

The Macro Effects of Unemployment Benefit Extensions: A Measurement Error Approach

Online Appendix

Gabriel Chodorow-Reich John Coglianese Loukas Karabarbounis

July 2018

A State Unemployment Rate Estimation Methodology

In this appendix we outline the BLS methodology for estimating the state unemployment rates. The BLS first introduced state space models in 1989 and began to apply these models to all states in 1996. Bureau of Labor Statistics (2014) provides an in-depth but non-technical overview of what follows and Tiller (1992) and Pfeiffermann and Tiller (1996) provide a more technical treatment.

The first step of the real-time estimation involves estimating the state space models separately for total unemployment and employment. The unemployment rate is constructed from these two estimates. Let $y_{s,t} + o_{s,t}$ denote the direct count of a variable such as state employment or unemployment from the CPS, where $o_{s,t}$ denotes any outlier component identified using intervention model methods. For each state, the observation equation is:

$$y_{s,t} = \alpha_{s,t}x_{s,t} + L_{s,t} + S_{s,t} + e_{s,t}, \tag{A.1}$$

where $x_{s,t}$ is an external regressor (insured unemployment for unemployment and CES payroll employment for employment), $L_{s,t}$ is a trend level, $S_{s,t}$ is a seasonal component, and $e_{s,t}$ is the observation error. The state space model employment or unemployment is $Y_{s,t} = \alpha_{s,t}x_{s,t} + L_{s,t} + S_{s,t} = y_{s,t} - e_{s,t}$.

The model state equations are:

$$\alpha_{s,t} = \alpha_{s,t-1} + \eta_{\alpha,s,t}, \quad (\text{A.2})$$

$$L_{s,t} = L_{s,t-1} + R_{s,t} + \eta_{L,s,t}, \quad (\text{A.3})$$

$$R_{s,t} = R_{s,t-1} + \eta_{R,s,t}, \quad (\text{A.4})$$

$$S_{s,t} = \sum_{j=1}^6 S_{j,s,t}, \quad (\text{A.5})$$

where $e_{s,t}$, $\eta_{\alpha,s,t}$, $\eta_{L,s,t}$, and $\eta_{R,s,t}$ are independent normal random variables, and $S_{j,s,t}$ are seasonal frequency functions. A generalized Kalman filter estimates the system.¹

BLS introduced a major update in 2005 with the incorporation of real-time benchmarking to Census Division and national totals. Each month, after estimation of the state space system, BLS would allocate the residual between the sum of model estimates of not seasonally adjusted series for Census Divisions ($L_t + I_t$) and the national CPS total pro rata to each division, and then repeat the process for states within a division.² In that way, the real-time sum of state employment and unemployment would always equal the national total. However, the pro rata allocation meant that state-specific residuals would “spillover” to neighboring states. In 2010, BLS began applying a one-sided moving average Henderson filter to the benchmarked series.

The most recent major update to the real-time model occurred in 2015 and involved three main changes. First, the benchmarking constraint now enters directly into the state space filter. The observation vector is augmented to include the difference between the sum of not seasonally adjusted model state unemployment and employment levels and their Census Division direct estimate (excluding identified outliers), and the estimation constrains the variance of the innovation in this component to be zero. Incorporating benchmarking within the state space filter more efficiently allocates the benchmark residual across states. Second, outlier components $o_{s,t}$ identified by intervention model methods are added back to the states from which they

¹Because of the rotating panel structure of the CPS sample, the observation equation errors may be serially correlated. The generalized Kalman filter uses GLS instead of OLS to find the conditional mean of the state vector given the updated observation vector.

²At the Census Division level the state space estimation excludes the external regressors insured unemployment or payroll employment. In terms of equations (A.1) to (A.5), $\alpha_{cd,t} = 0$ and $var(\eta_{cd,t}) = 0$.

originated after the state space estimation. Both of these changes reduce spillovers of unusual residuals across states within a division. Third, the 2015 redesign incorporated an improved seasonal adjustment procedure.

Table A.1 provides an overview of the importance of different components of the revision process using as a metric the R^2 from a regression of $\hat{u}_{s,t}$ on the components.³ The first row shows that the revisions to the CES employment data explain a small part of the unemployment rate revision. While the CES revisions themselves can be large, they enter into the unemployment rate only through the denominator and therefore have a smaller effect on the unemployment rate revision. The second row adds elements related to the 2015 LAUS redesign and the treatment of state-specific outliers in the CPS. Specifically, we add to the regression the difference between the vintage 2014 and vintage 2015 LAUS seasonally adjusted unemployment rates, the difference between the unemployment rate constructed directly from the CPS monthly files and the real-time LAUS seasonally unadjusted unemployment rate, the difference between the unemployment rate constructed directly from the CPS files and seasonally adjusted using an X-11 moving average and the average of the same variable for three months before and three months after the observation, and the labor force weighted average of the previous variable for other states in the same Census Division. These variables increase the explained part of $\hat{u}_{s,t}$ to 49%. In row 3, adding the component due to updated seasonal factors in the revised data further increases the explained part of $\hat{u}_{s,t}$ to 59%. Rows 4 and 5 next add lags and leads of $u_{s,t}$ to explore whether the path of the unemployment rate affects the revision through the state space smoother and symmetric filter. In row 4, adding 12 lags of the unemployment rate raises the R^2 by 0.02, while in row 5 adding the contemporaneous and 12 leads of the unemployment rate raises it by an additional 0.01.⁴ Overall, these components explain 62% of the variation in the unemployment rate revision. Because the LAUS process uses a nonlinear state space model, we would not expect a linear projection on the major sources of revisions to generate an R^2 of 1.

