A Macroeconomic Approach to Optimal Unemployment Insurance: Applications

Camille Landais, Pascal Michaillat, Emmanuel Saez *

March 9, 2017

Abstract

In the United States, unemployment insurance (UI) is more generous when unemployment is high. This paper examines whether this policy is desirable. In matching models, the optimal UI replacement rate is the Baily-Chetty replacement rate plus a correction measuring the effect of UI on welfare through labor market tightness. Empirical evidence suggests that tightness is inefficiently low in slumps but inefficiently high in booms, and that an increase in UI raises tightness. Hence, the correction is positive in slumps but negative in booms, and the optimal replacement rate is indeed countercyclical: it varies between 33% in booms and 50% in slumps. Since there remains uncertainty about the estimates of the statistics in the optimal UI formula, the paper provides a complete sensitivity analysis.

*Camille Landais: Department of Economics, London School of Economics, Houghton Street, London, WC2A 2AE, UK (email: c.landais@lse.ac.uk). Pascal Michaillat: Department of Economics, Brown University, Box B, Providence, RI 02912, USA (email: pascal_michaillat@brown.edu). Emmanuel Saez: Department of Economics, University of California–Berkeley, 530 Evans Hall #3880, Berkeley, CA 94720, USA (email: saez@econ.berkeley.edu).
We thank editor Matthew Shapiro, Daron Acemoglu, George Akerlof, Varanya Chaubey, Raj Chetty, Peter Diamond, Yuriy Gorodnichenko, Philipp Kircher, Etienne Lehmann, Robert Shimer, Johannes Spinnewijn, participants at many seminars and conferences, and anonymous referees for helpful discussions and comments. This work was supported by the Center for Equitable Growth at the University of California–Berkeley, the British Academy, the Economic and Social Research Council [grant number ES/K008641/1], the Institute for New Economic Thinking, and the Sandler Foundation.

In the United States, unemployment insurance (UI) is more generous when unemployment is high. This policy started as an exceptional measure after the 1957–1958 recession and became a permanent program in 1970. Despite its long history, the policy remains debated. This paper examines whether the policy is desirable from a welfare perspective.

We conduct the welfare analysis in a matching model. We extend the static model from a companion paper (Landais, Michaillat and Saez 2016) into a dynamic model better suited for quantitative applications (Section I). The model features most effects discussed in the policy debate: the effects of UI on job search, wages, job vacancies, and aggregate unemployment.[1] The optimal generosity of UI is given by a sufficient-statistic formula: the optimal replacement rate equals the Baily-Chetty replacement rate, a well-researched entity, plus a correction term measuring the effect of UI on welfare through labor market tightness.

Since little is known about the correction term in the optimal UI formula, the bulk of the analysis consists in studying how this term fluctuates over the business cycle. The correction term is the product of two factors: the effect of tightness on welfare and the effect of UI on tightness. We begin by estimating the first factor (Section II) and then turn to the second (Section III). Then, we multiply these factors and add the Baily-Chetty replacement rate to compute the optimal replacement rate in the United States (Section IV).

We start the analysis by estimating the first factor in the correction term: the effect of tightness on welfare. This is equivalent to assessing whether tightness is inefficiently low, efficient, or inefficiently high, at any point in time. In theory, the Hosios (1990) condition should tell us this. Yet, evaluating the Hosios condition has appeared to be prohibitively complicated: the difficulty is in measuring workers' bargaining power every month or quarter. So we proceed with a criterion that is mathematically equivalent to the Hosios condition but formulated with statistics that are more easily evaluated in the data. The criterion is that the effect of tightness on welfare is positive whenever the marginal social cost of unemployment is higher than its marginal social value.

Two social costs of unemployment are relevant to the effect of tightness on welfare. The first is a fiscal cost: unemployed workers deplete the government budget (they receive benefits) whereas employed workers contribute to it (they pay taxes). To assess this cost, we measure the generosity of UI. In our model, UI benefits last forever so the generosity of UI is governed by the level of benefits. In the Unites States, things are more complicated because the duration of UI benefits is finite and adjusted over the business cycle. To synthesize the actual generosity of UI—both level

[1] UI may also affect aggregate demand. This effect does not feature here but is studied by Kekre (2016).

and duration of benefits—we construct an effective replacement rate by averaging the replacement rate among all eligible unemployed workers, whether or not their benefits have expired. This effective replacement rate averages 42%.

The second social cost of unemployment is a utility cost: unemployed workers consume less than employed workers and incur a nonpecuniary cost. Although this nonpecuniary cost is often neglected in macroeconomic models, it is visible in the data—those who lose their job see their well-being fall more than those who lose an equal amount of income but remain employed. In fact, using reported well-being and revealed preferences, we estimate this nonpecuniary cost at 30% of the utility provided by an average wage.

To measure the effect of tightness on welfare, the marginal social costs of unemployment are then compared to its marginal social value, which is to reduce the firms' recruiting costs. This social value is high when firms devote a large share of their workforce to recruiting and when the unemployment rate is low. The main challenge in measuring the social value is assessing the share of the workforce devoted to recruiting. Using firm surveys conducted by the Census Bureau and Bureau of Labor Statistics (BLS), we infer the average share of recruiters in the workforce and compute how it varies over time. We find that the share of recruiters in the workforce averages 2.3% and is procyclical.

Overall, we find that tightness has a positive effect on welfare in bad times but a negative effect in good times—that is, tightness is inefficiently low in bad times but inefficiently high in good times. This is because the costs of unemployment are broadly acyclical while the value of unemployment is procyclical.

We then turn to the second factor in the correction term: the effect of UI on tightness. The literature has focused on the effect of UI on unemployment, estimating either the microelasticity or the macroelasticity of unemployment with respect to UI. But the effect of UI on tightness cannot be inferred from either of the elasticities on its own; it can only be inferred by comparing them. Indeed, UI has a positive effect on tightness whenever the macroelasticity is smaller than the microelasticity. To see why, imagine an increase in UI. Jobseekers search less, which raises unemployment by an amount measured by the microelasticity. Tightness also adjusts in equilibrium, further affecting unemployment, which increases by an overall amount measured by the macroelasticity. Now after the increase in UI, imagine that tightness goes up. For a given search effort, jobseekers find jobs more easily, which partially offsets the increase in unemployment caused by lower search effort. Hence, the macroelasticity is smaller than the microelasticity.

To measure the effect of UI on tightness, we therefore compare microelasticity and macroelasticity estimates. Microelasticity estimates from administrative data are generally larger than available macroelasticity estimates, suggesting that UI raises tightness. Marinescu (2016) also finds that UI raises tightness, by measuring tightness directly in data on vacancies and job from an employment website. In addition, an increase in UI seems to improve the prospects of uninsured jobseekers, indicating that tightness rises when UI goes up. Overall, then, current evidence points to a positive effect of UI on tightness.

With the Baily-Chetty replacement rate and the two factors from the correction term in hand, we compute the optimal replacement rate. At this stage we face a problem common to optimal policy formulas expressed with sufficient statistics: the statistics are implicit functions of the policy, so the formulas cannot be used to solve for the policy directly. To address this issue, we leverage empirical evidence to express all the statistics in our formula, including labor market variables, as functions of UI. This allows us to compute optimal UI using only the formula, without specifying a structural model.

Because the first factor (the effect of tightness on welfare) is countercyclical and the second factor (the effect of UI on tightness) is positive, the correction term is countercyclical. Our optimal UI formula then implies that the optimal replacement rate is countercyclical: as low as 33% in booms and as high as 50% in slumps.[2] How does this compare to the generosity of UI in the United States? We find that the average generosity of UI is close to optimal, that the benefit extensions after the 1990–1991 and 2008–2009 recessions were warranted, but that the elimination of benefit extensions in 2014 came prematurely.

As there remains uncertainty about the estimates we use, we provide a sensitivity analysis by solving the formula with a range of estimates for the key statistics. In particular, we consider the scenarios where macroelasticity equals microelasticity and macroelasticity is larger than microelasticity. In the first scenario, the optimal replacement rate is acyclical; in the second, it is procyclical. These two scenarios overlap with two other papers that study the business-cycle fluctuations of optimal UI. Kroft and Notowidigdo (2016) use a Baily-Chetty model, so they consider the scenario where macroelasticity equals microelasticity. Mitman and Rabinovich (2015) use a standard matching model, with Nash bargaining and linear production function, so they consider the scenario where macroelasticity is larger than microelasticity.

[2] The next step would be to determine how the optimal time profile of UI benefits fluctuates over the business cycle. For a first attempt at solving this problem, see Kolsrud et al. (2015).

I. Optimal UI in a Dynamic Model

We conduct the analysis in a dynamic model that extends the static model from our companion paper (Landais, Michaillat and Saez 2016). To improve the realism of the labor market, we introduce long-term employment relationships. Despite some differences in the derivation, the optimal UI formula remains the same as in the static model.

A. *The Model*

Here is a brief presentation of the model. (For more details and intuition, see our companion paper.) The model is set in continuous time. There is a measure 1 of identical workers and a measure 1 of identical firms. At time t, the number of employed workers is $l(t)$ and the number of unemployed workers is $u(t) = 1 - l(t)$. Each firm posts $v(t)$ vacancies to recruit workers. Each unemployed worker searches for a job with effort $e(t)$. The matching function m determines the number of worker-firm matches formed at time t: $m(t) = m(e(t) \cdot u(t), v(t))$, where $m(t)$ is the number of workers who find a job, $e(t) \cdot u(t)$ is aggregate job-search effort, and $v(t)$ is aggregate vacancies. The matching function has constant returns to scale and is differentiable and increasing in both arguments. The labor market tightness $\theta(t)$ is defined by the ratio of aggregate vacancies to aggregate job-search effort: $\theta(t) = v(t)/(e(t) \cdot u(t))$. The job-finding rate per unit of search effort is $f(\theta(t)) = m(t)/(e(t) \cdot u(t)) = m(1, \theta(t))$ and the job-finding rate is $e(t) \cdot f(\theta)$. The vacancy-filling rate is $q(\theta(t)) = m(t)/v(t) = m(1/\theta(t), 1)$. We denote by $1 - \eta$ and $-\eta$ the elasticities of f and q with respect to θ. We refer to $\eta \in (0,1)$ as the matching elasticity. Worker-firm matches separate for exogenous reasons at a rate $s > 0$. Technically, employment is a state variable with law of motion

$$\dot{l}(t) = e(t) \cdot f(\theta(t)) \cdot (1 - l(t)) - s \cdot l(t).$$

If e and $f(\theta)$ remain constant over time, employment converges to the steady-state level

$$l = \frac{e \cdot f(\theta)}{s + e \cdot f(\theta)}. \tag{1}$$

In US data, employment reaches this steady-state level quickly because labor market flows are large. In fact, Hall (2005*b*, Figure 1) shows that the employment rate obtained from (1) and the actual employment rate are indistinguishable. Therefore, as Hall (2005*a*) and Pissarides (2009) do, we simplify the analysis by ignoring the transitional dynamics of employment and assuming that employment is a jump variable that depends on search effort and tightness according to (1). Because the transitional dynamics of employment are ignored, the firms, workers, and government maximize a static objective at each instant.[3] Thus, the dynamic model behaves as a succession of static models, and optimal UI in the dynamic model can be described with a simple, static formula. To simplify notation, we now omit the time index t.

The representative firm employs l workers in total: n workers who produce output and $l-n$ workers who recruit employees by posting vacancies. All workers are paid a real wage w. The firm's production function is $y(n)$. The function y is differentiable, increasing, and concave. Since (1) holds, labor market flows are balanced: the number of new hires equals the number of job losers. Thus, the number of vacancies v posted by a firm with l employees satisfies $v \cdot q(\theta) = s \cdot l$, or $v = s \cdot l/q(\theta)$. Posting a vacancy requires ρ recruiters, so the number of recruiters in a firm with l employees is $\rho \cdot s \cdot l/q(\theta)$, and the number of producers in the firm is $n = l \cdot (1 - s \cdot \rho/q(\theta))$. The firm's recruiter-producer ratio $\tau(\theta)$ therefore satisfies

$$\tau(\theta) = \frac{s \cdot \rho}{q(\theta) - s \cdot \rho}. \tag{2}$$

The numbers of employees and producers are related by $l = [1 + \tau(\theta)] \cdot n$.

The firm sells its output on a perfectly competitive market. Taking θ and w as given, the firm chooses l to maximize profits $y(l/[1+\tau(\theta)]) - w \cdot l$. The labor demand $l^d(\theta, w)$ gives the profit-maximizing number of employees. It is implicitly defined by the first-order condition

$$y'\left(\frac{l}{1+\tau(\theta)}\right) = [1+\tau(\theta)] \cdot w.$$

The UI program provides consumption c^e to employed workers and consumption $c^u < c^e$ to unemployed workers. The generosity of UI is measured by the replacement rate

$$R \equiv 1 - \frac{c^e - c^u}{w}.$$

[3]The behavior of the firms, workers, and government approximates well their dynamic behavior—the behavior constrained by the law of motion of employment—as long as the job-separation rate, s, is much higher than the interest rate. This condition is satisfied in the United States, where $s \approx 3\%$ per month.

The government faces the budget constraint

$$y(n) = (1-l)\cdot c^u + l\cdot c^e. \tag{3}$$

Employed workers consume c^e, which yields utility $U(c^e)$. The function U is differentiable, increasing, and concave. Unemployed workers consume UI benefits c^u plus an amount h produced at home.[4] They derive utility $U(c^u+h)$ from their consumption. The disutility from home production is $\lambda(h)$. The function λ is differentiable, increasing, convex, and $\lambda(0)=0$. The disutility from job search is $\psi(e)$. The function ψ is differentiable, increasing, convex, and $\psi(0)=0$. In addition, unemployed workers suffer a disutility from unemployment z. Accordingly, the utility of an unemployed worker is $U(c^u+h)-z-\lambda(h)-\psi(e)$.[5]

Taking c^u as given, unemployed workers choose h to maximize $U(c^u+h)-\lambda(h)$. The home-production supply $h^s(c^u)$ gives the optimal level of home production. It is implicitly defined by the first-order condition

$$\lambda'(h) = U'\left(c^u+h\right). \tag{4}$$

The total consumption of unemployed workers is $c^h = c^u + h^s(c^u)$. It only depends on c^u.

Taking θ, c^e, c^h, and h as given, the representative worker chooses e to maximize expected utility

$$\frac{e\cdot f(\theta)}{s+e\cdot f(\theta)}\cdot U(c^e) + \frac{s}{s+e\cdot f(\theta)}\cdot\left[U(c^h)-z-\lambda(h)-\psi(e)\right]. \tag{5}$$

The effort supply $e^s(f(\theta),\Delta U)$ gives the optimal job-search effort. It is implicitly defined by the first-order condition

$$\psi'(e) = \frac{f(\theta)}{s+e\cdot f(\theta)}\cdot\left[\Delta U+\psi(e)\right], \tag{6}$$

$$\text{where}\quad \Delta U \equiv U(c^e)-U(c^h)+z+\lambda(h). \tag{7}$$

The utility loss from unemployment is $\Delta U+\psi(e)$. This utility loss can be expressed as $U(c^e)-$

[4]To simplify, we rule out saving and only allow workers to self insure against unemployment with home production.

[5]The disutility from work is normalized to zero; with a nonzero disutility from work, z would be redefined as the disutility from unemployment net of the disutility from work.

$U(c^h) + Z$, where

$$Z \equiv z + \lambda(h) + \psi(e) \tag{8}$$

is the total nonpecuniary cost of unemployment. To measure the total utility cost of unemployment (pecuniary and nonpecuniary) with a dimensionless number (not with utils), we define

$$K = \frac{U(c^e) - U(c^h) + Z}{w \cdot \phi} \tag{9}$$

$$\text{where} \quad \frac{1}{\phi} = \frac{l}{U'(c^e)} + \frac{1-l}{U'(c^h)}. \tag{10}$$

Job losers incur a utility loss $U(c^e) - U(c^h) + Z$. As ϕ is the harmonic mean of marginal utilities in the population, $\phi \cdot w$ is the average marginal utility provided by a wage. Accordingly, K measures the utility cost of unemployment as a fraction of the utility provided by a wage.

