for at least three quarters. Thus, the fact that job search decisions do not respond to changes in benefits seems consistent with the UI system.

In addition to the direct empirical measure from the ACS, we attempt to impute the worker search decisions using our county-pair data. Then, we can perform the same statistical analyses on our imputed measure of worker search.

To impute what fraction of workers are search in the county other than which they live, consider the following model. We consider the local economy to consist of a pair of counties A, B (consistent with our border-county pairs). The counties are populated by a labor forces of size n_t^A and n_t^B.

In any given period, a worker can be either employed (matched with a firm) or unemployed. In period t, firms in county A post vacancies in county A, v_t^A. An unemployed worker in county A can direct his search to either county A or county B. The number of new matches in county A in period t equals

$$M\left(\tilde{u}_t^A, v_t^A\right),$$

where $\tilde{u}_t^A$ is the measure of unemployed workers in period t searching in county A. The number of matches is the same for county B *mutatis mutandis*. We assume a constant returns to scale matching function M that is strictly increasing and strictly concave in both arguments. We define

$$\theta_t^A = \frac{v_t^A}{\tilde{u}_t^A}$$

to be the market tightness in county A in period t. We define the functions

$$f(\theta) = \frac{M(u,v)}{u} = M(1,\theta) \quad \text{and}$$
$$q(\theta) = \frac{M(u,v)}{v} = M\left(\frac{1}{\theta}, 1\right)$$

where $f(\theta)$ is the job-finding probability and $q(\theta)$ is the probability of filling a vacancy. By the assumptions on M made above, the function $f(\theta)$ is increasing in θ and $q(\theta)$ is decreasing in θ.

Existing matches are exogenously destroyed with exogenous time specific job separation probability δ_t.

Given these assumptions, the law of motion for unemployment for the two counties is:

$$u_{t+1}^{A} = \delta_t \left(n_A - u_t^A\right) + u_t^A \left(1 - x_t^A f\left(\theta_t^A\right) - \left(1 - x_t^A\right) f\left(\theta_t^B\right)\right) \tag{14}$$

$$u_{t+1}^{B} = \delta_t \left(n_B - u_t^B\right) + u_t^B \left(1 - x_t^B f\left(\theta_t^B\right) - \left(1 - x_t^B\right) f\left(\theta_t^A\right)\right) \tag{15}$$

where u_t^i is the number of unemployed in county i, x_t^i is the fraction of the unemployed in county i that search in county i.

We can thus write for the number of unemployed searching in county A and B respectively:

$$\tilde{u}_t^A = u_t^A x_t^A + (1 - x_t^B) u_t^B \tag{16}$$

$$\tilde{u}_t^B = u_t^B x_t^B + (1 - x_t^A) u_t^A \tag{17}$$

The separation data from the QWI are based on the location of the employer, not based on the residence of the employee. Thus, we assume that the separation rate is the same in both counties for the quarter, and solve for the δ that results in the correct number of total separations. We also need to control for time aggregation, because separations are only observed quarterly.

Thus, we can compute δ_t as follows:

$$S_t = s_t^A + s_t^B = \left(e_t^A + e_t^B\right) \delta_t \sum_{\tau=0}^{2} (1 - \delta_t)^{\tau}$$

Note that this equation simplifies to:

$$\delta_t^3 - 3\delta_t^2 + 3\delta_t = \frac{s_t^A + s_t^B}{e_t^A + e_t^B}$$

The solution to this cubic equation has one real root, so there exists a unique δ_t given by:

$$\delta_t = \left(\frac{s_t^A + s_t^B}{e_t^A + e_t^B} - 1\right)^{1/3} + 1 \tag{18}$$