³Because the procedure for the real-time data changed in 2005 and most of the UI errors in our sample occur during the Great Recession, we limit the sample in this table to 2005 to 2013.

⁴The incremental R^2 is not invariant to the ordering of variables. Including just the 12 lags of the unemployment rate produces an R^2 of 0.10. Adding the contemporaneous and 12 leads raises the R^2 to 0.15.

Table A.1: Determinants of Unemployment Rate Errors

Determinants	R^2
CES revisions	0.03
+ 2015 LAUS redesign and identification of outliers	0.49
+ Updated seasonal factors	0.59
+ 12 lags of unemployment rate	0.61
+ Contemporaneous and 12 leads of unemployment rate	0.62

Notes: The table reports the R^2 from a regression of the measurement error in the unemployment rate $\hat{u}_{s,t}$ on the regressors indicated in the left column. The sample is January 2005 to December 2013. In the first row, CES revisions are the log difference between the real-time and revised nonfarm seasonally unadjusted employment level from the CES. The second row adds the difference between the vintage 2014 and vintage 2015 LAUS seasonally adjusted unemployment rates, the difference between the unemployment rate constructed directly from the CPS monthly files and the real-time LAUS seasonally unadjusted unemployment rate, the difference between the unemployment rate constructed directly from the CPS files and seasonally adjusted using an X-11 moving average and the average of the same variable for three months before and three months after the observation, and the labor force weighted average of the previous variable for other states in the same Census Division. The third row adds the difference between the revised LAUS seasonally adjusted unemployment rate and the real-time seasonally unadjusted unemployment rate after rescaling the numerator and denominator by the revised seasonal factors for LAUS unemployment and employment. The fourth row adds 12 lags of the revised unemployment rate. The fifth row adds the contemporaneous and 12 leads of the revised unemployment rate.

Figure A.1 illustrates that in our example of Vermont the 2015 LAUS technical improvements account for all of the unemployment rate error during the period of the UI error in the beginning of 2010.

B Measurement Error in the Revised Data

In this appendix we examine the case in which the revised data measure the fundamentals with some error. Measurement error in the revised data introduces an attenuation bias in our estimated impulse responses. We derive an upper bound of this bias under the plausible assumption that the revised data measure fundamentals with less error than the real-time data. Even under this upper bound, we can reject the hypothesis that our estimated responses are consistent with large effects of UI benefit extensions on unemployment.

Our discussion applies to observations at the state-month level, but we drop state-month subscripts to ease the notation. Let the observed duration of benefits, T^* , be equal to the sum

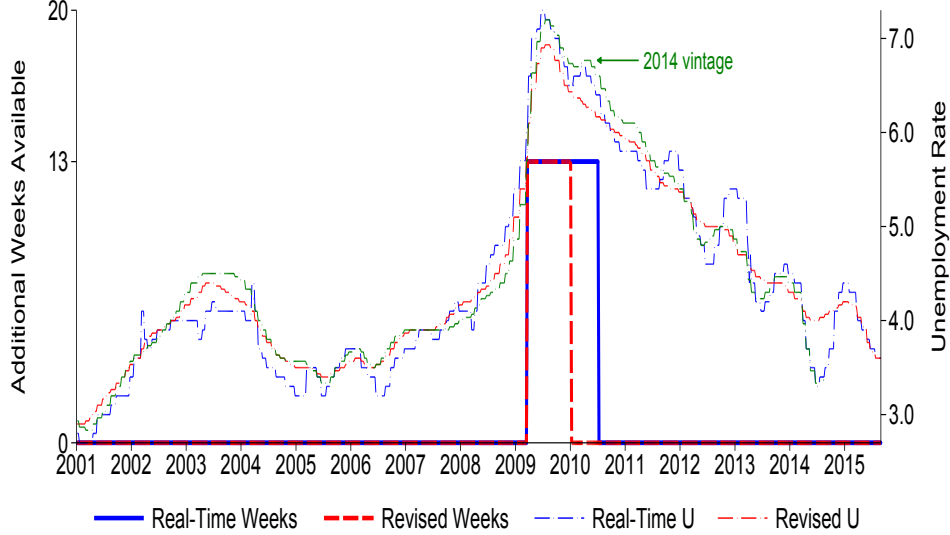


Figure A.1: Extended Benefits and Unemployment in Vermont

Notes: The figure plots the actual duration of benefits $T_{s,t}^*$ and the duration based on the revised data $T_{s,t}$ (left axis) together with the real-time $u_{s,t}^*$ and revised unemployment rates $u_{s,t}$ (right axis). The dashed green line shows the unemployment rate using the 2014 vintage of data.

of two orthogonal components:

$$T^* = T^F + T^E, \quad (\text{A.6})$$

where T^F denotes the duration of benefits using the true unemployment rate and T^E denotes the duration of benefits due to measurement error of the true unemployment rate. The true unemployment rate and T^F are unknown to the econometrician. We allow T to be based on an imperfect measure of the fundamentals:

$$T = T^F + T^X, \quad (\text{A.7})$$

where T^X is a component due to measurement error in the revised data.

The UI error that we defined in the main text, \hat{T} , can be written as:

$$\hat{T} = T^* - T = T^E - T^X. \quad (\text{A.8})$$

In the presence of measurement error in the revised data, the UI error \hat{T} is the difference between the measurement error in the true unemployment rate, T^E , and the measurement error in the revised data, T^X .