Finally, the labor supply

$$l^s(\theta, \Delta U) = \frac{e^s(f(\theta), \Delta U) \cdot f(\theta)}{s + e^s(f(\theta), \Delta U) \cdot f(\theta)}.$$

gives the number of workers who have a job when job search is optimal.

At any point in time, an equilibrium is parametrized by ΔU. In equilibrium, the wage is given by a wage schedule $w(\theta, \Delta U)$ and the tightness equalizes labor supply and demand:

$$l^s(\theta, \Delta U) = l^d(\theta, w(\theta, \Delta U)).$$

This equation defines the equilibrium level of tightness as an implicit function of ΔU, denoted $\theta(\Delta U)$. Once the equilibrium tightness is determined, it is simple to completely characterize the equilibrium: l is determined by $l = l^s(\theta, \Delta U)$, e by $e = e^s(f(\theta), \Delta U)$, n by $n = l/(1 + \tau(\theta))$, w by $w = w(\theta, \Delta U)$, c^e and c^u by (3) and (7), h by $h = h^s(c^u)$, and c^h by $c^h = c^u + h$.

B. *The Optimal UI Formula*

Having characterized the equilibrium, we now present the optimal UI formula. At any point in time, the government chooses ΔU to maximize social welfare, given by (5), subject to its budget constraint, given by (3), and the equilibrium constraints. The formula is obtained from the first-order condition of this maximization problem. (The formula is derived in Appendix A.)

Three elasticities enter the optimal UI formula: the microelasticity of unemployment with respect to UI

$$\varepsilon^m \equiv \frac{\Delta U}{1-l} \cdot \left.\frac{\partial l^s}{\partial \Delta U}\right|_{\theta},$$

which measures how job-search effort responds to UI; the discouraged-worker elasticity

$$\varepsilon^f \equiv \frac{f(\theta)}{e} \cdot \left.\frac{\partial e^s}{\partial f}\right|_{\Delta U},$$

which measures how job-search effort responds to labor market conditions; and the macroelasticity of unemployment with respect to UI

$$\varepsilon^M \equiv \frac{\Delta U}{1-l} \cdot \frac{dl}{d\Delta U},$$

which measures how the unemployment rate responds to UI. Then, the formula expresses the optimal replacement rate of UI with sufficient statistics:

$$(11) \qquad R = \underbrace{\frac{l \cdot \Delta U}{\varepsilon^m \cdot w} \cdot \left[\frac{1}{U'(c^e)} - \frac{1}{U'(c^h)}\right]}_{\text{Baily-Chetty replacement rate}} + \underbrace{\left[1 - \frac{\varepsilon^M}{\varepsilon^m}\right]}_{\text{elasticity wedge}} \cdot \underbrace{\frac{1}{1+\varepsilon^f} \cdot \left[K + \left(1+\varepsilon^f\right) \cdot R - \frac{\eta}{1-\eta} \cdot \frac{\tau(\theta)}{u}\right]}_{\text{efficiency term}}.$$

This formula is identical to the formulas in our companion paper (formula (23) and its extensions in Section V) once the formulas are expressed with the appropriate sufficient statistics.[6]

The formula shows that the optimal replacement rate equals the Baily-Chetty replacement rate plus a correction term—the product of the elasticity wedge and efficiency term. The Baily-Chetty replacement rate is the optimal replacement rate in partial equilibrium, when labor market tightness does not respond to UI. The correction term is the adjustment required to obtain the optimal replacement rate in general equilibrium, when tightness responds to UI. The correction term measures the effect of UI on welfare through tightness.

The two factors in the correction term have clear economic interpretations. The efficiency term measures the effect of tightness on welfare. It shows that an increase in tightness raises welfare whenever the marginal social cost of unemployment is high relative to its marginal so-

[6] In particular, $\tau(\theta)$ is replaced by $\tau(\theta)/u$ here because the correct sufficient statistic is $\tau(\theta)$ divided by the elasticity of the function $e \cdot f(\theta) \mapsto l$. In the static model, the function is defined by $l = e \cdot f(\theta)$ and has an elasticity of 1. In the dynamic model, the function is defined by (1) and has an elasticity of $1 - l = u$.

cial value. The marginal social cost of unemployment has two components: the utility cost of being unemployed relative to having a job, measured by K, and the fiscal cost of having one more unemployed worker, measured by R. The marginal social value of unemployment is the reduction in recruiting costs that higher unemployment makes possible; this reduction is measured by $[\eta/(1-\eta)]\cdot[\tau(\theta)/u]$. The elasticity wedge measures the effect of UI on tightness. An increase in UI raises tightness whenever the elasticity wedge is positive—that is, whenever the macroelasticity of unemployment with respect to UI (ε^M) is smaller than the microelasticity (ε^m).

II. The Effect of Labor Market Tightness on Social Welfare

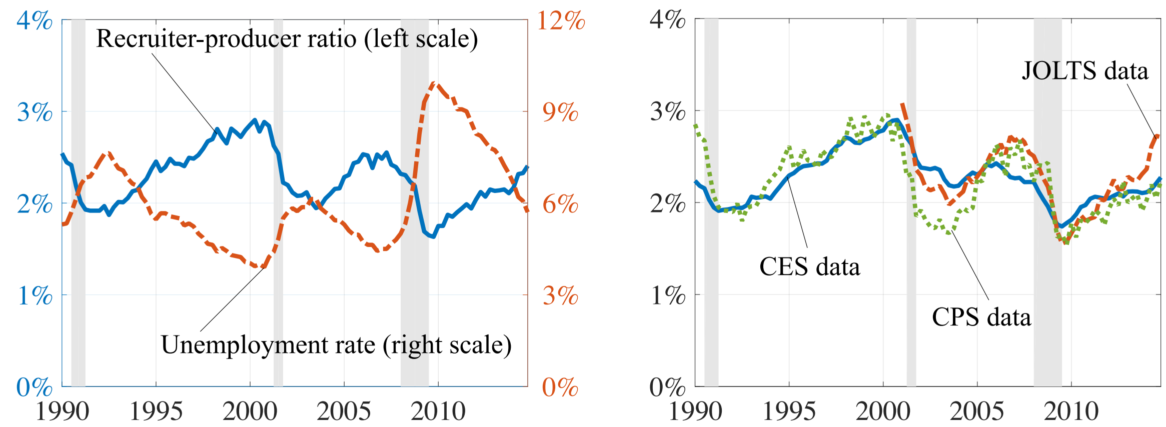
We have seen that whenever the efficiency term is positive, an increase in labor market tightness raises welfare; equivalently, tightness is inefficiently low. Here we apply this empirical criterion to evaluate the effect of tightness on welfare in the United States. Our main task is to estimate the novel statistics in the efficiency term: the recruiter-producer ratio, the UI replacement rate, and the nonpecuniary cost of unemployment.

A. Recruiter-Producer Ratio (τ)

We construct three measures of the recruiter-producer ratio. None of them is perfect, but they paint a consistent picture. Hence, we summarize the information they contain by combining them into a synthetic measure. We later use the synthetic measure to construct the efficiency term. In the empirical work throughout the paper, we use seasonally adjusted monthly data series, and we plot quarterly averages of monthly series.

The first measure of the recruiter-producer ratio is the most transparent. It is based on the size of the recruiting industry, denoted *rec*. The official name of the recruiting industry is "employment placement agencies and executive search services," and its North American Industry Classification System (NAICS) code is 56131. This industry comprises firms engaged in listing employment vacancies and referring or placing applicants for employment, and firms providing executive search, recruitment, and placement services. The number of workers in the industry is computed by the BLS from the Current Employment Statistics (CES) survey since 1990. On average, there are 280,700 workers in the industry.

Of course workers of the recruiting industry only constitute a small fraction of the workers allocated to recruiting in the economy. To measure the total amount of labor devoted to recruiting,



Panel A. Unemployment and recruiter-producer ratio

Panel B. Components of the recruiter-producer ratio

Figure 1: Unemployment Rate and Recruiter-Producer Ratio in the United States, 1990–2014

Notes: Panel A: The unemployment rate comes from CPS data. The recruiter-producer ratio is a synthetic measure that combines the three measures in panel B. Panel B: The recruiter-producer ratio depicted by the solid, blue line is constructed from (12) using CES data on the size of the recruiting industry (NAICS code 56131). The recruiter-producer ratio depicted by the dashed, red line is constructed from (2) and vacancy-filling and job-separation rates from JOLTS data. The recruiter-producer ratio depicted by the dotted, green line is constructed from (2) and vacancy-filling and job-separation rates from CPS data. The shaded areas represent the recessions identified by the National Bureau of Economic Research (NBER).

we scale up *rec* by a factor 8.4. The scaling factor is chosen to ensure that firms devote 2.5% of their labor to recruiting in 1997, thus matching the evidence from the 1997 National Employer Survey. In this survey, the Census Bureau asked 4,500 establishments about their recruiting process, and found that firms spend 2.5% of their labor costs on recruiting (Villena Roldan 2010). Unfortunately, outside of the 1997 National Employer Survey, we cannot observe workers who are not in the recruiting industry but spend time and effort recruiting for their own firm. Scaling-up *rec* is a crude way to account for them. Because the scaling factor is constant over time, we implicitly assume that the share of firms' recruiting outsourced to recruiting firms is constant over the business cycle—in reality this share could fluctuate.

Finally, we construct the recruiter-producer ratio as

$$\tau = \frac{8.4 \cdot rec}{l - 8.4 \cdot rec}, \tag{12}$$

where l is the number of workers in all private industries in CES data. This recruiter-producer ratio is the solid, blue line in Figure 1, panel B. The matching model predicts that when the labor market is slack, it is easy to fill vacancies so the share of the workforce devoted to recruiting is low. But there is a concern that the matching model does not properly describe firms' recruiting process: in bad times, firms may struggle to sift through the large number of applications that they receive, which translates in a higher vacancy- posting cost, such that the share of the workforce devoted to recruiting is actually higher. Our measure of recruiter-producer ratio offers new support for the prediction of the matching model. It shows that firms indeed devote a lower share of labor to recruiting in bad times than in good times: τ is as low as 1.9% after the Great Recession in 2009 and as high as 2.9% during the dot-com boom in 2000. An advantage of this evidence is that it does not assume any structure on the labor market and does not require vacancy data.

We have seen that our first measure of the recruiter-producer ratio has one limitation: it assumes that firms outsource a constant share of their recruiting over the business cycle. Since we cannot evaluate this assumption, we construct two additional measures of the recruiter-producer ratio that do not rely on it. The drawback of these two measures is to require assumptions about the structure of the labor market and more data series.

To construct our second measure of the recruiter-producer ratio, τ, we use equation (2), which relates τ to the vacancy-filling rate, q, the job-separation rate, s, and the vacancy-posting cost, ρ, in the matching model. We directly measure q and s in data constructed by the BLS from the Job Opening and Labor Turnover Survey (JOLTS). We measure q by $q = h/v$, where h and v are the number of hires and number of vacancies in nonfarm industries. We measure s by the separation rate in nonfarm industries. Last, we assume that ρ is constant and set $\rho = 0.81$ to ensure that, like the first recruiter-producer ratio, this one averages 2.7% in 2001.[7] The second measure of τ is the dashed, red line in Figure 1, panel B. It is procyclical because the vacancy-filling rate is countercyclical.

The second measure of the recruiter-producer ratio is to only be available for 2001–2014, while the first measure is available for 1990–2014. We now construct a third measure that is also available for 1990–2014. The drawback of this third measure is that the vacancy-filling and job-separation rates are measured only indirectly. To construct this third measure, we use (2) and data constructed by the BLS from the Current Population Survey (CPS). The job-separation s is constructed in Appendix B from CPS data. We compute q using $q = f/\theta = (e \cdot f)/(v/u)$. The job-finding rate $e \cdot f$ is also constructed in Appendix B from CPS data. To construct the vacancy-unemployment ratio v/u, we measure u with the number of unemployed workers in CPS data, and we measure

[7] In JOLTS in 2001, the average job-separation rate is $s = 4.1\%$ and the average vacancy-filling rate is $q = 1.23$, so we set $\rho = (1.23/0.041) \times 0.027 = 0.81$.

v with the help-wanted advertising index of Barnichon (2010), scaled up so that its average value matches the average number of vacancies in JOLTS data.[8] Finally, we set $\rho = 0.77$ to ensure that the average value of τ in 1997 is 2.5%, as in the National Employer Survey.[9] This third measure of τ is the dotted, green line in Figure 1, panel B. It is also procyclical because the vacancy-filling rate is countercyclical.

Despite being constructed from independent sources, the three measures of the recruiter-producer ratio are similar. We construct a synthetic measure by averaging the two available measures over 1990–2000 and averaging the three measures over 2001–2014. The synthetic measure is displayed in Figure 1, panel A. It averages 2.3% and is procyclical. It peaks at 2.9% in the 2000 boom, and bottoms at 1.6% in the 2009 slump.

In Figure 1, panel A, we also compare the recruiter-producer ratio to the unemployment rate in CPS data. The unemployment rate averages 6.1% and is countercyclical. It falls to 3.9% in 2000 and peaks at 9.9% in 2009. Recruiter-producer ratio τ and unemployment rate u are negatively correlated. Hence, the ratio τ/u featuring in the efficiency term is strongly procyclical. On average, the ratio is $2.3/6.1 = 0.38$. It peaks at 0.74 in 2000 and bottoms at 0.16 in 2009.

B. UI Replacement Rate (R)

The UI program in the United States is much more complex than in our model. In the model, UI provides benefits at a replacement rate R indefinitely. In the United States, UI benefits replace around 50% of prior wages, but only up to a maximum level and for a limited time. The normal duration of benefits is 26 weeks, but benefit duration is extended when unemployment goes up. The Extended Benefits program automatically extends duration by 13 weeks in states where the unemployment rate is above 6.5% and by 20 weeks in states where the unemployment rate is above 8%. Duration is often further extended in severe recessions: for example, in the wake of the Great Recession, the Emergency Unemployment Compensation program extended duration to 99 weeks.

To map the data to our model, we summarize the generosity of the UI program in the United

[8] The Barnichon index combines the online and print help-wanted advertising indices constructed by the Conference Board, which are standard proxies for vacancies. We rescale the Barnichon index to convert it into vacancies. The index averages 80.6 between December 2000 and December 2014. The average number of vacancies in JOLTS data over the same period is 3.71 million. Hence we multiply the Barnichon index by $3.71 \times 10^6/80.6 = 46.0 \times 10^3$ to obtain a proxy for the number of vacancies since 1990. JOLTS data are not available before December 2000, so we could not use them to measure vacancies from 1990.

[9] In 1997, the average job-separation rate is $s = 2.8\%$ and the average vacancy-filling rate is $q = 85\%$, so we set $\rho = (0.85/0.028) \times 0.025 = 0.77$.

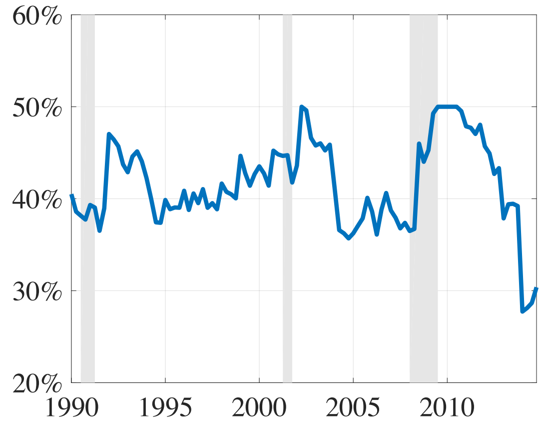


Figure 2: Effective UI Replacement Rate in the United States, 1990–2014

Notes: The effective UI replacement rate is constructed in Appendix C. It is computed as the average replacement rate among all unemployed workers who are currently eligible to UI or were eligible to UI earlier in their current unemployment spell. The shaded areas represent the recessions identified by the NBER.