We do not directly observe x_t^A, and thus we don't observe $\tilde{u}_t^A$ and θ_t^A, nor the matching function. We can measure the probabilities for an unemployed worker from counties A and B to find a job, ϕ_t^A and ϕ_t^B. These solve, using (14),

$$\phi_t^A = \frac{u_t^A - u_{t+1}^A + \delta_t \left(n_t^A - u_t^A\right)}{u_t^A} = x_t^A f\left(\theta_t^A\right) - \left(1 - x_t^A\right) f\left(\theta_t^B\right) \tag{19}$$

$$\phi_t^B = \frac{u_t^A - u_{t+1}^B + \delta_t \left(n_t^B - u_t^B\right)}{u_t^B} = x_t^B f\left(\theta_t^B\right) - \left(1 - x_t^B\right) f\left(\theta_t^A\right) \tag{20}$$

The last four equations have 4 unknowns, $x_t^A, x_t^B, f(\theta_t^A), f(\theta_t^B)$. These equations are not linearly independent and thus do not allows us to recover these 4 unknowns. Instead they give us a set of solutions S.

In order to proceed to identify x_t^A, x_t^B we assume that the matching function is a Cobb-Douglas function, $\mu u^\alpha v^{1-\alpha}$. Note, however, that we do not see the true level of vacancies. However, if we assume that we see the same *fraction*, γ, of total vacancies for both counties in a pair, we can still estimate the effective matching function given our observed vacancies. If we observe $\tilde{v} = \gamma v$, then the total number of matches is $\tilde{m}uu^\alpha \tilde{v}^{1-\alpha}$ where $\tilde{\mu} = \gamma^{1-\alpha}\mu$. Thus, we propose to identify $\tilde{\mu}$ and α in addition to the x's.

We allow $\tilde{\mu}$ to change over time, to capture any possible time trends in the adoption of online vacancies. The algorithm consists of selecting α, $\{\mu_t, x_t^A, x_t^B\}_{t=1}^T$ to minimize the error in the following equations:

$$
\begin{aligned}
\phi_t^A &= x_t^A f\left(\theta_t^A\right) - \left(1 - x_t^A\right) f\left(\theta_t^B\right) && (21)\\
\phi_t^B &= x_t^B f\left(\theta_t^B\right) - \left(1 - x_t^B\right) f\left(\theta_t^A\right) && (22)\\
\frac{q(\theta_t^A)}{q(\theta_t^B)} &= \left(\frac{\theta_t^B}{\theta_t^A}\right)^\alpha && (23)
\end{aligned}
$$

where we observe all left hand side variables for all t.

The imputation procedure generates $x_{p,i,t}$ for the duration of our sample. Using the quasi-difference estimator we find that regressing the imputed search decision of households on the difference in weeks of benefits available yields an insignificant coefficient. This result is consistent with the evidence from the ACS, again implying that issues of migration or working across state borders do no appear to be significant problem for our study.

Table 6: Effect of UI Benefits on Imputed Search Location Decisions

	Out of state work	
VARIABLES	Quasi-Difference	Diff-in-Diff
Weeks of Benefits	0.081	0.002
	(0.073)	(0.104)
Constant	-0.216	-0.013
	(0.131)	(0.147)
Observations	19,464	18,678
R-squared	0.110	

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6 Conclusion

In this paper we employed the state-of-the-art empirical methodology to measure the total effect of unemployment benefit extensions on unemployment. In particular, we exploited the discontinuity of unemployment insurance policies at state borders to identify their impact. Our estimator controls for the effect of expectations of future changes in benefits and has a simple economic interpretation. It is also robust to the heterogeneous impacts of aggregate shocks on local labor markets.

Our estimates imply that the macro elasticity is quantitatively large, much larger than the micro elasticity - which is the primary focus of an active existing literature. In fact, our estimates imply that unemployment benefit extensions account for most of the persistently high unemployment after the Great Recession.

One motivation for increasing unemployment benefit durations during the Great Recession, in addition to helping unemployed workers smooth their consumption, is its stimulative effect on the local demand, which is hypothesized to have beneficial employment effects. We cannot separately identify this effect, but, if present, it is much too small to overcome the dramatic negative effect on employment from the general equilibrium effect of benefit expansion on vacancy creation.