The three primitive objects of our analysis are T^F , T^E , and T^X . We write each variable $j = \{F, E, X\}$ as the sum of its expected value plus an innovation, $T^j = \mathbb{E}T^j + \epsilon^j$. All innovations ϵ^j 's are serially uncorrelated and uncorrelated with each other. The innovations in the measurement error components, ϵ^E and ϵ^X , are uncorrelated with the fundamentals F . By contrast, the innovation ϵ^F is potentially correlated with the fundamentals F .

Taking expectations in equation (A.6) and using the definition of the innovations, we write the innovation in the real-time duration of benefits as:

$$\epsilon^{T^*} = \epsilon^F + \epsilon^E. \quad (\text{A.9})$$

Similarly, using equations (A.7) and (A.8), we write the innovation in the duration of UI benefits under the revised data and the innovation in the UI error (which we called ϵ in the main text) as:

$$\epsilon^T = \epsilon^F + \epsilon^X, \quad (\text{A.10})$$

$$\epsilon^{\hat{T}} = \epsilon^E - \epsilon^X. \quad (\text{A.11})$$

Suppose the relationship between some outcome variable y (that could be measured in a future period) and the innovation in the duration of benefits under the real-time data is:

$$y = \beta\epsilon^{T^*} + \gamma F, \quad (\text{A.12})$$

where F collects all other factors that affect y . The fundamentals in F are potentially correlated with ϵ^T through ϵ^F but are uncorrelated with the measurement error component ϵ^E . Using equations (A.9) and (A.11) we can write:

$$y = \beta\epsilon^F + \beta\epsilon^X + \beta\epsilon^{\hat{T}} + \gamma F. \quad (\text{A.13})$$

The OLS coefficient in a bivariate regression of y on $\epsilon^{\hat{T}}$ is given by:

$$\beta^{\text{OLS}} = \frac{\text{Cov}(y, \epsilon^{\hat{T}})}{\text{Var}(\epsilon^{\hat{T}})} = \frac{\text{Cov}(\beta\epsilon^X + \beta\epsilon^{\hat{T}}, \epsilon^{\hat{T}})}{\text{Var}(\epsilon^{\hat{T}})} = \beta \left(1 - \frac{\text{Var}(\epsilon^X)}{\text{Var}(\epsilon^{\hat{T}})} \right), \quad (\text{A.14})$$

where the second equality uses equation (A.13) and the fact that $\text{Cov}(F, \epsilon^{\hat{T}}) = \text{Cov}(\epsilon^F, \epsilon^{\hat{T}}) = 0$, and the third equality uses the fact that $\text{Cov}(\epsilon^X, \epsilon^{\hat{T}}) = \text{Cov}(\epsilon^X, \epsilon^E - \epsilon^X) = -\text{Var}(\epsilon^X)$. If

the revised data measure the true fundamentals without any error up to a constant, $\text{Var}(\epsilon^X) = 0$, then the OLS estimator is unbiased $\beta^{\text{OLS}} = \beta$. The attenuation bias is increasing in the variance of the measurement error in the revised data relative to the variance of the UI error, $\text{Var}(\epsilon^X) / \text{Var}(\epsilon^{\hat{T}})$.

We now show that attenuation bias in our estimates is too small to affect our main conclusions under the plausible assumption that revised data do not deteriorate the quality of measurement of true fundamentals. We say that the revised data are a (weakly) better measure of the true fundamentals than the real-time data if the measurement error in the revised data has a (weakly) lower variance:

$$\text{Var}(\epsilon^X) \leq \text{Var}(\epsilon^E). \quad (\text{A.15})$$

The assumption that the revised data contain less measurement error than the real-time data places an upper bound on the attenuation bias. From equation (A.11), we see that $\text{Var}(\epsilon^{\hat{T}}) = \text{Var}(\epsilon^X) + \text{Var}(\epsilon^E)$ and, therefore, under assumption (A.15) less than 50 percent of the variance of $\epsilon^{\hat{T}}$ is attributed to ϵ^X :

$$\frac{\text{Var}(\epsilon^X)}{\text{Var}(\epsilon^{\hat{T}})} \leq 0.5. \quad (\text{A.16})$$

We estimate in the data an upper bound of $\beta^{\text{OLS}} = 0.02$. Using the upper bound of the bias $\text{Var}(\epsilon^X) / \text{Var}(\epsilon^T) = 0.50$, the true coefficient could be as large as $\beta = 0.04$. Using a standard error of 0.02, this β is still 4.5 standard errors below the 0.14 level that would rationalize a large effect of extended benefits on unemployment during the Great Recession.

This calculation is very conservative because it assumes that revisions do not improve measurement and uses the upper bound of our estimates of β . In Section 5.4 we provided evidence that revisions are informative about actual spending patterns and beliefs. This implies that $\text{Var}(\epsilon^X) / \text{Var}(\epsilon^{\hat{T}})$ is likely to be smaller than 0.5. Indeed, we find in the data that there is smaller variance of outcomes in the revised data and, consistent with our assumption that $\text{Var}(\epsilon^X) \leq \text{Var}(\epsilon^E)$, that $\text{Var}(\epsilon^T) < \text{Var}(\epsilon^{T^*})$. If we apply, for example, $\text{Var}(\epsilon^X) / \text{Var}(\epsilon^{\hat{T}}) = 0.25$ to our maximum estimate of $\beta^{\text{OLS}} = 0.02$, we obtain that the true

coefficient is $\beta < 0.03$. In general, the more informative is the revised data for the true fundamentals, the lower is $\text{Var}(\epsilon^X) / \text{Var}(\epsilon^{\hat{T}})$ and the smaller is the attenuation bias.