States with an effective replacement rate. The effective replacement rate gives the average replacement rate among all unemployed workers who are currently eligible to UI or were eligible to UI earlier in their current unemployment spell. It synthesizes the level and duration of benefits; in particular, when the duration of benefits increases, a larger share of jobseekers receive UI, and the effective replacement rate rises. The effective replacement rate is constructed in Appendix C and plotted in Figure 2.

While the nominal replacement rate of UI is about 50%, our effective replacement rate is only 42% on average because benefits have a finite duration (jobseekers who stop receiving UI have a replacement rate of zero). And while the nominal replacement rate does not vary over time, the effective replacement rate does because benefit duration varies. In fact, the effective replacement rate rises after each recession of the 1990–2014 period. The reason is that the potential duration of benefits was extended after each recession—more precisely, benefit duration was extended more than unemployment duration increased. After the 2001 and 2008–2009 recessions, the effective replacement rate even reached 50%, implying that almost no eligible workers saw their benefits expire during their unemployment spell. After the UI extensions expired in January 2014, the effective replacement rate plunged to 28%, the lowest in the period. This is because many jobseekers had been unemployed for a long time in 2014; these jobseekers all lost their benefits when benefit duration was shortened.

C. *Nonpecuniary Cost of Unemployment (Z)*

The nonpecuniary cost of unemployment measures the difference between the well-being of an unemployed worker and that of an employed worker with the same consumption level. It is high if unemployed workers suffer high mental or physical health costs, and if home production or job search are costly compared to employment. It is low if unemployed workers enjoy leisure.

In well-being surveys, Di Tella, MacCulloch and Oswald (2003) find that even after controlling for income and other personal characteristics, being unemployed is very costly. In the US General Social Survey (GSS), they find that a worker becoming unemployed suffers as much as someone divorcing or someone dropping from the top to the bottom income quartile (Table 5). In the Eurobarometer survey, they are able to quantify the cost of unemployment. They find that becoming unemployed is as bad as losing \$3,500 of income a year (p. 819). In the countries and years in their data, the average GDP per capita is \$7,809 and the average unemployment rate is 8.6% (Table 6). With a labor share of 0.7, the average wage per worker is $w = 0.7 \times \$7809/(1-0.086) = \$5980$. Since the average marginal utility from \$1 in the population is ϕ, they find a nonpecuniary cost of unemployment of $Z = (3500/5980) \times w \times \phi = 0.6 \times w \times \phi$. Other studies using well-being surveys find even larger estimates of Z.[10]

One potential issue with estimates of Z from well-being surveys is that they are not based on observed choices. Borgschulte and Martorell (2016) address this limitation. They study how servicemembers' choice between reenlisting and exiting the military is affected by the unemployment rate in the local labor market where they would enter. Using rich military personnel records, they find that servicemembers would forgo 1.5% in reenlistment earnings to avoid an unemployment rate higher by one percentage point. With log utility, this choice implies that $0.01 \times \left[\ln(c^e/c^h) + Z\right] = 0.015 \times \phi \times w$, or $Z = \left[1.5 - \ln(c^e/c^h)/(\phi \times w)\right] \times \phi \times w$. With a consumption drop upon unemployment below 20% (Appendix D) and a labor share above 0.5, we find that $\ln(c^e/c^h)/(\phi \times w) \leq 0.5$, which implies $Z \geq \phi \times w$.[11] This estimate of Z is even larger than the estimate from Di Tella, MacCulloch and Oswald (2003).

[10] Using the GSS, Blanchflower and Oswald (2004, p. 1373, p. 1382) find that becoming unemployed is as bad as losing \$60,000 of income a year. The average yearly income in their data is below \$20,000, so they identify a huge nonpecuniary cost of unemployment: $Z \geq 3 \times w \times \phi$. Using the German Socio-Economic Panel, Winkelmann and Winkelmann (1998) also find that the nonpecuniary cost of unemployment is much larger than the pecuniary cost.

[11] With a consumption drop upon unemployment below 20%, $1 - c^h/c^e \leq 0.2$ so $c^e/c^h \geq 1/0.8$. With log utility, $1/\phi = l \cdot c^e + (1-l) \cdot c^h \leq c^e$ so $1/(\phi \cdot w) \leq c^e/w$. With a labor share $\alpha \geq 0.5$, we infer from Appendix E that $c^e/w \leq l/\alpha + (1-l) \leq 1/\alpha \leq 2$. Combining these results, we have $\ln(c^e/c^h)/(\phi \times w) \leq -2 \times \ln(0.8) \leq 0.5$.

In sum, workers suffer a possibly large nonpecuniary cost of unemployment. This finding contrasts with the typical calibration in macroeconomic models: there, unemployed workers derive utility from consumption and additional utility from leisure, which amounts to setting $Z < 0$. To reach a compromise between the typical calibration and the evidence above, we set $Z = 0.3 \times \phi \times w$. This is the mid-point between $Z = 0$, the calibration in Shimer (2005), and $Z = 0.6 \times \phi \times w$, the estimate from Di Tella, MacCulloch and Oswald (2003). We will consider the cases $Z = 0$ and $Z = 0.6 \times \phi \times w$ in the sensitivity analysis of Section IV.

Finally, we assume that Z does not depend on labor market conditions. It is true that people get used to many traumatic events, returning to a normal level of well-being after an initial period of adaptation (Kahneman et al. 2004, p. 429). If there was adaptation to unemployment, the average value of Z could be lower when unemployment is higher because then unemployment spells last longer so on average unemployed workers are more habituated to unemployment. But adaptation does not occur with unemployment: people remain unhappy for a long time after losing their job (Winkelmann and Winkelmann 1998; Lucas et al. 2004). Hence, it seems reasonable to assume that Z is independent of the average duration of unemployment spells.

D. The Efficiency Term

With the evidence collected in this section and evidence from the literature, we construct the efficiency term between 1990 and 2014. We only summarize the construction here: the evidence from the literature is described in Appendix D and the derivations are in Appendix E.

We begin by estimating the utility cost of unemployment, K. We set the consumption drop upon unemployment to 12% and the coefficient of relative risk aversion to 1. These estimates combined with our estimate of the nonpecuniary cost of unemployment imply that $K = 46\%$. This means that a worker who becomes unemployed loses 46% of the utility provided by a wage.

Of course, the utility cost of unemployment depends on the generosity of UI. (In contrast, labor market conditions do not affect the utility cost of unemployment.) The generosity of UI affects the utility cost because it affects the consumption of unemployed workers and job search. Since UI generosity varies over time, we determine how it affects the utility cost of unemployment. The cost $K = 46\%$ is an average value, achieved when the UI replacement rate takes its average value $R = 42\%$. For a generic R, we find that

$$K = 0.46 - 1.32 \times (R - 0.42). \tag{13}$$

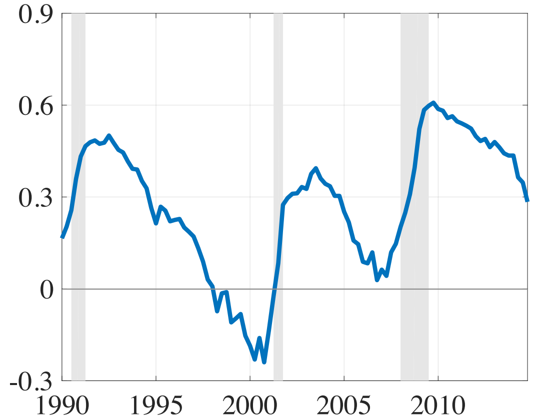


Figure 3: Efficiency Term in the United States, 1990–2014

Notes: The efficiency term is constructed using (14). When the efficiency term is zero, labor market tightness is at its efficient level; when it is positive, labor market tightness is inefficiently low; and when it is negative, labor market tightness is inefficiently high. The shaded areas represent the recessions identified by the NBER.

When UI becomes more generous, it is less costly to be unemployed because the consumption drop upon unemployment and job search are reduced.

Finally, we set the discouraged-worker elasticity to $\varepsilon^f = 0$ and the matching elasticity to $\eta = 0.6$. We obtain

$$\text{efficiency term} = 0.88 - 0.32 \times (R - 0.42) - 1.5 \times \frac{\tau}{u}. \tag{14}$$

Then we compute the efficiency term using the times series for τ/u and R from Figures 1 and 2. The efficiency term is plotted in Figure 3.

Normally the efficiency term is slightly positive: it averages 0.3 over 1990–2014. In bad times it is very positive: it reaches 0.5 in 1992, in the wake of the 1990–1991 recession, 0.4 in 2003, after the 2001 recession, and 0.6 in 2009, at the end of the Great Recession. It is only negative in very good times: it falls below 0 between 1999 and 2001, during the dot-com bubble, with a trough at -0.2 in 2000. This pattern implies that the labor market is inefficiently slack during slumps and inefficiently tight only during strong booms. On average the labor market seems a bit too slack.

The efficiency term is countercyclical mostly because the ratio τ/u is procyclical. The ratio τ/u fluctuate more widely than the replacement rate (τ/u varies between 0.16 and 0.74 while R varies between 0.28 and 0.5), and the coefficient in front of τ/u is larger than that in front of the replacement rate (1.5 against 0.32), so that τ/u drives most of the fluctuations of the efficiency term. We have seen that τ/u governs the marginal social value of unemployment, which is to reduce the resources that firms devote to recruiting. Hence, the efficiency term is countercyclical because the reduction in recruiting costs achieved by adding one unemployed worker is high in booms and low in slumps.

Of course there remains some uncertainty about the estimates of the statistics in the efficiency term. Section IV provides a sensitivity analysis illustrating how the results change with alternative values of the nonpecuniary cost of unemployment, matching elasticity, consumption drop upon unemployment, and coefficient of relative risk aversion. These statistics affect the level of the efficiency term, but not its cyclical behavior. The takeaway of Figure 3 is therefore not the level of the efficiency term but its sharp countercyclical fluctuations. These fluctuations imply that an increase in labor market tightness yields a much larger welfare gain in slumps than in booms.

III. The Effect of UI on Labor Market Tightness

We have seen that an increase in UI raises tightness whenever the macroelasticity of unemployment with respect to UI (ε^M) is smaller than the microelasticity (ε^m), or equivalently whenever the elasticity wedge ($1-\varepsilon^M/\varepsilon^m$) is positive. Here we apply this criterion to evaluate the effect of UI on tightness. We start by comparing estimates of the macroelasticity and microelasticity obtained in various studies. Next, we review estimates of the elasticity wedge obtained directly from the response of tightness to UI. Finally, we review evidence on the various channels through which UI affects tightness.

A. Microelasticity and Macroelasticity of Unemployment with Respect to UI

We review estimates of the microelasticity and macroelasticity of unemployment with respect to UI. Then we compare their magnitude to measure the elasticity wedge.

Estimates of the Microelasticity (ε^m). The ideal experiment to estimate the microelasticity is to offer more generous UI benefits to a randomly selected and small subset of jobseekers and compare unemployment durations between treated and control jobseekers. In practice, the microelasticity is estimated by comparing individuals with different benefits in the same labor market while controlling for individual characteristics. We consider only studies estimating the microelasticity from variations in the potential duration of UI benefits (not their level) because all the studies estimating the macroelasticity use variations in benefit duration.[12]

A large literature has estimated the microelasticity, and provides compelling evidence that a worker who receives more generous UI stays unemployed longer.[13] Katz and Meyer (1990) provide high-quality estimates of the microelasticity by exploiting variations in benefit duration in the Continuous Wage and Benefit History (CWBH) dataset, an administrative dataset covering twelve US states for 1978–1983. Across specifications, they obtain microelasticities in the range 0.36–0.53.[14] Using a regression kink design on the same data, Landais (2015) estimates microelasticities in the range 0.41–0.85 (Table 3, column (1), row "ε_B").

Estimates of the Macroelasticity (ε^M). Estimating the macroelasticity is more difficult than estimating the microelasticity because it requires exogenous variations in UI benefits across comparable labor markets, instead of exogenous variations across comparable individuals within a labor market. The ideal experiment to estimate the macroelasticity is to offer more generous UI benefits to all individuals in a randomly selected subset of isolated labor markets and compare unemployment rates between treated and control labor markets. Identifying exogenous variations in UI across labor markets is difficult; as a result, few estimates of the macroelasticity are available.

An early estimate of the macroelasticity comes from the study by Card and Levine (2000). They analyze a natural experiment in New Jersey, where UI benefits were extended from 26 to 39 weeks in 1996 for political and not economic reasons, minimizing the need to control for other aggregate shocks and the endogeneity of policy. They estimate that the extension reduced the exit rate from unemployment by 16.6% (p. 136 and Table 6, column (2)). This translates into a macroelasticity $\varepsilon^M = 0.166/\left[(39-26)/26\right] = 0.32$.

Several papers use the UI benefit extensions enacted in the United States in the 2009–2012 period to estimate the macroelasticity. Exploiting these variations is challenging because benefits

[12] Most studies measure the elasticity of unemployment duration or the elasticity of the exit rate from unemployment with respect to UI. These elasticities are nearly identical to the elasticity of the unemployment rate with respect to UI. Indeed, the exit rate from unemployment is $e \cdot f(\theta)$ and the average duration of unemployment is $1/(e \cdot f(\theta))$. The unemployment rate is $u = s/(s + e \cdot f(\theta))$, but $s \ll e \cdot f(\theta)$ in US data, so $u \approx s/(e \cdot f(\theta))$. Thus, the elasticities of the exit rate from unemployment, unemployment duration, and unemployment rate are approximately equal.

[13] See Krueger and Meyer (2002) and Chetty and Finkelstein (2013) for surveys.

[14] On Table 3, they find that reducing the potential duration of benefits from 39 to 35 weeks lowers the duration of unemployment spells from 18.4 to 17.6 weeks, so that $\varepsilon^m = \left[(18.4-17.6)/18.4\right]/\left[(35-39)/39\right] = 0.42$. They also find that reducing the potential duration of benefits from 39 to 26 weeks lowers the duration of unemployment spells from 18.4 to 16.2 weeks, so that $\varepsilon^m = \left[(18.4-16.2)/18.4\right]/\left[(35-26)/39\right] = 0.36$. They repeat the analysis in Table 4 for a different empirical specification. They find $\varepsilon^m = \left[(14.7-13.9)/14.7\right]/\left[(35-39)/39\right] = 0.53$ and $\varepsilon^m = \left[(14.7-12.6)/14.7\right]/\left[(35-26)/39\right] = 0.43$.

were extended in response to the rise in unemployment at the onset of the Great Recession. Thus, these papers face a severe endogeneity problem when measuring the effect of UI on unemployment.