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APPENDICES

I A Simple Equilibrium Search Model

In this Appendix we evaluate the performance of our empirical methods on the data generated by a calibrated model. The model is an extension of Mortensen and Pissarides (1994) to allow for unemployment benefit expiration.

Agents. In any given period, a worker can be either employed (matched with a firm) or unemployed. Workers are risk-neutral have expected lifetime utility

$$U = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t c_t$$

where $\mathbb{E}_0$ is the period-0 expectation operator, $\beta \in (0, 1)$ is the discount factor, c_t denotes consumption in period t. An unemployed worker produces h, which stands for the combined value of leisure and home production. In addition, unemployed workers may be eligible for benefits b. Unemployed workers who are eligible for benefits lose their benefits stochastically at rate $e_t(\cdot)$, which depends on the state unemployment rate.

Firms are risk-neutral and maximize profits. Workers and firms have the same discount factor β. A firm can be either matched to a worker or vacant. A firm posting a vacancy incurs a flow cost k.

Matching. The number of new matches in period t is given by:

$$M(u_t, v_t)$$

where u_t is the number of unemployed in period t, and v_t is the number of vacancies. The matching function is assumed to be constant returns to scale, and strictly increasing and strictly concave in both arguments. We define

$$\theta_t = \frac{v_t}{u_t}$$

as the market tightness in period t. We then define the functions:

$$f(\theta) = \frac{M(u, v)}{u} = M(1, \theta) \quad \text{and}$$
$$q(\theta) = \frac{M(u, v)}{v} = M\left(\frac{1}{\theta}, 1\right)$$

where $f(\theta)$ is the job-finding probability and $q(\theta)$ is the probability of filling a vacancy. By the assumptions on M made above, the function $f(\theta)$ is increasing in θ and $q(\theta)$ is decreasing in θ.

Existing matches are exogenously destroyed with exogenous job separation probability δ.

A matched worker-firm pair produces output z_t, which follows a first order Markov process. Firms pay workers a wage w_t, which is determined through bargaining.

Thus, the period profit of a matched firm is given by:

$$\pi_t = z_t - w_t$$

The flow value for a firm employing a worker is

$$J_t = z_t - w_t - \tau + \beta(1-\delta) J_{t+1} \tag{A1}$$

and the free entry condition must hold, so that

$$k = \beta q(\theta_t) J_{t+1} \tag{A2}$$

The value functions for workers can be written as:

$$W_t = w_t + \beta(1-\delta) W_{t+1} + \beta\delta(1-e_t) U_{t+1}^E + \beta\delta e_t U_{t+1}^I \tag{A3}$$

$$\begin{aligned} U_t^E &= h + b + \beta f(\theta_t) W_{t+1} \\ &\quad + \beta(1-f(\theta_t))(1-e_t) U_{t+1}^E + \beta(1-f(\theta_t)) e_t U_{t+1}^I \end{aligned} \tag{A4}$$

$$U_t^I = h + \beta f(\theta_t) W_{t+1} + \beta(1-f(\theta_t)) U_{t+1}^I \tag{A5}$$

Define the surplus of being employed as $\Delta_t^E = W_t - U_t^E$. Also define the surplus for an unemployed worker of being eligible: $\Phi_t = U_t^E - U_t^I$. The laws of motion for these quantities are:

$$\Delta_t^E = w_t - h - b + \beta(1-\delta-f(\theta_t)) \Delta_{t+1}^E + \beta(1-\delta-f(\theta_t)) e\Phi_{t+1} \tag{A6}$$

$$\Phi_t = b + \beta(1-f(\theta_t))(1-e) \Phi_{t+1} \tag{A7}$$

Next, define the total surplus from a match $Y_t = W_t - U_t^E + J_t$, and use the fact that $J_t = (1-\xi) Y_t$ to get

$$Y_t = \bar{z} - h - b - \tau + \beta(1-\delta-\xi f(\theta_t)) Y_{t+1} + \beta(1-\delta-f(\theta_t)) e\Phi_{t+1} \tag{A8}$$

And from (A2),

$$\frac{k}{\beta\left(1-\xi\right)q\left(\theta_t\right)} = \bar{z} - h - b - \tau + \left(1-\delta-\xi f\left(\theta_{t+1}\right)\right)\frac{k}{\left(1-\xi\right)q\left(\theta_{t+1}\right)} + \beta\left(1-\delta-f\left(\theta_{t+1}\right)\right)e\Phi_{t+1} \tag{A9}$$

Equations (A7) and (A9), together with the laws of motion for employment and the measure of eligible unemployed workers, completely characterize the equilibrium.