C Model Appendix

This appendix contains a self-contained description of our model validation exercise.

C.1 Model Description

Labor Market and Eligibility Flows. Each period a measure u_t of unemployed search for jobs and a measure $1 - u_t$ of employed produce output. Unemployed individuals find jobs at a rate f_t which is determined in equilibrium. Employed individuals separate from their jobs at an exogenous rate δ_t . The law of motion for unemployment is:

$$u_{t+1} = (1 - f_t)u_t + \delta_t(1 - u_t). \quad (\text{A.17})$$

Employed individuals who lose their jobs become eligible for UI benefits with probability γ . There are u_t^E unemployed who are eligible for and receive UI benefits. Eligible unemployed who do not find jobs lose their eligibility with probability e_t . The key policy variable in our model is the (expected) duration of benefits T_t^* which equals the inverse of the expiration probability, $T_t^* = 1/e_t$.⁵ Finally, there are $u_t - u_t^E$ ineligible unemployed. Ineligible unemployed who do not find jobs remain ineligible for UI benefits.

We denote by $\omega_t = u_t^E/u_t$ the fraction of unemployed who are eligible for and receive UI. This fraction evolves according to the law of motion:⁶

$$\omega_{t+1} = \frac{\delta_t \gamma (1 - u_t)}{u_{t+1}} + \left(\frac{u_t (1 - f_t) (1 - e_t)}{u_{t+1}} \right) \omega_t. \quad (\text{A.18})$$

⁵For expository reasons, in the model T_t^* denotes the total duration of benefits (including the regular benefits), whereas in the data we defined T_t^* as the extension of benefits beyond their regular duration.

⁶In the data we have a measure of the fraction of unemployed who receive UI benefits (what we called ϕ in the empirical analysis) based on administrative data on UI payments. Constructing a high quality panel of take-up rates at the state-month level is not feasible with currently available data. A difference relative to the model of Chodorow-Reich and Karabarbounis (2016) is that, because of this data unavailability, here we do not consider the take-up decision of an unemployed who is eligible for benefits. Therefore, we use interchangeably the terms eligibility for UI benefits and receipt of UI benefits.

Household Values. All individuals are risk-neutral and discount the future with a factor β . Employed individuals consume their wage earnings w_t . The value of an individual who begins period t as employed is given by:

$$W_t = w_t + \beta(1 - \delta_t)\mathbb{E}_t W_{t+1} + \beta\delta_t (\gamma\mathbb{E}_t U_{t+1}^E + (1 - \gamma)\mathbb{E}_t U_{t+1}^I), \quad (\text{A.19})$$

where U_t^E denotes the value of an eligible unemployed and U_t^I denotes the value of an ineligible unemployed. These values are given by:

$$U_t^E = \xi + B + \beta f_t \mathbb{E}_t W_{t+1} + \beta(1 - f_t) (e_t \mathbb{E}_t U_{t+1}^I + (1 - e_t) \mathbb{E}_t U_{t+1}^E), \quad (\text{A.20})$$

$$U_t^I = \xi + \beta f_t \mathbb{E}_t W_{t+1} + \beta(1 - f_t) \mathbb{E}_t U_{t+1}^I, \quad (\text{A.21})$$

where ξ is the value of non-market work and B is the UI benefit per eligible unemployed.⁷ We assume that both ξ and B are constant over time. This allows us to focus entirely on the role of benefit extensions for fluctuations in the opportunity cost of employment.⁸

Surplus and Opportunity Cost of Employment. Firms bargaining with workers over wages cannot discriminate with respect to workers' eligibility status. Therefore, there is a common wage for all unemployed. This implies that we need to keep track of values and flows for the *average* unemployed. We define the value of the average unemployed individual as:

$$U_t = \omega_t U_t^E + (1 - \omega_t) U_t^I. \quad (\text{A.22})$$

The surplus of employment for the average unemployed is given by the difference between the value of working and the value of unemployment. We take:

$$S_t = W_t - U_t = w_t - z_t + \beta(1 - \delta_t - f_t)\mathbb{E}_t S_{t+1}, \quad (\text{A.23})$$

⁷Benefit extensions were federally funded between 2009 and 2013. We think of our model as applying to an individual state during this period and, therefore, we do not impose UI taxes on firms.

⁸In previous work (Chodorow-Reich and Karabarbounis, 2016), we found that the ξ component of the opportunity cost is procyclical. Benefit extensions typically occur when unemployment is high and ξ is low. However, our empirical exercise compares two states with different duration of benefits that have the same economic fundamentals and, therefore, it is appropriate to not control for ξ in our regressions. The constancy of ξ in the model is conservative for our conclusions in this section. Allowing ξ to respond endogenously would lead to an even smaller effect of benefit extensions on unemployment because the decline in ξ would tend to offset the increase in the value of benefits (denoted b below) in the opportunity cost $z = \xi + b$.

where z_t denotes the (flow) opportunity cost of employment for the average unemployed.

The opportunity cost of employment is defined as the flow utility that an unemployed forgoes upon moving to employment. It is given by:

$$z_t = \xi + \underbrace{\omega_t B - (\delta_t(\gamma - \omega_t) + (1 - f_t)\omega_t e_t)}_{b_t} \beta (\mathbb{E}_t U_{t+1}^E - \mathbb{E}_t U_{t+1}^I), \quad (\text{A.24})$$

where b_t denotes the benefit component of the opportunity cost of employment. The expression nests the standard model (for instance, Shimer, 2005) that has $b_t = B$ if $e_t = 0$, that is when benefits do not expire, and $\gamma = \omega_t = 1$, that is when all unemployed are eligible for benefits. More generally, the flow utility loss b_t of moving an average unemployed to employment is lower than the benefit B . The difference occurs because some unemployed are not eligible for benefits and, even for those unemployed who are eligible, benefits will eventually expire.⁹ Additionally, b_t is in general time varying. Extending benefits, which here means a decline in the expiration probability e_t , increases the fraction of unemployed who are eligible ω_t and raises b_t and the opportunity cost of employment z_t .