To address the endogeneity issue, Hagedorn et al. (2016) compare border counties across states with different benefit durations. They find that permanently increasing benefit duration from 26 to 99 weeks would increase the unemployment rate from 5% to 9.1% (p. 14). This translates into a macroelasticity $\varepsilon^M = [(9.1-5)/5]\,/\,[(99-26)/26] = 0.29$. This relatively large estimate has been challenged by several studies, however. For instance, Dieterle, Bartalotti and Brummet (2016) show that the key identifying assumption of Hagedorn et al. (2016)—economic smoothness at border counties straddling two states—does not seem to hold: individuals cross state borders to search for jobs in the high-benefit state. Using a more flexible regression discontinuity approach, they find that permanently increasing benefit duration from 26 to 99 weeks would only increase the unemployment rate from 5% to 6.1% (p. 4). This a translate into a smaller macroelasticity: $\varepsilon^M = [(6.1-5)/5]\,/\,[(99-26)/26] = 0.08$.[15]

Two other studies address the endogeneity issue by exploiting variations in UI due to measurement errors in the real-time state unemployment rates used to trigger UI extensions. Coglianese (2015) uses differences between the real-time unemployment rates and the definitive unemployment rates, obtained after revisions. He finds that an increase in UI caused by the measurement error and not the true labor market conditions raises employment growth, although he cannot rule out zero effect. This implies that the macroelasticity is at most zero. Chodorow-Reich and Karabarbounis (2016) use variations between the real-time unemployment rates and the unemployment rates obtained after exogenous sampling errors in the CPS are corrected. They estimate that raising benefit duration from 26 to 99 weeks would increase the unemployment rate by at most 0.3 percentage point (p. 4), which translates into a minuscule macroelasticity: $\varepsilon^M = 0.02$.[16] There is a concern, however, that this measurement-error approach does not completely solve the endogeneity issue (Hagedorn, Manovskii and Mitman 2016).

Mixed Estimates. Rothstein (2011), Farber and Valletta (2015), and Valletta (2014) study the effects of the UI extensions during the Great Recession, without trying to disentangle micro and macro effects. They use CPS data.[17] They rely on variations in benefit duration across states

[15] Coglianese (2015), Amaral and Ice (2014), and Boone et al. (2016) also replicate the estimation of Hagedorn et al. (2016) and find that the results are sensitive to the empirical specification and time period.

[16] The average unemployment rate in 2008, when the extensions were enacted, was 5.8%. The macroelasticity therefore is $\varepsilon^M = [0.3/5.8]\,/\,[(99-26)/26] = 0.02$.

[17] These studies have to rely on lower-quality, survey data because higher-quality, administrative data have not made

and over time, thus estimating a mixture of microelasticity and macroelasticity.[18] Rothstein (2011) obtains a mixed elasticity around 0.06.[19] Farber and Valletta (2015) find that an additional month of benefits raises unemployment duration by 0.06 months (Table 6, column (1)). Their estimate is one third of that from Katz and Meyer (1990) (p. 901): it implies a mixed elasticity of $0.45/3 = 0.15$. Valletta (2014) finds that a 10-week increase in benefit duration translates into a 1.5-week increase in unemployment spells, which translates into a mixed elasticity of 0.39.[20] Taken together, the three studies provide an average mixed elasticity of 0.2.

Implied Estimates of the Elasticity Wedge ($1-\varepsilon^M/\varepsilon^m$). The microelasticity estimates obtained in administrative data are in the 0.4–0.8 range. In contrast, macroelasticity estimates are in the 0–0.3 range. Hence, available evidence suggests that the macroelasticity is smaller than the microelasticity and the elasticity wedge is positive. A lower bound on the elasticity wedge is $1-\varepsilon^M/\varepsilon^m = 1-0.3/0.4 = 0.25$, and an upper bound is $1-\varepsilon^M/\varepsilon^m = 1-0.1/0.6 = 0.8$.

One way to obtain a negative elasticity wedge would be to compare the large macroelasticity obtained by Hagedorn et al. (2016) with the small elasticity obtained by Rothstein (2011), Farber and Valletta (2015), and Valletta (2014). The elasticity wedge implied by these studies is $1-\varepsilon^M/\varepsilon^m = 1-0.29/0.2 = -0.45$. Yet, this comparison is difficult to interpret because Rothstein, Farber, and Valletta estimate a mixture of microelasticity and macroelasticity. In fact, Hagedorn et al. (2016, p. 31) note that their macroelasticity estimate is lower than the microelasticity estimates obtained in administrative data by Katz and Meyer (1990) and others.

Comparing microelasticity to macroelasticity obtained in different contexts has a drawback, however: elasticities may vary across the business cycle or across policy variations. Therefore, it is better to estimate microelasticity and macroelasticity in the same context. This is what Johnston and Mas (2016) do. They analyze an unexpected 16-week reduction in benefit duration in Missouri in 2011. Implementing a regression discontinuity design in administrative data, they find that a jobseeker whose benefits are shortened by one month finds a job 0.3 month earlier, which trans-

accessible to researchers.

[18] Many studies have simultaneously used UI variations within and across labor markets (Krueger and Meyer 2002). By doing so, they estimate a mixture of microelasticity and macroelasticity.

[19] Table 3, columns 1–5 show that the benefit extensions reduced the exit rate from unemployment by 1.7–2.3 percentage points from a base of 22.4%. This represents a reduction in the exit rate from unemployment by $2/22.4 = 9\%$. Since the potential duration of benefits increased to 65 weeks in 2010 from a base of 26 weeks (p. 145), this finding translates into an elasticity of $(0.09)/[(65-26)/26] = 0.06$.

[20] The average unemployment duration in the data is 28.2 weeks, and the average benefit duration is 74.2 weeks (Table 2, column (1)). The estimated effects therefore translate into an elasticity $(1.5/28.2)/(10/74.2) = 0.39$.

lates into a microelasticity between 0.37 and 0.78 (p. 30). Then, with a difference-in-differences estimator taking other US states as a control, they find a reduction in the Missouri unemployment rate commensurate to that implied by the microelasticity (p. 34). This finding implies that the macroelasticity equals the microelasticity, or $1-\varepsilon^M/\varepsilon^m=0$.

B. Response of Tightness to UI

It is usually impossible to observe the labor market tightness because job-search effort is unobservable. In these circumstances, comparing microelasticity and macroelasticity of unemployment with respect to UI is a natural avenue to estimate the effect of UI on tightness. An exception is Marinescu (2016): using data on vacancies and job applications from CareerBuilder.com, a major employment website, she is able to measure tightness over time and thus directly estimate the effect UI on tightness. She considers the UI benefit extensions implemented in the United States in 2008–2011. With an event-study approach, she finds that the extensions reduced the number of job applications sent but had no effect on vacancies. Since tightness is the ratio of vacancies to aggregate search effort, the increase in UI raised tightness and the elasticity wedge is positive. Marinescu reports an elasticity wedge of $1-\varepsilon^M/\varepsilon^m=0.4$ (p. 31).

Another way to measure the effect of UI on tightness is an experiment where the treatment is receiving more generous UI benefits and the design has a double randomization: (i) some randomly selected labor markets are treated and some are not, and (ii) within treated labor markets, all but a randomly selected subset of jobseekers are treated. Control jobseekers in treated markets are only affected by the change in tightness in their labor market. Hence, tightness goes up, and the elasticity wedge is positive, when the unemployment duration of control jobseekers in control labor markets is longer than that of control jobseekers in treated labor markets.

Two US studies employ a design that is conceptually similar to a double randomization, with the practical limitation that the treatment (receiving UI) is not randomly assigned. Levine (1993) studies the spillovers between insured and uninsured jobseekers. In microdata from the CPS, he finds that when UI increases and insured jobseekers search less, the job-finding probability of uninsured jobseekers goes up (p. 79). This finding implies a positive elasticity wedge. Moreover, in state-level unemployment data, he finds that when UI increases, the unemployment rate of insured jobseekers goes up and the unemployment rate of uninsured jobseekers goes down in such a way the aggregate unemployment rate does not change (Table 5, columns 1–3). This suggests that the macroelasticity is 0 and the elasticity wedge is 1. Farber and Valletta (2015) also observe spillovers: they find that ineligible unemployed workers find a job faster after the benefit extensions of the 2007–2012 period (p. 894). This finding implies a positive elasticity wedge.

Evidence from other countries also points to a positive elasticity wedge. Lalive, Landais and Zweimüller (2015) estimate the elasticity wedge in administrative data for Austria. They use a natural experiment offering the desired design: the Regional Extended Benefit Program implemented in 1988–1993. The treatment is an increase in benefit duration from 52 to 209 weeks for eligible unemployed workers in a subset of regions. They find that ineligible unemployed workers in treated labor markets experienced significantly lower unemployment duration, which implies a positive elasticity wedge. They report $1-\varepsilon^M/\varepsilon^m = 0.21$ (p. 3567).

C. Rat-Race and Job-Creation Channels

In matching models, UI affects tightness through the rat-race and job-creation channels (Landais, Michaillat and Saez 2016, Figure 4). Several papers study these two channels, providing additional evidence on how UI affects tightness.

A good way to determine whether the rat-race channel is present is to examine whether an increase in search effort by some jobseekers, induced for example by job-search programs, reduces the job-finding probability of the other jobseekers in the same labor market. This strategy has been implemented in two European countries. Crepon et al. (2013) analyzes a large-scale randomized experiment in France. Some young educated jobseekers are treated by receiving job-search assistance. The experiment has a double-randomization design: (i) some areas are treated and some are not, (ii) within treated areas some jobseekers are treated and some are not. They find that treated jobseekers have a higher job-finding probability than control jobseekers in the same area, and critically, that control jobseekers in treated areas face a lower job-finding probability than control jobseekers in control areas. Using a smaller-scale randomized field experiment in Denmark, Gautier et al. (2012) obtain similar results. Their treatment is a job-search assistance program. They find that control jobseekers in treated regions find jobs more slowly than jobseekers in control regions. Both studies find that the presence of jobseekers who search intensely hurts the prospects of the other jobseekers in the same labor market. This finding suggests that the number of jobs in the labor market is somewhat limited and that the rat-race channel operates. In fact, the results from

France translate into an elasticity wedge $1-\varepsilon^M/\varepsilon^m = 0.4$.[21]

A good way to measure the job-creation channel is to investigate whether more generous UI leads to higher wages. Several studies estimate the effect of UI on wages in US data and find no effect. Johnston and Mas (2016, p. 21) find that re-employment earnings do not change after a cut in the duration of UI benefits. Marinescu (2016, p. 23) finds that benefit duration does not affect wages advertised by firms. Finally, in high-frequency longitudinal survey data on more than 6,000 unemployed workers in New Jersey, Krueger and Mueller (2016, p. 175) find no relationship between reported reservation wages and the generosity of UI benefits. They obtain this finding by cross-sectional analysis and by analyzing the response of reservation wages to an extension of UI benefits from 79 weeks to 99 weeks. The results are similar outside the United States: for example, using administrative data from Austria, Card, Chetty and Weber (2007, p. 1514) find that extended UI benefits do not affect wages in subsequent jobs.[22] As UI does not seem to affect wages, the job-creation channel is likely to be small.

D. *The Elasticity Wedge*

Microelasticity estimates obtained in administrative data are at least as large as available macroelasticity estimates, suggesting that the elasticity wedge is positive. Comparing the estimates yields a lower bound on the elasticity wedge of $1-\varepsilon^M/\varepsilon^m = 0$ and an upper bound of $1-\varepsilon^M/\varepsilon^m = 0.8$. By measuring directly the response of labor market tightness to UI, Marinescu (2016) obtains an estimate that falls in the middle of this range: $1-\varepsilon^M/\varepsilon^m = 0.4$. The finding that an increase in UI improves the prospects of uninsured jobseekers, coupled with evidence in favor of the rat-race channel but not the job-creation channel, offer further support for a positive elasticity wedge. Based on this evidence, we set the average value of the elasticity wedge to $1-\varepsilon^M/\varepsilon^m = 0.4$. This calibration implies that an increase UI raises tightness.

[21] Let e^C be the effort of control jobseekers, $e^T > e^C$ the effort of treated jobseekers, f^C the job-finding rate in control areas, and f^T the job-finding rate in treated areas. Crepon et al. (2013, Table IX, panel B, column 1) find that treated jobseekers face a higher job-finding probability than control jobseekers in the same area: $\left[e^T - e^C\right] \cdot f^T = 5.7\%$. But control jobseekers in treated areas face a lower job-finding probability than control jobseekers in control areas: $e^C \cdot \left[f^T - f^C\right] = -2.1\%$. Therefore the job-finding probability of treated jobseekers in treated areas is higher than that of control jobseekers in control areas by only $\left[e^T \cdot f^T\right] - \left[e^C \cdot f^C\right] = 5.7\% - 2.1\% = 3.6\%$. As ε^m is proportional to $\left[e^T - e^C\right] \cdot f^T$ and ε^M to $\left[e^T \cdot f^T\right] - \left[e^C \cdot f^C\right]$, the implied elasticity wedge is $1-\varepsilon^M/\varepsilon^m = 1-3.6/5.7 = 0.4$.

[22] By inducing longer unemployment durations, a more generous UI could have a negative effect on wages if the duration of unemployment affects the productivity of jobseekers or is interpreted by employers as a negative signal. Schmieder, von Wachter and Bender (2016) use administrative data for Germany to disentangle this negative effect from the positive effect of UI on wages through bargaining. They control for the duration of the unemployment spell and find a negative effect of UI on wages through longer unemployment durations but no effect through bargaining.

Clearly, there remains significant uncertainty about the exact value of the elasticity wedge. By comparing the macroelasticity obtained by Hagedorn et al. (2016) with the elasticities obtained by Rothstein (2011), Valletta (2014), and Farber and Valletta (2015), it is even possible to obtain a negative elasticity wedge, around $1-\varepsilon^M/\varepsilon^m = -0.4$.[23] Thus, to accommodate the range of possible estimates, we will consider the cases $1-\varepsilon^M/\varepsilon^m = 0$ and $1-\varepsilon^M/\varepsilon^m = -0.4$ in the sensitivity analysis of Section IV.

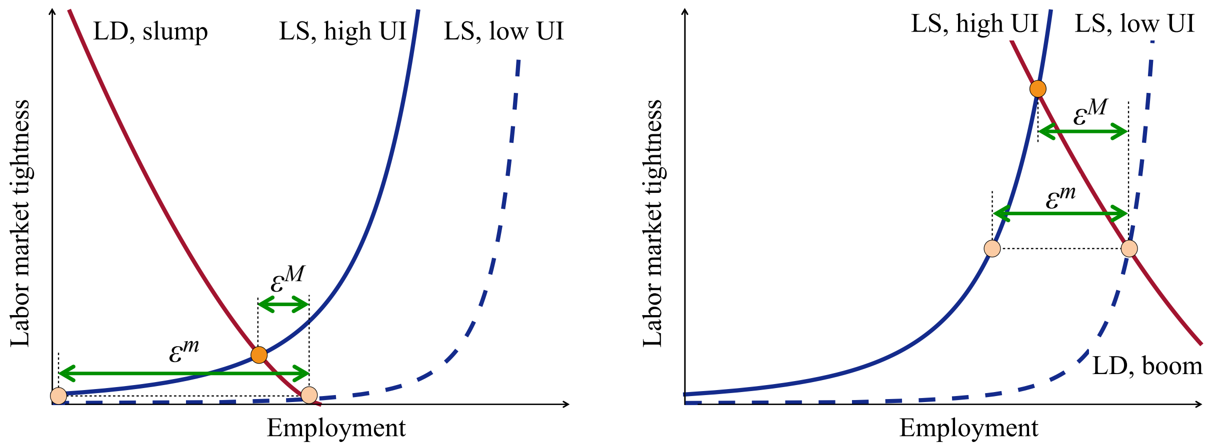
Having studied the average value of the elasticity wedge, we examine how the elasticity wedge depends on labor market conditions. Some evidence obtained in US data suggests that the elasticity wedge is higher in bad times than in good times. Valletta (2014) finds that uninsured jobseekers find jobs more rapidly after the UI extensions of the Great Recession, but this spillover is only present in states with high unemployment (p. 18). This result suggests that an increase in UI raises labor market tightness when unemployment is high but not otherwise, which means that the elasticity wedge is positive when unemployment is high but closer to zero otherwise. Toohey (2017) obtains additional evidence by exploiting variations in job-search requirements across US states and over time. He finds that when search requirements are more stringent, UI recipients search more and find jobs faster (pp. 21–25). But increasing search effort has a smaller effect on the unemployment rate in bad times than in good times (pp. 25–32). This finding implies that the elasticity wedge is larger in bad times. Evidence from European countries also suggests that the elasticity wedge is larger in bad times. Lalive, Landais and Zweimüller (2015, p. 3590) finds that the elasticity wedge is larger in slack labor markets. Crepon et al. (2013, pp. 565–567, p. 575) also find that the rat-race channel is stronger in areas and periods with higher unemployment.