Using Equations (A1) and (A8) we can derive the equation for the wage:

$$w_t = \xi z_t + \left(1-\xi\right)\left(h-b\right) + \xi\theta_t k - \beta(1-\xi)(1-\delta-f)e\Phi_{t+1} \tag{A10}$$

The law of motion for employment follows:

$$L_{t+1} = (1-\delta)L_t + f(\theta_t)\left(1-L_t\right). \tag{A11}$$

We assume that both the state and county economies evolve according to the model described above. However, for the state economy the benefit policy e_t is a function of the state unemployment rate. The county productivity is assumed to be uncorrelated with the state productivity and that the county unemployment rate is small relative to state unemployment. Thus, the county takes the state productivity process and endogenously generated process for state unemployment as exogenous.

I.1 Equilibrium Definition

Taking as given an initial condition $\left(z_0^S, L_0^S, z_0^C, L_0^C\right)$, where S superscripts denote state and C superscripts denote county, we define an equilibrium given policy:

Definition Given a policy $(b, e_t(\cdot))$ and an initial condition $\left(z_0^S, L_0^S, z_0^C, L_0^C\right)$ an equilibrium is a sequence of $\left(z_t^S, L_t^S, z_t^C, L_t^S\right)$-measurable functions for wages w_t, market tightness θ_t, employment L_t, and value functions

$$\left\{W_t, U_t^E, U_t^I, J_t, V_t, \Delta_t\right\}$$

such that:

1. The value functions satisfy the worker and firm Bellman equations (A1), (A2),(A3), (A4), (A5)

2. Free entry: The value V_t of a vacant firm is zero for all $\left(z_t^S, L_t^S, z_t^C, L_t^S\right)$

3. Nash bargaining: The wage satisfies equation (A10)

4. Law of motion for employment : Employment and the measure of eligible unemployed workers satisfy (A11)

5. Law of motion for state employment: The state unemployment process satisfies (A11) for the state economy.

I.2 Calibration

We calibrate the model to be consistent key labor market statistics. The model period is taken to be one week. We match the elasticity of wages with respect to labor productivity, the average labor market tightness and the average job finding rate. The calibrated parameters are summarized in the Table A-1. The remainder of the parameters are calibrated externally, using the same values as Hagedorn and Manovskii (2008).

Table A-1: Internally Calibrated Parameters

	Parameter	Value	Target	Data	Model
h	Value of non-market activity	0.6568	$\mathcal{E}_{w,z}$	0.449	0.449
ξ	Bargaining power	0	Mean of $(v/(1-L)$	0.259	0.259
χ	Matching parameter	0.367	Mean job finding rate	0.139	0.139

Note: $\mathcal{E}_{w,z}$ is the elasticity of wages with respect to productivity.

I.3 Simulation Exercise

The goal of the simulation exercise is to generate synthetic data at the county level comparable to the actual data. As such, we simulate two states and two counties. The two states and counties have the same process for productivity. The counties, consistent with our border county assumption, have the same *realized sequence of shocks*. The two states, however, have different realized sequences of productivity shocks. As such, the endogenous process for state unemployment will be different. Thus, the two counties will have a different time series of unemployment benefits. The benefit policy is taken to be an expiration rate of $1/26$ when state unemployment is less than eight percent and $1/39$ otherwise.

In order to calculate the permanent effect of a change in benefits, we permanently decrease the benefit expiration rate and compute the new average unemployment in the simulated economy. The imputed permanent and actual permanent effects are summarized in Table A-2. Our empirical specification performs very well on model generated data.