Firm Value, Matching, and Bargaining. The value of a firm from matching with a worker is given by:

$$J_t = p_t - w_t + \beta(1 - \delta_t)\mathbb{E}_t J_{t+1}, \quad (\text{A.25})$$

where p_t denotes aggregate labor productivity. There is free entry and, therefore, the expected value of creating a vacancy equals zero:

$$\frac{\kappa}{q_t} = \beta \mathbb{E}_t J_{t+1}, \quad (\text{A.26})$$

where κ denotes the upfront cost that an entrant pays to create a vacancy and q_t denotes the rate at which vacancies are filled.

Trade in the labor market is facilitated by a constant returns to scale matching technology that converts searching by the unemployed and vacancies by firms into new matches, $m_t =$

⁹The first effect is captured by the first term of b_t which is lower than B when $\omega_t < 1$. The second effect is captured by the second term which is positive because $\gamma > \omega_t$ and $\mathbb{E}_t U_{t+1}^E > \mathbb{E}_t U_{t+1}^I$.

$Mv_t^\eta u_t^{1-\eta}$. We denote by η the elasticity of the matching function with respect to vacancies. We define market tightness as $\theta_t = v_t/u_t$. An unemployed matches with a firm at a rate $f_t(\theta_t) = m_t/u_t$ and firms fill vacancies at a rate $q_t(\theta_t) = m_t/v_t = f_t(\theta_t)/\theta_t$.

Firms and workers split the surplus from an additional match according to the generalized Nash bargaining solution. We denote by μ the bargaining power of workers. The wage is chosen to maximize the product $S_t^\mu J_t^{1-\mu}$, where J_t in equation (A.25) is a firm's surplus of employing a worker and S_t in equation (A.23) is the surplus that the average unemployed derives from becoming employed. This leads to a standard wage equation:

$$w_t = \mu p_t + (1 - \mu)z_t + \mu\kappa\theta_t. \quad (\text{A.27})$$

The wage is an increasing function of labor productivity, the opportunity cost, and market tightness.

UI Policy. The duration of UI benefits is given by $T_t^* = T_t + \hat{T}_t$, where T_t denotes the duration of UI benefits in the absence of any measurement error and \hat{T}_t is the UI error. Consistent with the results in Section 5.4 that agents respond only to the revised unemployment rate, we assume that firms and workers know the underlying fundamentals (for instance, u_t , p_t , w_t etc.) at the beginning of each period. The statistical agency makes errors in the measurement of the true unemployment rate which result in UI errors \hat{T}_t .

The process for T_t is:

$$T_t = \begin{cases} T^1, & \text{if } 0 \leq u_t < \bar{u}^1, \\ T^2, & \text{if } \bar{u}^1 \leq u_t < \bar{u}^2, \\ \dots & \\ T^J, & \text{if } \bar{u}^{J-1} \leq u_t < \bar{u}^J = 1. \end{cases} \quad (\text{A.28})$$

The UI error follows a first-order Markov process $\pi_T \left(\hat{T}_t \mid \hat{T}_{t-1}; u_t \right)$. As in the data, the unemployment rate enters into the Markov process to capture the fact that UI errors occur only in particular regions of the state space.¹⁰

¹⁰The timing convention in our model follows the convention in the DMP literature in which the unemployment

Equilibrium. The state vector of the economy is given by $\mathbf{x}_t = [u_t, \omega_t, p_t, \delta_t, \hat{T}_t]$. Given exogenous and known processes for p_t , δ_t , and \hat{T}_t , an equilibrium of this model consists of functions of the state vector:

$$\{u_{t+1}(\mathbf{x}_t), \omega_{t+1}(\mathbf{x}_t), \theta_t(\mathbf{x}_t), W_t(\mathbf{x}_t), U_t^E(\mathbf{x}_t), U_t^I(\mathbf{x}_t), w_t(\mathbf{x}_t), J_t(\mathbf{x}_t), b_t(\mathbf{x}_t), T_t(\mathbf{x}_t)\},$$

such that: (i) The law of motion for unemployment (A.17) and the law of motion for eligibility (A.18) are satisfied. (ii) Worker values in equations (A.19), (A.20), and (A.21) are satisfied. (iii) The firm value is given by equation (A.25) and the free-entry condition (A.26) holds. (iv) Wages are determined by equation (A.27), where the opportunity cost of employment is given by equation (A.24). (v) The duration of UI benefits in the absence of measurement error is given by the schedule (A.28). Starting from each state vector \mathbf{x}_t , we have 10 equations to solve for the 10 unknowns.