The evidence suggests that the elasticity wedge increases when labor market conditions deteriorate, but it is not precise enough to quantify the increase. We therefore rely on more structural evidence to quantify the increase. We use the job-rationing model of Michaillat (2012), because it is consistent with a positive elasticity wedge and the rat-race channel. (The model is presented in Section IV.D, and the derivations are in Appendix E.) In the model, the elasticity wedge is

$$1-\frac{\varepsilon^M}{\varepsilon^m} = 1\bigg/\left(1+\frac{\eta}{1-\eta}\cdot\frac{\alpha}{1-\alpha}\cdot\frac{1}{1+\varepsilon^f}\cdot\frac{\tau(\theta)}{u}\right) > 0, \tag{15}$$

where the parameter α comes from the production function $y(n) = a\cdot n^{\alpha}$. Since the ratio τ/u is

[23] As we have seen, however, this estimate is difficult to interpret because Rothstein, Farber, and Valletta's studies estimate a mixture of microelasticity and macroelasticity.



Panel A. High elasticity wedge in a slump

Panel B. Low elasticity wedge in a boom

Figure 4: Countercyclicality of the Elasticity Wedge in the Job-Rationing Model

Notes: The figure depicts labor demand (LD) and labor supply (LS) as a function of labor market tightness. It shows the effect of a more generous UI on labor supply and depicts the microelasticity ε^m and macroelasticity ε^M. These elasticities describe the partial-equilibrium (ε^m) and general-equilibrium (ε^M) responses of employment to UI. Comparing ε^m and ε^M gives the elasticity wedge: $1-\varepsilon^M/\varepsilon^m$. The two panels contrast a slump, which is an equilibrium with low technology, to a boom, which is an equilibrium with high technology.

procyclical, this elasticity wedge is countercyclical, in line with the evidence.

The mechanism generating a countercyclical elasticity wedge in the job-rationing model is illustrated in Figure 4. Imagine that UI becomes more generous. Since the microelasticity is positive, jobseekers search less (labor supply shifts inward). If the tightness did not respond, firms would want to employ the same number of workers as before, but they would not be able to because the lower search effort reduces the number of workers that firms are able to hire (labor demand is higher than labor supply at the current tightness). Firms would respond to the shortage of new hires by posting more vacancies (a movement along the labor supply curve). In a slump (panel A), the matching process is congested by search effort since there are many jobseekers and few vacancies. Hence, the extra vacancies are filled with high probability and employment comes back around its initial level. Accordingly, the macroelasticity is much smaller than the microelasticity. Conversely, in a boom (panel B), the matching process is congested by vacancies. Hence, the extra vacancies are filled with low probability and employment does not grow much. In this case, the macroelasticity is only slightly smaller than the microelasticity.[24]

Using (15), we compute the derivative of $1-\varepsilon^M/\varepsilon^m$ with respect to τ/u. This derivative is

[24]The countercyclicality of the elasticity wedge is closely connected to the countercyclicality of the government multiplier in Michaillat (2014). Both rely on how labor market congestion fluctuates over the business cycle.

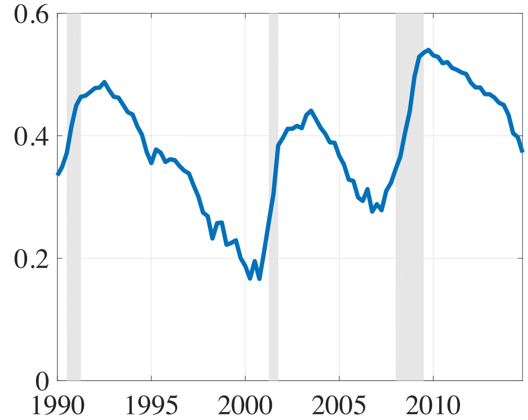


Figure 5: Elasticity Wedge in the United States, 1990–2014

Notes: The elasticity wedge is constructed using (16). The elasticity wedge is positive whenever the macroelasticity of unemployment with respect to UI is smaller than the microelasticity of unemployment with respect to UI. A positive elasticity wedge indicates that an increase in UI raises labor market tightness. The shaded areas represent the recessions identified by the NBER.

obviously negative. We calibrate the parameters of the model so that $1-\varepsilon^M/\varepsilon^m = 0.4$ when τ/u takes its average value of 0.38. This requires $(\eta \cdot \alpha) / \left[(1-\eta)\cdot(1-\alpha)\cdot(1+\varepsilon^f)\right] = 4$. Using this number, we find that the derivative of $1-\varepsilon^M/\varepsilon^m$ with respect to τ/u is -0.65 when $\tau/u = 0.38$. Thus, the linear approximation of the elasticity wedge around its average value is

$$(16) \qquad 1-\frac{\varepsilon^M}{\varepsilon^m} = 0.4 - 0.65 \times \left(\frac{\tau}{u} - 0.38\right).$$

This linear equation says that the elasticity wedge is 0.4 when τ/u takes its average value of 0.38 and that the wedge is lower when τ/u is higher (which happens in good times).

From (16) and the time series for u and τ displayed in Figure 1, we construct a time series for the elasticity wedge. This time series is displayed in Figure 5. The elasticity wedge fluctuates in a countercyclical fashion around 0.4. At the end of the 1990–1991 recession, the wedge reached 0.49; at the end of the Great Recession, it reached 0.54; but in the boom of 2000, it fell to 0.17. With this calibration, when UI becomes more generous, the increase in unemployment caused by lower search effort is offset by an increase in tightness; furthermore, the offset is large in bad times (large elasticity wedge) but small in good times (small elasticity wedge).

IV. Applications of the Optimal UI Formula

We have found that an increase in tightness yields larger welfare gains in slumps than in booms, and that an increase in UI raises tightness. Combining this evidence with available knowledge about the Baily-Chetty replacement rate, we determine the optimal UI replacement rate in the United States between 1990 and 2014. There remains uncertainty about the estimates of the statistics in the optimal UI formula, so we offer a comprehensive sensitivity analysis.

A. The Welfare Effect of a Small Change in UI

We begin with an exercise typical in the literature (for example, Chetty 2008): evaluating our optimal UI formula at the current replacement rate. If the formula holds, we infer that the current replacement rate is optimal. If it does not hold, we can determine whether the current replacement rate is inefficiently high or inefficiently low. In the next subsection, we will go one step further and use the formula to solve for the optimal replacement rate.

Our aim here is to compare the right-hand and left-hand sides of formula (11) at the current policy. The replacement rate, efficiency term, and elasticity wedge at the current policy are plotted in Figures 2, 3, and 5. The last thing to do is compute the Baily-Chetty replacement rate at the current policy. The Baily-Chetty replacement rate is well researched, so we have estimates for its key statistics: as described in Appendix D, we set the coefficient of relative risk aversion to 1, the consumption drop upon unemployment to 12%, and the microelasticity of unemployment duration with respect to benefit level to 0.4. As there is some uncertainty about the exact estimates of these statistics, Section IV provides a sensitivity analysis illustrating how the results change with different estimates. Thus, as explained in Appendix E, we find that

$$\text{(17)}\quad \text{Baily-Chetty replacement rate} = 4.6\times[0.46-1.32\times(R-0.42)]\times[0.12-0.26\times(R-0.42)]\,.$$

The Baily-Chetty replacement rate depends on the replacement rate R, because R affects the terms ΔU and $U'(c^h)$. On the other hand, the Baily-Chetty replacement rate does not depend on labor market conditions. This is because empirical evidence suggests that the consumption drop upon unemployment and microelasticity do not depend much on labor market conditions. We compute the Baily-Chetty replacement rate with (17) and the times series for R in Figure 2.

Figure 6 displays the difference between the right-hand side and left-hand side of formula (11).

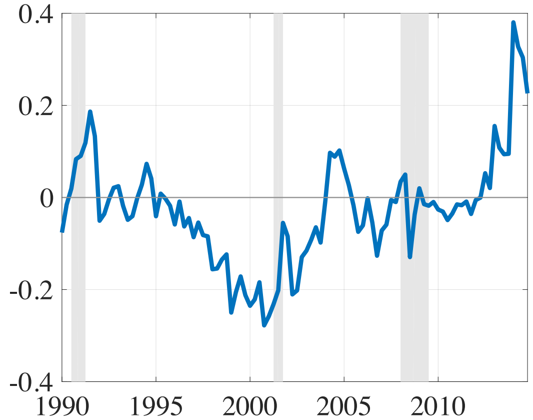


Figure 6: Welfare Effect of a Small UI Increase in the United States, 1990–2014

Notes: The welfare effect of a small increase in UI equals the Baily-Chetty replacement rate + the elasticity wedge × the efficiency term - the current replacement rate. The Baily-Chetty replacement rate is constructed using (17). The elasticity wedge is constructed using (16) and depicted in Figure 5. The efficiency term is constructed using (14) and depicted in Figure 3. The current replacement rate is constructed in Appendix C and depicted in Figure 2. When the welfare effect is positive, the current replacement rate is too low. When the welfare effect is negative, the current replacement rate is too high. The shaded areas represent the recessions identified by the NBER.

When the difference is positive, a small increase in UI raises welfare and the current replacement rate is too low. When it is negative, a small increase in UI reduces welfare and the current replacement rate is too high. The average difference is broadly zero, which means that the average replacement rate in the United States is close to optimal between 1990 and 2014. There are two periods when UI seems suboptimal, however. First, UI was too generous in 1997–2001, during the dot-com boom. Second, while the increase in UI during the Great Recession was broadly optimal, UI was inefficiently low after 2013. Since unemployment duration was high after the Great Recession, many jobseekers lost their benefits when benefit duration was reduced to normal levels in 2014. This lead to a dramatic reduction in the generosity of UI, which fell below the level warranted by our formula.

B. *The Optimal UI Replacement Rate*

We now use our optimal UI formula to compute the optimal replacement rate over the business cycle. Here, a technical challenge arises: in optimal policy formulas expressed with sufficient statistics, the statistics are implicit functions of the policy and economic conditions. Thus, such formulas cannot be used to directly solve for the policy. To address this issue, we extend the method of Gruber (1997) and express all the statistics in our formula as a function of UI and labor market conditions. We also take into account how labor market conditions are affected by changes in UI. With this approach, we can compute optimal UI using solely our formula, without specifying an underlying structural model.

In the analysis, all the statistics have been expressed as a function of the replacement rate R and the ratio τ/u, which characterizes labor market conditions. Yet, as R changes, it affects θ and u and therefore $\tau(\theta)$ and $\tau(\theta)/u$. To solve for the optimal replacement rate, we have to link τ/u to R. In Appendix E, we derive a relation between τ/u and R by linearizing the function $R \mapsto \tau/u$ around the observed values $\hat{R}$ and $\hat{\tau}/\hat{u}$. We find that

$$\frac{\tau}{u} = \frac{\hat{\tau}}{\hat{u}} + 0.01 \times \left(R - \hat{R}\right). \tag{18}$$

Here the response of τ/u to R is very small (the derivative is 0.01), but this result is not general. Under some of the alternative calibrations in the sensitivity analysis, the response is stronger.

We now rewrite formula (11). Using (14), (16), and (17), and (18), we obtain

$$\begin{aligned} R = {} & 4.6 \times [0.46 - 1.32 \times (R - 0.42)] \times [0.12 - 0.26 \times (R - 0.42)] \\ & + \left[0.4 - 0.65 \times \left(\frac{\hat{\tau}}{\hat{u}} - 0.38 + 0.01 \times \left(R - \hat{R}\right)\right)\right] \\ & \times \left[0.88 - 0.32 \times (R - 0.42) - 1.5 \times \left(\frac{\hat{\tau}}{\hat{u}} + 0.01 \times \left(R - \hat{R}\right)\right)\right]. \end{aligned} \tag{19}$$

Then, using this formula and the series for $\hat{\tau}/\hat{u}$ and $\hat{R}$ plotted in Figures 1 and 3, we solve for R over the 1990–2014 period. The optimal replacement rate is displayed on Figure 7, together with the effective replacement rate in the United States.

The average generosity of UI in the United States is close to optimal: the US replacement rate averages 42% while the optimal replacement rate averages 40%. Additional evidence is necessary to cement this finding, however, because the level of the optimal replacement rate is sensitive to the values of statistics that have not been precisely estimated yet.

Moreover, the effective replacement rate in the United States seems to be adjusted nearly optimally when recessions occur. After the 1990–1991 recession the US replacement rate rose to 47%, which was close to the optimum of 46%. And after the Great Recession the US replacement rate rose to 50%, which was the optimum. An exception is the 2001 recession: then the US replacement rate reached 50% , which was much higher than the optimum of 41%.

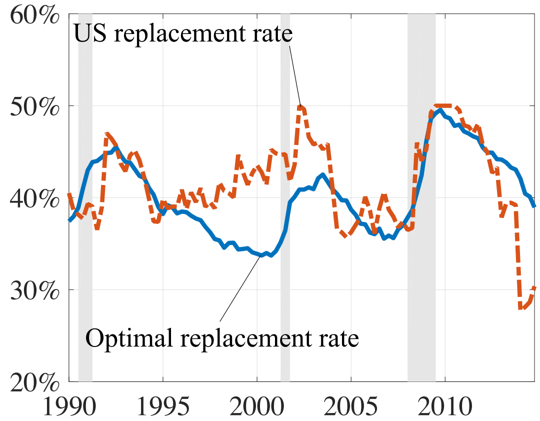


Figure 7: Optimal UI Replacement Rate in the United States, 1990–2014

Notes: The optimal UI replacement rate (solid, blue line) is obtained by solving formula (19). The effective UI replacement rate in the United States (dashed, red line) is constructed in Appendix C. The shaded areas represent the recessions identified by the NBER.

In contrast, UI was excessively generous during the dot-com boom and insufficiently generous after the Great Recession. At the peak of the boom in 2000, the US replacement rate remained around 45% while the optimum fell to 33%. And after the Great Recession, the US replacement rate plunged to 28% while the optimum was much higher, at 39%.

C. *Sensitivity Analysis*

There remains uncertainty about the estimates of the statistics in the optimal UI formula. Here we explore the sensitivity of the optimal replacement rate to the estimates of several key statistics. The results are presented in Figure 8: in each panel, we plot the benchmark optimal replacement rate from Figure 7 (solid, blue line) and two alternative optimal replacement rates obtained by changing the value of one statistic (dotted, green line and dashed, red line). We find that the cyclicality of the optimal replacement rate is only affected by the sign of the elasticity wedge. On the other hand, the level of the optimal replacement rate is affected by the values of all the statistics. (The derivations are relegated to Appendix F.)

Elasticity Wedge $(1-\varepsilon^M/\varepsilon^m)$. Our optimal UI formula shows that the sign of the elasticity wedge determines the cyclicality of the optimal replacement rate. Indeed, the correction term in the formula is procyclical with a negative wedge, acyclical with a zero wedge, and countercyclical with a positive wedge. Since the Baily-Chetty replacement rate does not depend on the state of the labor market (see expression (17)), the fluctuations of the correction term directly translate into fluctuations of the optimal replacement rate. This is what we see in panel A. The panel displays the optimal replacement rates obtained with a zero elasticity wedge, a negative elasticity wedge of $1-\varepsilon^M/\varepsilon^m = -0.4$, and the benchmark elasticity wedge from Figure 5—this benchmark has a positive average value of $1-\varepsilon^M/\varepsilon^m = 0.4$ and is countercyclical. When the elasticity wedge is positive, the optimal replacement rate is countercyclical, varying between 33% in bad times and 50% in good times. When the elasticity wedge is zero, the optimal replacement rate is constant at 35%. And when the elasticity wedge is negative, the optimal replacement rate becomes procyclical, varying between 27% in bad times and 39% in good times.