Table A-2: Permanent and Inputed Effect in Model Generated Data

Statistic	Permanent Effect	Imputed Permanent Effect
Tightness	-0.5101	-0.5160
Unemployment	0.2656	0.2680
Vacancies	-0.2445	-0.2551

II Appendix Figures

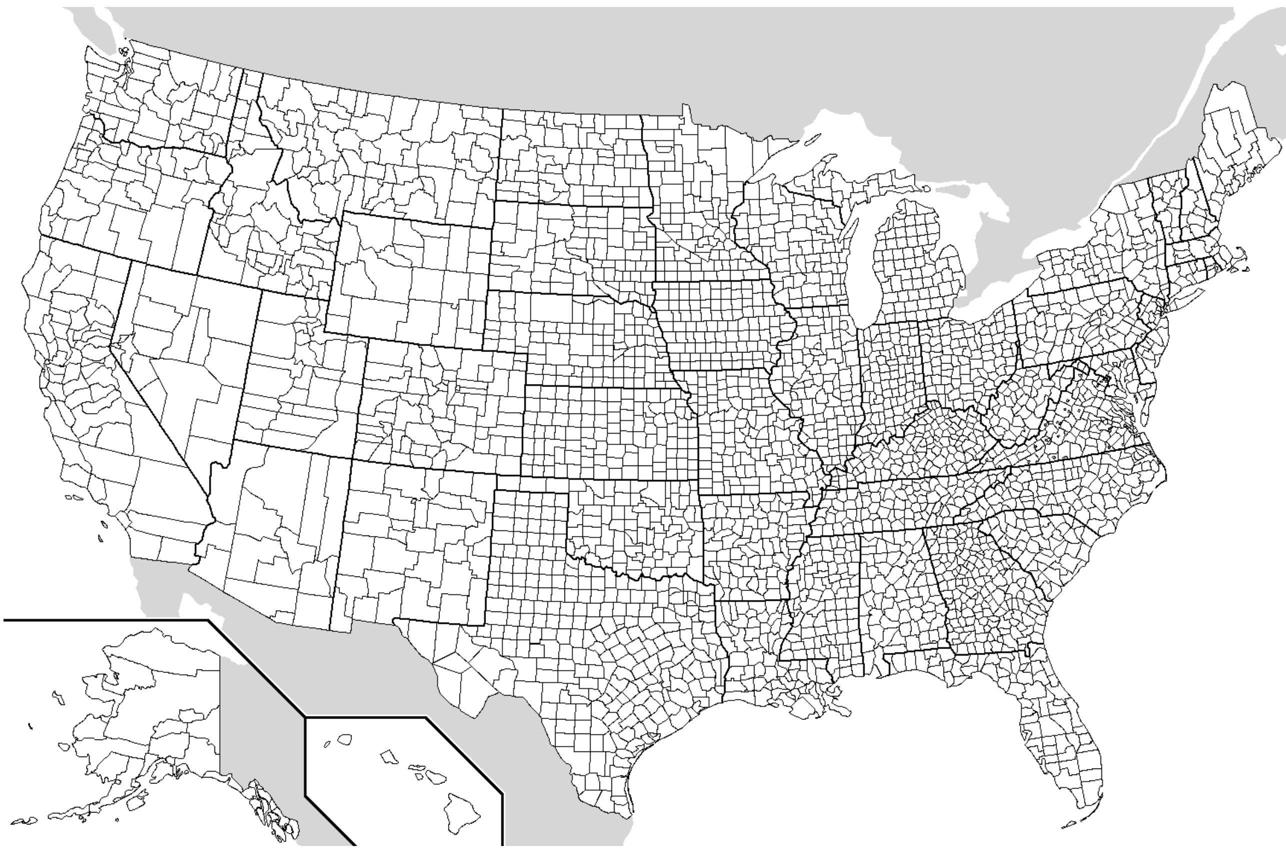
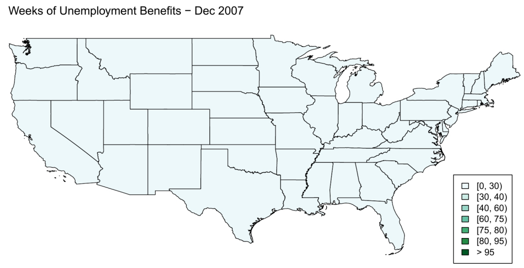


Figure A-1: Map of U.S.A. with state and county outlines.