Effects of UI Policy in the Model. An increase in the current duration of benefits ($T_t^* = 1/e_t$) affects equilibrium outcomes to the extent that firms and workers expect it to persist in future periods. Combining equations (A.25) and (A.26), the decision to create a vacancy in the current period depends on the expectation of the present discounted value of firm profits:

$$\frac{\kappa}{q_t(\theta_t)} = \mathbb{E}_t \sum_{j=1}^{\infty} \beta^j \left(\prod_{i=1}^j \frac{(1 - \delta_{t+i-1})}{(1 - \delta_t)} \right) (p_{t+j} - w_{t+j}), \quad (\text{A.29})$$

where $q_t(\theta_t)$ is a decreasing function of current market tightness $\theta_t = v_t/u_t$. By raising the fraction of unemployed who are eligible for UI, an extension of benefits increases future opportunity costs and wages. The increase in wages lowers the expected present value of firm profits and decreases firms' willingness to create vacancies in the current period. The decline in vacancies makes it more difficult for the unemployed to find jobs, which increases the unemployment rate.

rate u_t is a state variable and has been determined in period $t - 1$. For this reason UI policy in the model depends on u_t . We remind the reader that in the data the unemployment rate in period $t - 1$ determines the extension of benefits in period t .

Table A.2: Parameter Values

β	ρ	σ	η	μ	δ	ξ	M	γ	B	κ
0.997	0.91	0.008	0.60	0.40	0.035	0.81	0.60	0.72	{0.26, 0.10}	{0.05, 0.17}

C.2 Parameterization

A model period corresponds to a month. The schedule for the T_t component of UI benefit duration is:

$$T_t = \begin{cases} 6, & \text{if } u_t < 0.065, \\ 9, & \text{if } 0.065 \leq u_t < 0.08, \\ 12, & \text{if } 0.08 \leq u_t < 0.09, \\ 20, & \text{if } 0.09 \leq u_t. \end{cases} \quad (\text{A.30})$$

For the UI error component, \hat{T}_t , we estimate the probabilities $\pi_T(\hat{T}_t | \hat{T}_{t-1}; u_t)$ in the data separately for each region $u_t < 0.06$, $0.06 \leq u_t < 0.065$, and $u_t \geq 0.065$.

Table A.2 lists values for other parameters of the model. The discount factor equals $\beta = 0.997$. Log productivity follows an AR(1) process $\log p_{t+1} = \rho \log p_t + \sigma \nu_t^p$, with $\nu_t^p \sim N(0, 1)$, where from the data we estimate that at monthly frequency $\rho = 0.91$ and $\sigma = 0.008$. The mean separation rate is $\delta = 0.035$. We set the elasticity of the matching function with respect to vacancies to $\eta = 0.60$, worker's bargaining power to $\mu = 0.40$, and the value of non-market work to $\xi = 0.81$. We then calibrate four parameters, M , γ , B , and κ , to hit four targets in the steady state of the model with no benefit extensions (so $T^* = 6$ months).¹¹

We parameterize two versions of the model. In the “low b ” model we pick B such that $b = 0.06$ in the steady state and so $z = \xi + b = 0.87$. The value of $b = 0.06$ accords with the

¹¹We target $\theta^T = 1$, $u^T = 0.055$, $\omega^T = 0.65$, and $b^T = \{0.06, 0.15\}$. Because we do not consider the take-up decision of the unemployed, B should be understood as the after-tax value of benefits for the average eligible unemployed. This differs from the replacement rate per recipient because of taxes, utility costs of taking up benefits, and a take-up rate below one.

finding in Chodorow-Reich and Karabarbounis (2016) that benefits comprise a small fraction of the average opportunity cost.¹² In the “high b ” model we pick B such that $b = 0.15$ and $z = \xi + b = 0.96$. The value of $z = 0.96$ was found by Hagedorn and Manovskii (2008) to match the rigidity of wages with respect to productivity.

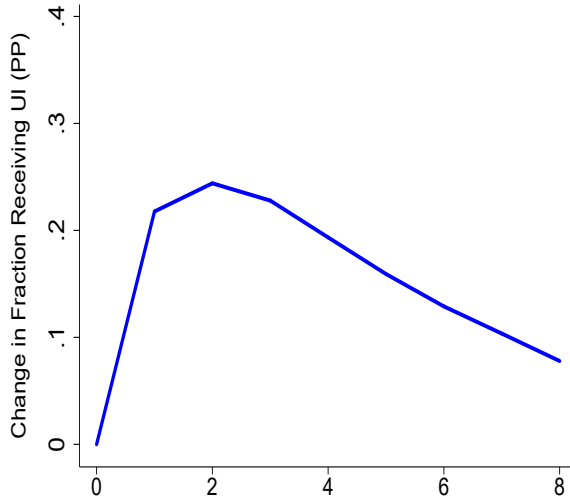
C.3 Computation

We solve the model globally by iterating on the equilibrium conditions. We begin by guessing functions $\theta^0(u_t, \omega_t, p_t, \delta_t, \hat{T}_t)$ and $b^0(u_t, \omega_t, p_t, \delta_t, \hat{T}_t)$ defined over grids of state variables. Given these guesses, we obtain $f(\cdot)$, $T(\cdot)$, $u'(\cdot)$ and $\omega'(\cdot)$, where primes denote next period values, and use equation (A.27) to obtain the wage function $w(\cdot)$. Next, we iterate on equation (A.25) to solve for firm value $J(\cdot)$. Finally, we use the free-entry condition (A.26) and the definition of the opportunity cost in equation (A.24) to obtain the implied $\theta^1(\cdot)$ and $b^1(\cdot)$ functions. We update the guesses and repeat until convergence. To evaluate value functions at points u' and ω' we use linear interpolation. When solving for the equilibrium policy functions, we impose that the probabilities $f(\cdot)$ and $q(\cdot)$ lie between zero and one. These restrictions also guarantee that v and θ are always positive.