Microelasticity of Unemployment Duration with Respect to Benefit Level (ε_b^m). A higher microelasticity ε_b^m and thus a higher microelasticity ε^m yields a lower Baily-Chetty replacement rate and thus a lower optimal replacement rate. This is what we see in panel B. The panel displays the optimal replacement rates obtained with a low microelasticity $\varepsilon_b^m = 0.2$, a high microelasticity $\varepsilon_b^m = 0.6$, and the benchmark microelasticity $\varepsilon_b^m = 0.4$. With $\varepsilon_b^m = 0.2$, the optimal replacement rate is higher than the benchmark: 48% on average, with a minimum of 43% and a maximum of 55%. With $\varepsilon_b^m = 0.6$, the optimal replacement rate is lower: 36% on average, with a minimum of 28% and a maximum of 46%.

Nonpecuniary Cost of Unemployment (Z). A higher nonpecuniary cost of unemployment primarily raises the utility cost of unemployment, K, and thus the efficiency term.[25] Since the elasticity wedge is positive, a higher nonpecuniary cost raises the correction term and yields a higher optimal replacement rate. This is what we see in panel C. The panel displays the optimal replacement rates obtained with a low nonpecuniary cost $Z = 0$, a high nonpecuniary cost $Z = 0.6 \times \phi \times w$, and the benchmark nonpecuniary cost $Z = 0.3 \times \phi \times w$. With $Z = 0$, the optimal replacement rate is lower than the benchmark: 38% on average, with a minimum of 35% and a maximum of 42%. With $Z = 0.6 \times \phi \times w$, the optimal replacement rate is higher: 45% on average, with a minimum of 35% and a maximum of 58%.

Matching Elasticity (η). A higher matching elasticity increases the term $[\eta/(1-\eta)] \cdot (\tau/u)$ and thus lowers the efficiency term. Since the elasticity wedge is positive, a higher matching elasticity

[25] The nonpecuniary cost has secondary effects on the Baily-Chetty replacement rate through the factor ΔU.

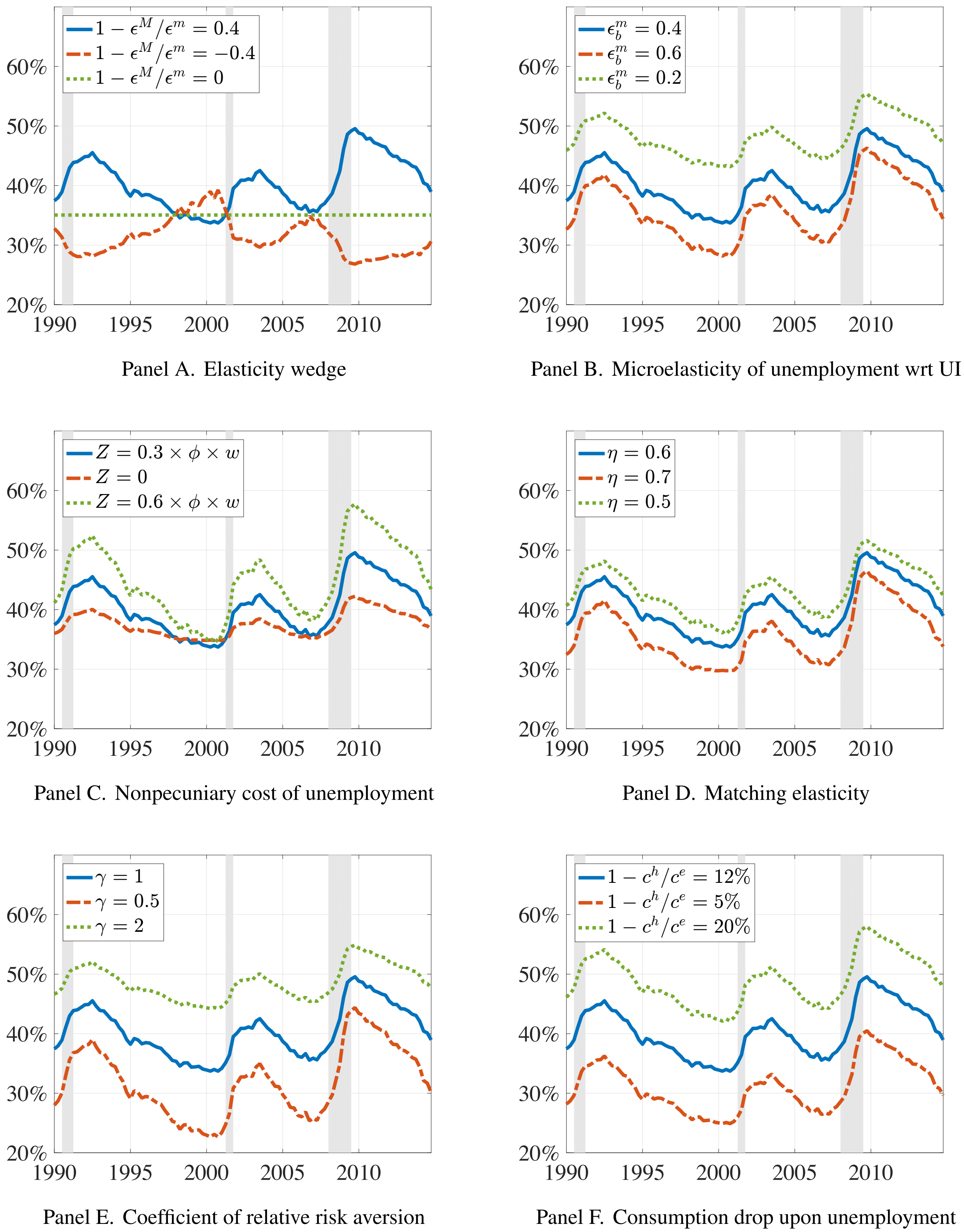


Figure 8: Sensitivity of the Optimal UI Replacement Rate to the Value of Six Key Statistics

Notes: The figure applies to the US labor market for the 1990–2014 period. The optimal UI replacement rates are constructed by solving formulas akin to (19). These formulas are derived in Appendix F. The shaded areas represent the recessions identified by the NBER.

lowers the correction term and yields a lower optimal replacement rate. This is what we see in panel D. The panel displays the optimal replacement rates obtained with a low matching elasticity $\eta = 0.5$, a high matching elasticity $\eta = 0.7$, and the benchmark matching elasticity $\eta = 0.6$. With $\eta = 0.5$, the optimal replacement rate is higher than the benchmark: 43% on average, with a minimum of 36% and a maximum of 52%. With $\eta = 0.7$, the optimal replacement rate is lower: 36% on average, with a minimum of 30% and a maximum of 47%.

Coefficient of Relative Risk Aversion (γ). A higher coefficient of relative risk aversion raises the gap between marginal utilities, $1/U'(c^e) - 1/U'(c^h)$. Thus, it raises the Baily-Chetty replacement rate and yields a higher optimal replacement rate. This is what we see in panel E. The panel displays the optimal replacement rates obtained with a low risk aversion $\gamma = 0.5$, a high risk aversion $\gamma = 2$, and the benchmark risk aversion $\gamma = 1$. With $\gamma = 0.5$, the optimal replacement rate is lower than the benchmark: 32% on average, with a minimum of 23% and a maximum of 44%. With $\gamma = 2$, the optimal replacement rate is higher: 49% on average, with a minimum of 44% and a maximum of 55%.

Consumption Drop Upon Unemployment ($1 - c^h/c^e$). A higher consumption drop upon unemployment raises the gap between marginal utilities, $1/U'(c^e) - 1/U'(c^h)$, and the utility cost of unemployment, K. Thus, it raises the Baily-Chetty replacement rate, the efficiency term, and the correction term (since the elasticity wedge is positive). As a result, a higher consumption drop yields a higher optimal replacement rate. This is what we see in panel F. The panel displays the optimal replacement rates obtained with a low consumption drop $1 - c^h/c^e = 5\%$, a high consumption drop $1 - c^h/c^e = 20\%$, and the benchmark consumption drop $1 - c^h/c^e = 12\%$. With $1 - c^h/c^e = 5\%$, the optimal replacement rate is lower than the benchmark: 31% on average, with a minimum of 25% and a maximum of 41%. With $1 - c^h/c^e = 20\%$, the optimal replacement rate is higher: 49% on average, with a minimum of 42% and a maximum of 58%.

D. Accuracy

Given that the optimal UI formula (19) relies on several approximations, it is important to check its accuracy. We now simulate a matching model to verify that in a fully specified, structural model, solving (19) yields a similar policy as solving the exact optimal UI formula (11).

The matching model used for the simulations is the job-rationing model from Michaillat (2012). This model generates a positive elasticity wedge and is therefore consistent with our preferred estimate of $1-\varepsilon^M/\varepsilon^m = 0.4$, unlike other matching models.[26] Furthermore, because real wages are somewhat rigid in the model, technology shocks generate inefficient fluctuations in tightness, consistent with the fluctuations of the efficiency term in Figure 3.[27]

To obtain the job-rationing model, we specialize our generic matching model. First, we specify a concave production function: $y(n) = a \cdot n^{\alpha}$. The parameter $a > 0$ measures the technology of the firm, and the parameter $\alpha \in (0,1)$ captures decreasing marginal returns to labor. Second, we specify a wage schedule that is independent of UI and partially rigid with respect to technology: $w = \omega \cdot a^{1-\zeta}$. The parameter $\omega > 0$ determines the wage level, and the parameter $\zeta \in (0,1]$ measures the rigidity of wages with respect to technology. If $\zeta = 0$, wages are flexible: they are proportional to technology. If $\zeta = 1$, wages are fully rigid: they do not respond to technology. Under these assumptions, labor demand is

$$l^d(\theta,a) = \left[\frac{\alpha}{\omega} \cdot \frac{a^{\zeta}}{(1+\tau(\theta))^{\alpha}}\right]^{1/(1-\alpha)}. \tag{20}$$

Labor demand is decreasing in tightness because when tightness is higher, hiring a worker requires more recruiters and is therefore less profitable. Labor demand is increasing in technology because when technology rises, the wage grows less than proportionally (by wage rigidity), so hiring a worker is more profitable. Labor demand is independent of UI because the wage is.

We calibrate the job-rationing model to match the empirical evidence presented in the paper. (The calibration is relegated to Appendix G.) We compare three UI programs: in the first, the replacement rate remains constant at 42%, the average US value; in the second, the replacement rate solves the approximate optimal UI formula (19) using the ratio $\hat{\tau}/\hat{u}$ observed when $\hat{R} = 42\%$; and in the third, the replacement rate solves the exact optimal UI formula (11). The first program is a simplified version of the UI program in the US. The second program is the program that would be implemented by a policymaker living under the first program and using formula (19). The third

[26] Landais, Michaillat and Saez (2016, Section IV) show that different matching models generate different elasticity wedges. The job-rationing model generates a positive wedge. In contrast, the standard model of Pissarides (2000) generates a negative wedge and the fixed-wage model of Hall (2005*a*) generates a zero wedge.

[27] Technology shocks are a conventional and convenient way to generate business cycles in matching models. Michaillat and Saez (2015) show that these models also accommodate other shocks, particularly aggregate demand shocks. What we need to match the evidence in Figure 3 are labor demand shocks—whether these are aggregate demand or technology shocks is unimportant.

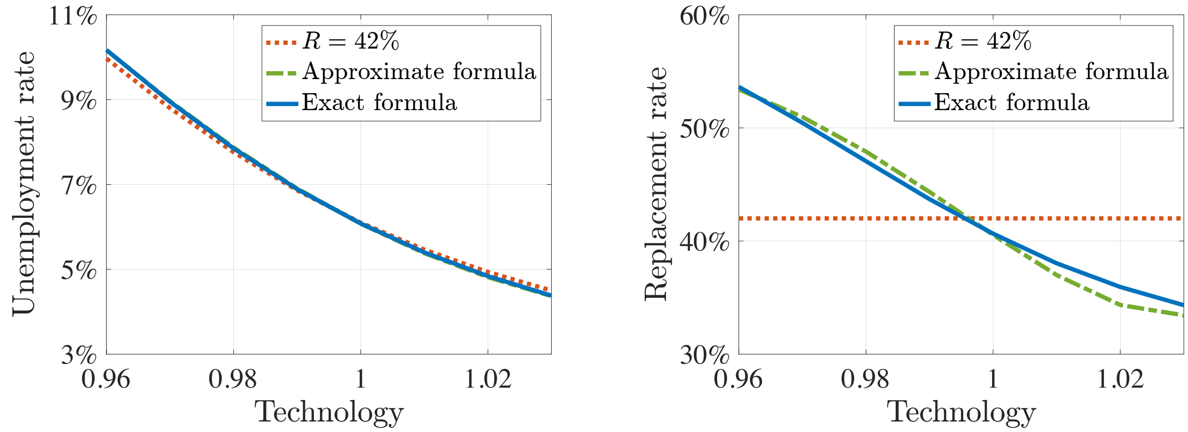


Figure 9: Accuracy of the Approximate Optimal UI Formula

Notes: This figure compares equilibria where the replacement rate is set at $R = 42\%$ (dotted, red line), set using the exact optimal UI formula (11) (solid, blue line), and set using the approximate optimal UI formula (19) (dashed, green line). The equilibria are parametrized by various levels of technology. The results are obtained by simulating the job-rationing model from Michaillat (2012) with the calibration presented in Appendix G.

program is the optimal UI program in the model. Under each program, we compute equilibria spanning the business cycle: a slump is an equilibrium with low technology and thus low labor demand and high unemployment; a boom is an equilibrium with high technology and thus high labor demand and low unemployment.

The main results are displayed in Figure 9. (Additional results are provided in Appendix H.) When technology increases from 0.96 to 1.03 and the replacement rate remains constant, the unemployment rate falls from 10.0% to 4.5%. As noted by Michaillat (2012), the modest amount of wage rigidity observed in microdata—which we use to calibrate the wage schedule—generates large fluctuations in unemployment. Of course, the unemployment rate responds when the replacement rate adjusts from its original level of 42% to the levels given by formulas (11) and (19). In slumps these levels are above 42% so the unemployment rate rises above its original level; in booms these levels are below 42% so the unemployment rate falls below its original level. The responses of the unemployment rate are small, however, because the macroelasticity of unemployment with respect to UI is not large, especially in slumps.

As the unemployment rate u falls, the recruiter-producer ratio τ and ratio τ/u increase. As a consequence, the replacement rate given by the approximate formula (19) falls from 53% to 33%. At the same time, the replacement rate given by the exact formula (11) falls from 54% to 34%. In fact, the deviation between the two replacement rates is always less than 2 percentage points. Hence, despite the approximations required to derive formula (19), the formula is quite accurate.