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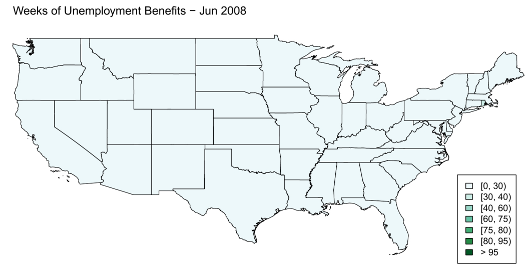

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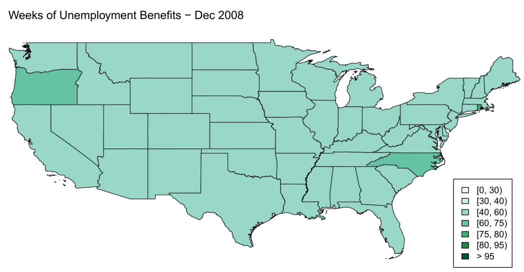

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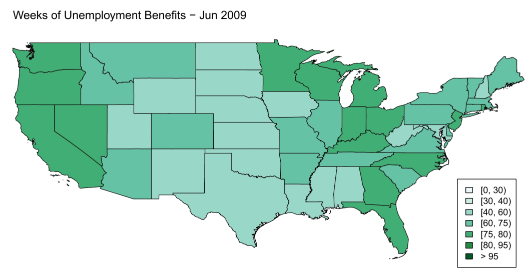

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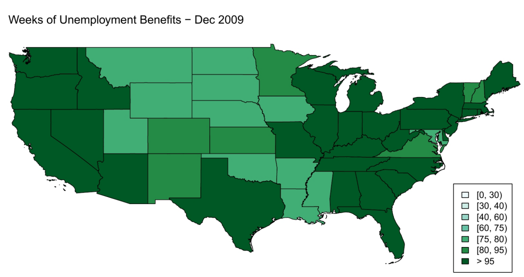

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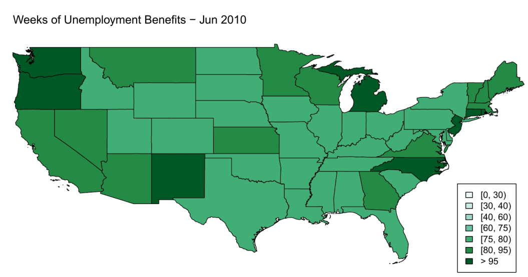

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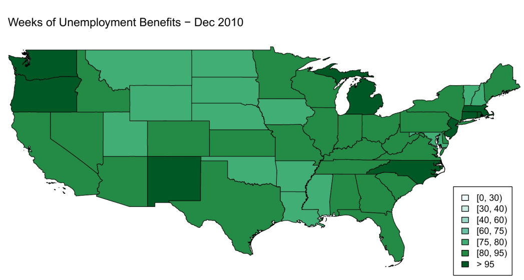

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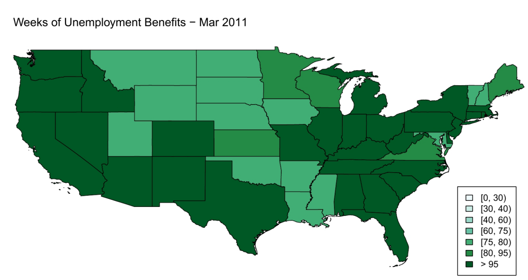

(h) March 2011.

Figure A-2: Unemployment benefit duration across U.S. states during the Great Recession. Selected months.