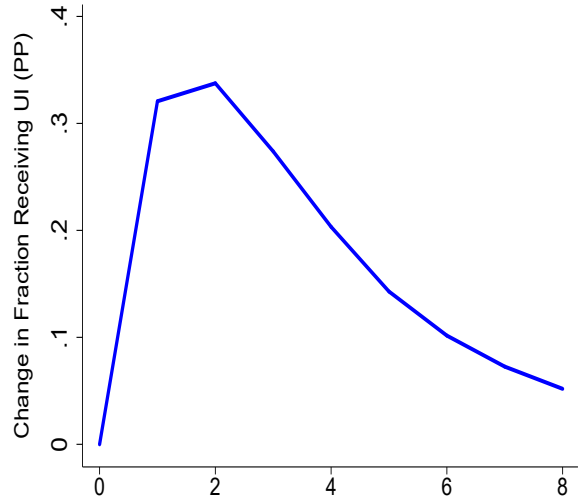
C.4 Additional Results

In Figures A.2, A.3, and A.4, we present the impulses of the fraction of unemployed receiving UI, the log opportunity cost, and log vacancies to a one-month increase in the UI error innovation. In Figures A.5 and A.6 we depict the path of productivity and separations shocks underlying the experiment depicted in Figure 8 in the main text. In each figure, the left panel corresponds to the high b model and the right panel corresponds to the low b model.

¹²Our calibration is conservative in the sense that reducing the level of ξ would produce even smaller effects of UI policy on aggregate outcomes. Chodorow-Reich and Karabarbounis (2016) show that, with standard preferences, z is between 0.47 and 0.75. Hornstein, Krusell, and Violante (2011) argue that z has to be even smaller in order for models to generate large frictional wage dispersion. Hall and Mueller (2015) also arrive at a small value of z given the large observed dispersion in the value of a job. Costain and Reiter (2008) first pointed out that models with a high level of z generate stronger effects of policies on labor market outcomes than the effects found in cross-country comparisons.



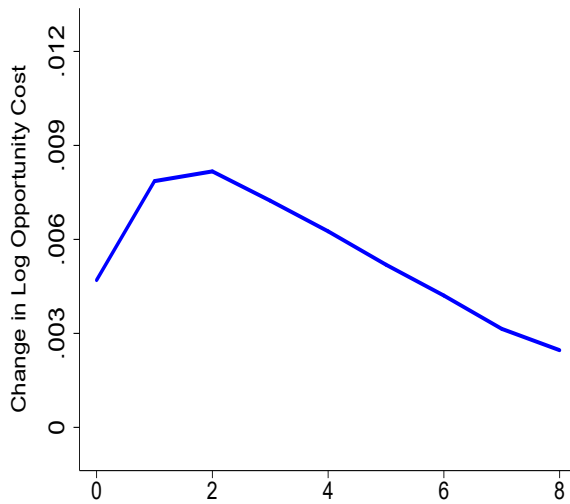
(a) High b Model



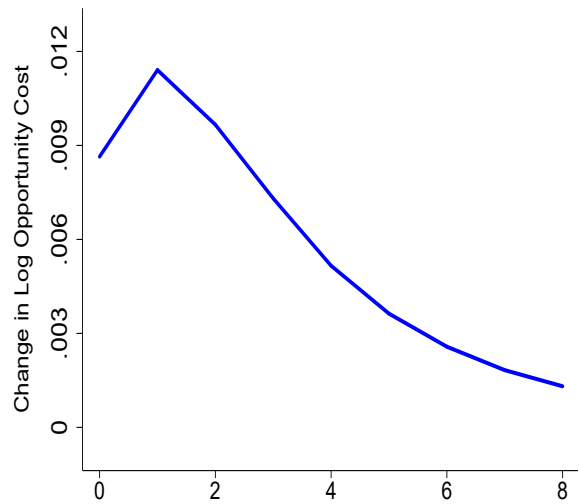
(b) Low b Model

Figure A.2: Impulse Response of Fraction Receiving UI in the Model

Notes: The figure plots the coefficients on ϵ_t from the regression $\omega_{t+h} = \beta(h)\epsilon_t + \sum_{j=0}^{11} \gamma_j(h)u_{t-j} + \nu_{t+h}$ using data generated from model simulations.