E. The Welfare Gains from Optimal UI

To conclude the analysis, we use the simulations of the job-rationing model to assess the welfare gains achieved by moving from two natural starting points—the Baily-Chetty replacement rate and the average US replacement rate $R = 42\%$—to the optimal replacement rate. At each stage of the business cycle, using (5), we compute the welfare gain ΔSW achieved by switching to the optimal policy. We make the welfare gains more concrete by comparing them with the welfare gains achieved by reducing unemployment. We compute $\Delta SW^u = \Delta SW / \left[u \times \left(U(c^e) - U(c^h) + Z\right)\right]$. A welfare gain $\Delta SW^u = 1\%$ corresponds to the welfare gain achieved by moving 1% of the unemployed workers from unemployment to employment.[28]

The main results are displayed in Figure 10. (Additional results are provided in Appendix H.) The left-hand panel displays the replacement rate of 42%, the Baily-Chetty replacement rate, and the optimal replacement rate over the business cycle. The corresponding unemployment rates are displayed in Figure 9 (the unemployment rate in the Baily-Chetty case is not displayed but virtually the same). While the optimal replacement is countercyclical, the Baily-Chetty replacement rate is slightly procyclical. In addition, the Baily-Chetty replacement rate is lower: it averages 35% while the optimal replacement rate averages 40%. The cyclical behaviors of the Baily-Chetty and optimal replacement rates are different because the correction term in the optimal UI formula is countercyclical. Their average levels are different because the correction term is positive on average.

The right-hand panel shows the welfare gains achieved by switching to optimal UI. In good times, moving from the Baily-Chetty replacement rate to the optimal replacement rate generates no welfare gain because the Baily-Chetty replacement rate is approximately optimal. But in bad times, it generates sizable welfare gains because the Baily-Chetty replacement rate is well below the optimal replacement rate. When the unemployment rate is 10%, for instance, the Baily-Chetty replacement rate is below the optimum by more than 20 percentage points and the welfare gain is about 4.3%—that is, switching to optimal UI is equivalent to reducing unemployment by 4.3%, or 0.4 percentage points.

In normal times, moving from a replacement rate of 42% to the optimal replacement rate generates no welfare gains because $R = 42\%$ is approximately optimal. But in good and bad times, it

[28] Moving one worker from unemployment to employment increases welfare by $\left(U(c^e) - U(c^h) + Z\right)$; hence, $u \times \left(U(c^e) - U(c^h) + Z\right)$ is the welfare gain achieved by moving all the unemployed workers to employment.

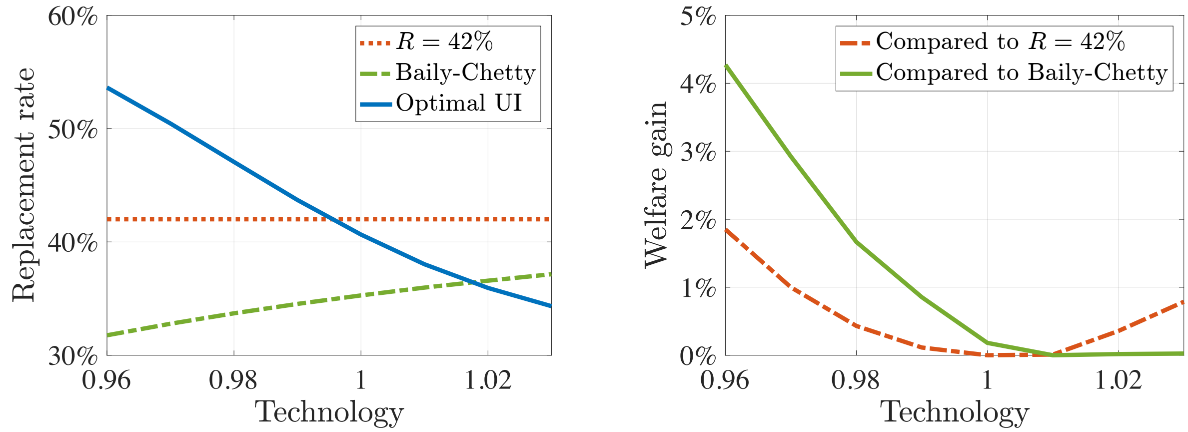


Figure 10: Welfare Gains from Optimal UI

Notes: The left-hand panel depicts a replacement rate of $R = 42\%$ (dotted, red line), the Baily-Chetty replacement rate (dashed, green line), and the optimal replacement rate (solid, blue line). The optimal replacement rate is computed using formula (11) and the Baily-Chetty replacement rate using the expression in (11). The right-hand panel describes the welfare gains achieved by moving from $R = 42\%$ to the optimal replacement rate (dashed, red line) and from the Baily-Chetty replacement rate to the optimal replacement rate (solid, green line). The welfare gains are measured in terms of unemployment: a gain of 1% corresponds to the welfare gain achieved by moving 1% of unemployed workers from unemployment to employment. The equilibria are parametrized by various levels of technology. The results are obtained by simulating the job-rationing model from Michaillat (2012) with the calibration in Appendix G.

generates modest gains. When the unemployment rate is 10%, the optimal replacement rate is 12 percentage points above 42% and the welfare gain is 1.9%. When the unemployment rate is 4.5%, the optimal replacement rate is 8 percentage points below 42% and the welfare gain is 0.8%.

Finally, we compute the average welfare gains achieved by switching to optimal UI. To calculate the average gains, we use the empirical distribution of the unemployment rate over 1990–2014. Given that both the replacement rate of 42% and the Baily-Chetty replacement rate are close to optimal when the unemployment rate is about average, the average gains are small. Moving from $R = 42\%$ to the optimal replacement rate generates an average welfare gain of 0.5%, and moving from the Baily-Chetty to the optimal replacement rate generates an average welfare gain of 0.8%.

V. Summary and Additional Applications

In this paper we have explored how the optimal generosity of UI varies over the business cycle in the United States. The analysis is based on the sufficient-statistic formula developed in a companion paper. The formula says that the optimal replacement rate of UI is the Baily-Chetty replacement rate plus a correction term that measures the effect of UI on welfare through labor market tightness. Using median estimates of the statistics in the formula, we have found that tightness is inefficiently low in slumps and inefficiently high in booms, and that an increase in UI raises tightness. Thus, the correction term in the formula is countercyclical, making the optimal replacement rate countercyclical. The results may obviously need to be amended as new estimates become available.

We have found that the efficiency term is positive in slumps but negative in booms. In theory, labor market tightness can be at an efficient or an inefficient level. But this finding implies that tightness is inefficiently low in slumps and inefficiently high in booms. Thus the stabilization of the labor market remains incomplete.

We have also found that the macroelasticity of unemployment with respect to UI is smaller than the microelasticity. This finding points to the policies that could be used to stabilize the labor market. Typical matching models predict that policies stimulating labor supply (such as search requirements, search monitoring, or placement assistance) are effective in reducing unemployment in slumps, but policies stimulating labor demand (such as public employment) are not. The finding that the macroelasticity is smaller than the microelasticity suggests that the job-rationing model of Michaillat (2012) may be better suited to describe the labor market. This model predicts that, to reduce unemployment in bad times, policies stimulating labor demand would be more effective than policies stimulating labor supply (Michaillat 2012, 2014).

Furthermore, we have measured the share of the workforce allocated to recruiting and the nonpecuniary cost of unemployment. These measures might be useful in the context of other macroeconomic policies because they provide a way to measure the unemployment gap (Michaillat and Saez 2016). In turn, the unemployment gap is a key determinant of the optimal level of several macroeconomic policies: monetary policy (Michaillat and Saez 2016), government debt (Michaillat and Saez 2014), and the provision of public goods (Michaillat and Saez 2015).

Finally, we have computed the optimal replacement rate of UI using solely the formula—without specifying a structural model. Our approach was to leverage empirical evidence to express the statistics in the formula as functions of UI and labor market conditions, and to describe how labor market conditions are affected by changes in UI. We believe that this formula-based approach could be applied to other macroeconomic policies.

References

Amaral, Pedro, and Jessica Ice. 2014. "Reassessing the Effects of Extending Unemployment Insurance Benefits." Federal Reserve Bank of Cleveland Economic Commentary 2014-23.

Barnichon, Regis. 2010. "Building a Composite Help-Wanted Index." *Economics Letters*, 109(3): 175–178.

Blanchflower, David G., and Andrew J. Oswald. 2004. "Well-Being Over Time in Britain and the USA." *Journal of Public Economics*, 88(7–8): 1359–1386.

Boone, Christopher, Arindrajit Dube, Lucas Goodman, and Ethan Kaplan. 2016. "Unemployment Insurance Generosity and Aggregate Employment." Institute for the Study of Labor (IZA) Discussion Paper 10439.

Borgschulte, Mark, and Paco Martorell. 2016. "Paying to Avoid Recession: Using Reenlistment to Estimate the Cost of Unemployment." Institute for the Study of Labor (IZA) Discussion Paper 9680.

Card, David, and Phillip B. Levine. 2000. "Extended Benefits and the Duration of UI Spells: Evidence from the New Jersey Extended Benefit Program." *Journal of Public Economics*, 78(1–2): 107–138.

Card, David, Raj Chetty, and Andrea Weber. 2007. "Cash-On-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market." *Quarterly Journal of Economics*, 122(4): 1511–1560.

Chetty, Raj. 2008. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy*, 116(2): 173–234.

Chetty, Raj, and Amy Finkelstein. 2013. "Social Insurance: Connecting Theory to Data." In *Handbook of Public Economics*. Vol. 5, , ed. Alan J. Auerbach, Raj Chetty, Martin Feldstein and Emmanuel Saez, 111–193. Amsterdam:Elsevier.

Chodorow-Reich, Gabriel, and Loukas Karabarbounis. 2016. "The Limited Macroeconomic Effects of Unemployment Benefit Extensions." National Bureau of Economic Research (NBER) Working Paper 22163.

Coglianese, John. 2015. "Do Unemployment Insurance Extensions Reduce Employment?" http://scholar.harvard.edu/files/coglianese/files/coglianese_2015_ui_extensions.pdf.

Crepon, Bruno, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora. 2013. "Do Labor Market Policies Have Displacement Effect? Evidence from a Clustered Randomized Experiment." *Quarterly Journal of Economics*, 128(2): 531–580.

Dieterle, Steven, Otavio Bartalotti, and Quentin Brummet. 2016. "Revisiting the Effects of Unemployment Insurance Extensions on Unemployment: A Measurement Error-Corrected Regression Discontinuity Approach." Edinburgh School of Economics Discussion Paper 268.

Di Tella, Rafael, Robert J. MacCulloch, and Andrew J. Oswald. 2003. "The Macroeconomics of Happiness." *Review of Economics and Statistics*, 85(4): 809–827.

Farber, Henry S., and Robert Valletta. 2015. "Do Extended Unemployment Benefits Lengthen Unemployment Spells? Evidence from Recent Cycles in the U.S. Labor Market." *Journal of Human Resources*, 50(4): 873–909.

Gautier, Pieter, Paul Muller, Bas van der Klaauw, Michael Rosholm, and Michael Svarer. 2012. "Estimating Equilibrium Effects of Job Search Assistance." Institute for the Study of Labor (IZA) Discussion Paper 6748.

Gruber, Jonathan. 1997. "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review*, 87(1): 192–205.

Hagedorn, Marcus, Fatih Karahan, Iourii Manovskii, and Kurt Mitman. 2016. "Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects." National Bureau of Economic Research (NBER) Working Paper 19499.

Hagedorn, Marcus, Iourii Manovskii, and Kurt Mitman. 2016. "Interpreting Recent Quasi-Experimental Evidence on the Effects of Unemployment Benefit Extensions." National Bureau of Economic Research (NBER) Working Paper 22280.

Hall, Robert E. 2005*a*. " Employment Fluctuations with Equilibrium Wage Stickiness." *American Economic Review*, 95(1): 50–65.

Hall, Robert E. 2005*b*. "Employment Efficiency and Sticky Wages: Evidence from Flows in the Labor Market." *Review of Economics and Statistics*, 87(3): 397–407.

Hosios, Arthur J. 1990. "On the Efficiency of Matching and Related Models of Search and Unemployment." *Review of Economic Studies*, 57(2): 279–298.

Johnston, Andrew, and Alexandre Mas. 2016. "Potential Unemployment Insurance Duration and Labor Supply: The Individual and Market-Level Response to a Benefit Cut." National Bureau of Economic Research (NBER) Working Paper 22411.

Kahneman, Daniel, Alan B. Krueger, David Schkade, Norbert Schwarz, and Arthur Stone. 2004. "Toward National Well-Being Accounts." *American Economic Review*, 94(2): 429–434.

Katz, Lawrence F., and Bruce D. Meyer. 1990. "The Impact of the Potential Duration of Unemployment Benefits on the Duration of Unemployment." *Journal of Public Economics*, 41(1): 45–72.

Kekre, Rohan. 2016. "Unemployment Insurance In Macroeconomic Stabilization." https://sites.google.com/site/rohankekre/JMP_rkekre_v070616.pdf.

Kolsrud, Jonas, Camille Landais, Peter Nilsson, and Johannes Spinnewijn. 2015. "The Optimal Timing of Unemployment Benefits: Theory and Evidence from Sweden." Institute for the Study of Labor (IZA) Discussion Paper 9185.

Kroft, Kory, and Matthew J. Notowidigdo. 2016. "Should Unemployment Insurance Vary With the Unemployment Rate? Theory and Evidence." *Review of Economic Studies*, 83(3): 1092–1124.

Krueger, Alan B., and Andreas I. Mueller. 2016. "A Contribution to the Empirics of Reservation Wages." *American Economic Journal: Economic Policy*, 8(1): 142–179.

Krueger, Alan B., and Bruce D. Meyer. 2002. "Labor Supply Effects of Social Insurance." In *Handbook of Public Economics*. Vol. 4, , ed. Alan J. Auerbach and Martin Feldstein, 2327–2392. Amsterdam:Elsevier.

Lalive, Rafael, Camille Landais, and Josef Zweimüller. 2015. "Market Externalities of Large Unemployment Insurance Extension Programs." *American Economic Review*, 105(12): 3564–3596.

Landais, Camille. 2015. "Assessing the Welfare Effects of Unemployment Benefits Using the Regression Kink Design." *American Economic Journal: Economic Policy*, 7(4): 243–278.

Landais, Camille, Pascal Michaillat, and Emmanuel Saez. 2016. "A Macroeconomic Approach to Optimal Unemployment Insurance: Theory." *American Economic Journal: Economic Policy*, forthcoming.

Levine, Phillip B. 1993. "Spillover Effects Between the Insured and Uninsured Unemployed." *Industrial and Labor Relations Review*, 47(1): 73–86.

Lucas, Richard E., Andrew E. Clark, Yannis Georgellis, and Ed Diener. 2004. "Unemployment alters the set point for life satisfaction." *Psychological Science*, 15(1): 8–13.

Marinescu, Ioana. 2016. "The General Equilibrium Impacts of Unemployment Insurance: Evidence from a Large Online Job Board." National Bureau of Economic Research (NBER) Working Paper 22447.

Michaillat, Pascal. 2012. "Do Matching Frictions Explain Unemployment? Not in Bad Times." *American Economic Review*, 102(4): 1721–1750.

Michaillat, Pascal. 2014. "A Theory of Countercyclical Government Multiplier." *American Economic Journal: Macroeconomics*, 6(1): 190–217.

Michaillat, Pascal, and Emmanuel Saez. 2014. "An Economical Business-Cycle Model." National Bureau of Economic Research (NBER) Working Paper 19777.

Michaillat, Pascal, and Emmanuel Saez. 2015. "The Optimal Use of Government Purchases for Stabilization." National Bureau of Economic Research (NBER) Working Paper 21322.

Michaillat, Pascal, and Emmanuel Saez. 2016. "Monetary Policy and Unemployment: A Matching Approach." http://www.pascalmichaillat.org/9.html.

Mitman, Kurt, and Stanislav Rabinovich. 2015. "Optimal Unemployment Insurance in an Equilibrium Business-Cycle Model." *Journal of Monetary Economics*, 71: 99–118.

Pissarides, Christopher A. 2000. *Equilibrium Unemployment Theory*. . 2nd ed., Cambridge, MA:MIT

Press.

Pissarides, Christopher A. 2009. "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica*, 77(5): 1339–1369.