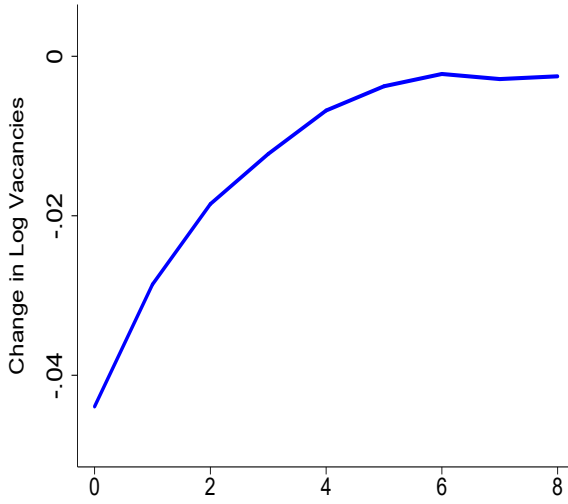
(a) High b Model



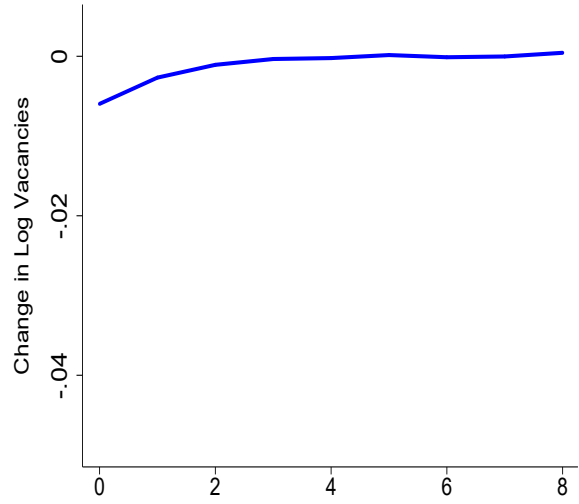
(b) Low b Model

Figure A.3: Impulse Response of Log Opportunity Cost in the Model

Notes: The figure plots the coefficients on ϵ_t from the regression $\log b_{t+h} = \beta(h)\epsilon_t + \sum_{j=0}^{11} \gamma_j(h)u_{t-j} + \nu_{t+h}$ using data generated from model simulations.



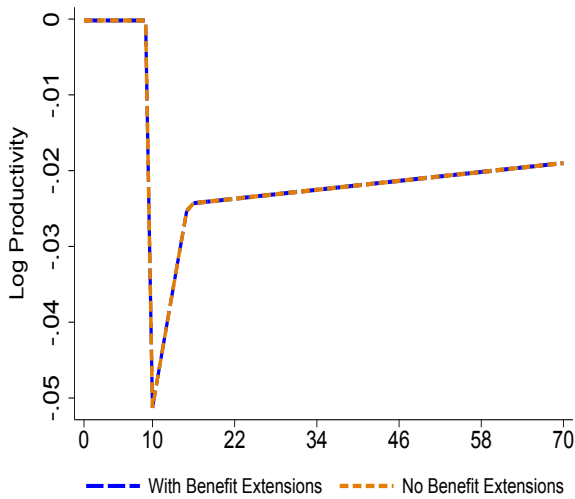
(a) High b Model



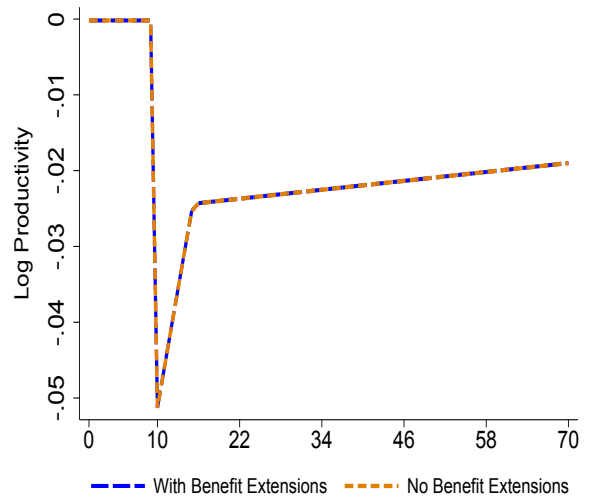
(b) Low b Model

Figure A.4: Impulse Response of Log Vacancies in the Model

Notes: The figure plots the coefficients on ϵ_t from the regression $\log v_{t+h} = \beta(h)\epsilon_t + \sum_{j=0}^{11} \gamma_j(h)u_{t-j} + \nu_{t+h}$ using data generated from model simulations.



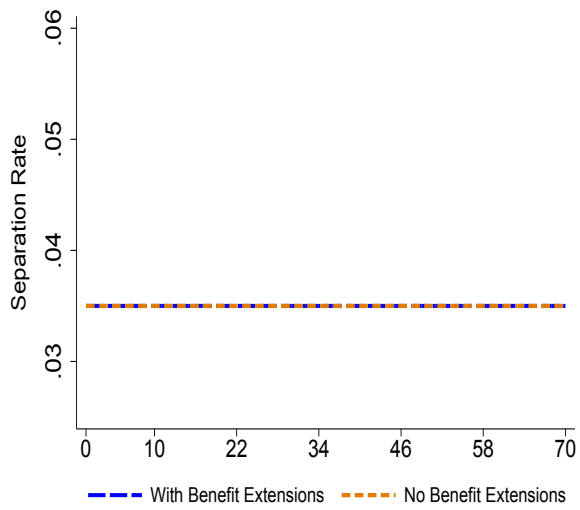
(a) High b Model



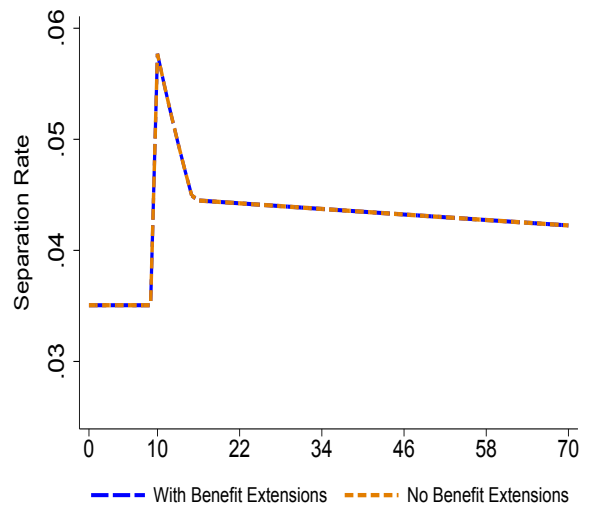
(b) Low b Model

Figure A.5: Productivity Path in the Model

Notes: The figure plots the path of productivity used to generate the simulation in Figure 8.



(a) High b Model



(b) Low b Model

Figure A.6: Separations in the Model

Notes: The figure plots the path of the separation rate used to generate the simulation in Figure 8.