Rothstein, Jesse. 2011. "Unemployment Insurance and Job Search in the Great Recession." *Brookings Papers on Economic Activity*, 43(2): 143–213.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender. 2016. "The Causal Effect of Unemployment Duration on Wages: Evidence from Unemployment Insurance Extensions." *American Economic Review*, 106(03): 739–777.

Shimer, Robert. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." *American Economic Review*, 95(1): 25–49.

Toohey, Desmond. 2017. "The Effectiveness of Work-Search Requirements over the Business Cycle: Evidence for Job Rationing."

Valletta, Robert G. 2014. "Recent Extensions of U.S. Unemployment Benefits: Search Responses in Alternative Labor Market States." *IZA Journal of Labor Policy*, 3(18).

Villena Roldan, Benjamin. 2010. "Aggregate Implications of Employer Search and Recruiting Selection." Center for Applied Economics (CEA), University of Chile Working Paper 271.

Winkelmann, Liliana, and Rainer Winkelmann. 1998. "Why are the Unemployed So Unhappy? Evidence from Panel Data." *Economica*, 65(257): 1–15.

Appendix A. Derivation of the Optimal UI Formula

We derive the optimal UI formula (11) following the derivation of formula (23) in our companion paper (Landais, Michaillat and Saez 2016). While we condensate the derivation to avoid repetition, we work out the steps that are modified by home production, the nonpecuniary cost of unemployment, and labor market flows.

Social welfare is a function of ΔU and θ:

$$\begin{aligned} SW(\theta,\Delta U) = & \frac{e^s(f(\theta),\Delta U)\cdot f(\theta)}{s+e^s(f(\theta),\Delta U)\cdot f(\theta)}\cdot(\Delta U+\psi(e^s(f(\theta),\Delta U))) \\ & + U(c^u(\theta,\Delta U)+h^s(c^u(\theta,\Delta U))) - z - \lambda(h^s(c^u(\theta,\Delta U))) - \psi(e^s(f(\theta),\Delta U)). \end{aligned}$$

The consumption level $c^u(\theta,\Delta U)$ is implicitly defined by

$$\begin{aligned} y\left(\frac{l^s(\theta,\Delta U)}{1+\tau(\theta)}\right) = & (1-l^s(\theta,\Delta U))\cdot c^u(\theta,\Delta U) \\ & + l^s(\theta,\Delta U)\cdot U^{-1}\left(U(c^u(\theta,\Delta U)+h^s(c^u(\theta,\Delta U)) - z - \lambda(h^s(c^u(\theta,\Delta U))) + \Delta U\right). \end{aligned}$$

We first compute the elasticity of the labor supply with respect to tightness. The labor supply can be written as $l^s(\theta,\Delta U) = \Lambda(e^s(f(\theta),\Delta U)\cdot f(\theta))$, where $\Lambda(x)\equiv x/(s+f(x))$. Given that the elasticity of $\Lambda(x)$ with respect to x is $1-\Lambda(x)$, the elasticity of $l^s(\theta,\Delta U)$ with respect to θ is

$$\text{(A1)} \qquad \frac{\theta}{l}\cdot\left.\frac{\partial l^s}{\partial\theta}\right|_{\Delta U} = (1-l)\cdot(1+\varepsilon^f)\cdot(1-\eta).$$

The only difference with formula (14) in our companion paper is the extra factor $1-l$. This factor arises because the labor supply is $\Lambda(e^s(f(\theta),\Delta U)\cdot f(\theta))$ in the dynamic model instead of $e^s(f(\theta),\Delta U)\cdot f(\theta)$ in the static model, and the elasticity of $\Lambda(x)$ with respect to x is $1-\Lambda(x)$.

Next, we compute the partial derivatives of the social welfare function. We start with the partial derivative with respect to θ. First, we recompute equation (13) from our companion paper. Since workers choose home production to maximize $U(c^u+h)-\lambda(h)$, changes in $h^s(c^u(\theta,\Delta U))$ resulting from changes in θ have no impact on social welfare. Hence, the introduction of home production does not add new terms to the partial derivative. The presence of home production only changes $U'(c^u)$ into $U'(c^h)$. Accordingly, equation (13) becomes

$$\text{(A2)} \qquad \frac{\partial SW}{\partial\theta} = (1-l)\cdot\frac{l}{\theta}\cdot(1-\eta)\cdot(\Delta U+\psi(e)) + U'(c^h)\cdot\frac{\partial c^u}{\partial\theta}.$$

The factor $1-l$ in the first term appears because the environment is dynamic, as in (A1). The fact that the environment is dynamic also changes ΔU into $\Delta U+\psi(e)$ in the first term.

Next we recompute equation (15) from our companion paper. First, in the dynamic environment, equation (A1) implies that

$$\frac{\partial l^s}{\partial\theta} = (1-l)\cdot\frac{l}{\theta}\cdot(1-\eta)\cdot(1+\varepsilon^f).$$

Second, with home production, the derivative of

$$c^e(c^u, \Delta U) = U^{-1}\left(U(c^u + h^s(c^u)) - z - \lambda(h^s(c^u)) + \Delta U\right)$$

with respect to c^u is

$$\frac{\partial c^e}{\partial c^u} = \frac{U'(c^h)}{U'(c^e)}.$$

Because unemployed workers choose home production to maximize $U(c^u + h) - \lambda(h)$, changes in h^s resulting from changes in c^u have no impact on c^e. Hence, equation (15) becomes

$$\text{(A3)}\quad (1-l)\cdot\frac{l}{\theta}\cdot(1-\eta)\cdot(1+\varepsilon^f)\cdot(w-\Delta c) - \frac{l}{\theta}\cdot\eta\cdot\tau(\theta)\cdot w = \left[\frac{l}{U'(c^e)} + \frac{1-l}{U'(c^h)}\right]\cdot U'(c^h)\cdot\frac{\partial c^u}{\partial\theta},$$

where $\Delta c \equiv c^e - c^u$. This equation is the same as equation (15) except for the factor $1-l$ in the left-hand side and the change of $U'(c^u)$ into $U'(c^h)$.

Combining (A2) and (A3), we recompute equation (10) from our companion paper:

$$\text{(A4)}\qquad \left.\frac{\partial SW}{\partial\theta}\right|_{\Delta U} = (1-l)\cdot\frac{l}{\theta}\cdot(1-\eta)\cdot\phi\cdot w\cdot\left[\frac{\Delta U + \psi(e)}{\phi\cdot w} + R\cdot\left(1+\varepsilon^f\right) - \frac{\eta}{1-\eta}\cdot\frac{\tau(\theta)}{u}\right],$$

where ϕ is the harmonic mean of workers' marginal consumption utilities, given by (10).

We continue by computing the partial derivative of social welfare with respect to ΔU. First, we recompute the equation (16) from our companion paper. Applying again the envelope theorem for the changes in h^s and e^s resulting from changes in ΔU, we find that this equation becomes

$$\text{(A5)}\qquad \frac{\partial SW}{\partial\Delta U} = l + U'(c^h)\cdot\frac{\partial c^u}{\partial\Delta U}.$$

Next we recompute equation (17) from our companion paper. Using the work that we have done to obtain (A3), we find

$$\text{(A6)}\qquad \frac{1-l}{\Delta U}\cdot\varepsilon^m\cdot(w-\Delta c) - \frac{l}{U'(c^e)} = \left(\frac{l}{U'(c^e)} + \frac{1-l}{U'(c^h)}\cdot\right)\cdot U'(c^h)\cdot\frac{\partial c^u}{\partial\Delta U}.$$

Combining (A5) and (A6), we recompute equation (11) from the companion paper:

$$\text{(A7)}\qquad \left.\frac{\partial SW}{\partial\Delta U}\right|_{\theta} = (1-l)\cdot\frac{\phi\cdot w}{\Delta U}\cdot\varepsilon^m\cdot\left[R - \frac{l}{w}\cdot\frac{\Delta U}{\varepsilon^m}\cdot\left(\frac{1}{U'(c^e)} - \frac{1}{U'(c^h)}\right)\right].$$

The last step before obtaining the optimal UI formula is to link the elasticity wedge to the equilibrium response of tightness to UI. Using (A1), we find that

$$\text{(A8)}\qquad \varepsilon^M = \varepsilon^m + l\cdot(1-\eta)\cdot\left(1+\varepsilon^f\right)\cdot\frac{\Delta U}{\theta}\cdot\frac{d\theta}{d\Delta U}.$$

This equation replaces equation (22) in the companion paper. The only difference with equation (22) is that a factor l replaces the factor $l/(1-l)$.

The first-order condition of the government's problem is

$$0 = \left.\frac{\partial SW}{\partial \Delta U}\right|_{\theta} + \left.\frac{\partial SW}{\partial \theta}\right|_{\Delta U} \cdot \frac{d\theta}{d\Delta U}.$$

Using the partial derivatives of $SW(\theta, \Delta U)$ given by (A4) and (A7) and the derivative $d\theta/d\Delta U$ implied by (A8), we obtain formula (11).

Appendix B. Job-Finding and Job-Separation Rates in CPS data

We follow the method developed by Shimer (2012, pp. 130–133) to compute job-finding and job-separation rates in CPS data for the 1990–2014 period. In Section II.A we use these rates to compute the recruiter-producer ratio plotted in Figure 1.

We assume that unemployed workers find a job according to a Poisson process with monthly arrival rate $e(t) \cdot f(t)$. The job-finding rate $e(t) \cdot f(t)$ satisfies $e(t) \cdot f(t) = -\ln(1 - F(t))$, where $F(t)$ is the monthly job-finding probability. Each month t, we measure $F(t)$ by

$$F(t) = 1 - \frac{u(t+1) - u^s(t+1)}{u(t)}, \tag{A9}$$

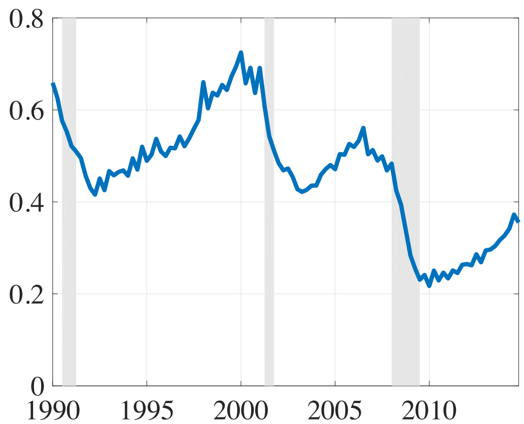
where $u(t)$ is the number of unemployed persons and $u^s(t)$ is the number of short-term unemployed persons. We measure $u(t)$ and $u^s(t)$ in CPS data. The number of short-term unemployed persons is the number of unemployed persons with zero to four weeks duration, adjusted after 1994 as in Shimer (2012). We then construct $e(t) \cdot f(t)$ from $F(t)$. The job-finding rate $e(t) \cdot f(t)$ is displayed in panel A of Figure A1.

The next panels in Figure A1 explain how the job-finding rate is transformed before being used to compute the recruiter-producer ratio. Panel B displays the vacancy-unemployment ratio v/u constructed in Section II.A. Panel C then displays the vacancy-filling rate constructed as $q(t) = [e(t) \cdot f(t)] / [v(t)/u(t)]$. This vacancy-filling rate is used to construct the third measure of the recruiter-producer ratio. For comparison, panel C also displays the vacancy-filling rate constructed from JOLTS data in Section II.A. This vacancy-filling rate is used to construct the second measure of the recruiter-producer ratio.

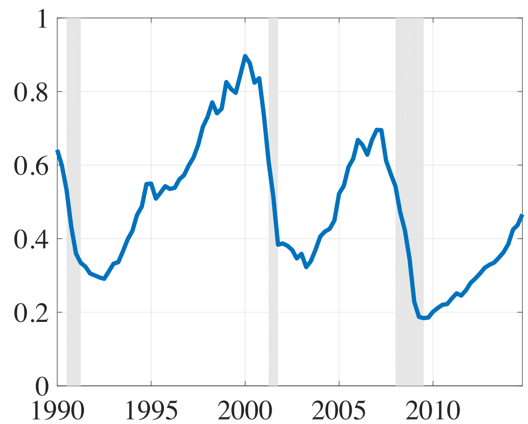
The job-separation rate $s(t)$ is implicitly defined by

$$u(t+1) = \left(1 - e^{-e(t)\cdot f(t) - s(t)}\right) \cdot \frac{s(t)}{e(t) \cdot f(t) + s(t)} \cdot h(t) + e^{-e(t)\cdot f(t) - s(t)} \cdot u(t), \tag{A10}$$

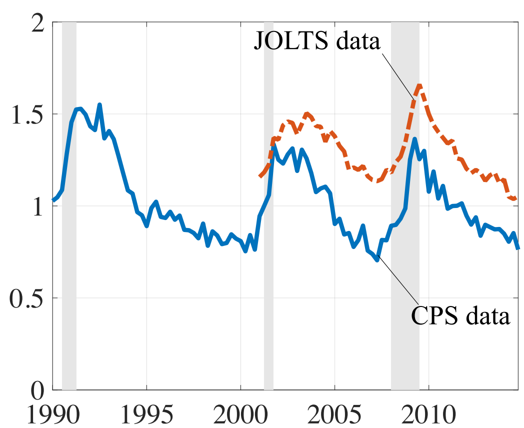
where $h(t)$ is the number of persons in the labor force, $u(t)$ is the number of unemployed persons, and $e(t) \cdot f(t)$ is the monthly job-finding rate. We measure $u(t)$ and $h(t)$ in CPS data and use the series for $e(t) \cdot f(t)$ constructed above. We solve the equation for each t to construct $s(t)$. The rate $s(t)$ is displayed in Figure A1, panel D. The job-separation rate is used to construct the third measure of the recruiter-producer ratio. For comparison, the panel also displays the job-separation rate constructed from JOLTS data in Section II.A. This job-separation rate is used to construct the second measure of the recruiter-producer ratio.



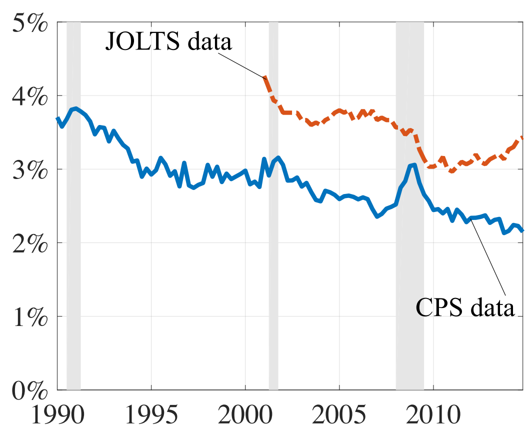
Panel A. Monthly job-finding rate



Panel B. Vacancy-unemployment ratio



Panel C. Monthly vacancy-filling rate



Panel D. Monthly job-separation rate

Figure A1: Vacancy-Filling and Job-Separation Rates in the United States, 1990–2014

Notes: Panel A: The solid, blue line is the job-finding rate constructed from CPS data using equation (A9). Panel B: The solid, blue line is the vacancy-unemployment ratio v/u, where v is the help-wanted advertising index from Barnichon (2010), scaled to match the number of vacancies in JOLTS data, and u is the number of unemployed persons in CPS data. Panel C: The solid, blue line is the vacancy-filling rate $q = (e \cdot f)/(v/u)$, where $e \cdot f$ is the time series in panel A and v/u is the time series in panel B. The dashed, red line is the vacancy-filling rate $q = h/v$, where h and v are the numbers of hires and vacancies in nonfarm industries in JOLTS data. Panel D: The solid, blue line is the job-separation rate constructed from CPS data. The dashed, red line is the separation rate in nonfarm industries in JOLTS data. The shaded areas represent the recessions identified by the NBER.

Appendix C. Construction of the Effective Replacement Rate of the UI Program in the United States

We construct the effective replacement rate of the UI program in the United States. This replacement rate is plotted in Figure 2.

We define the effective replacement rate as the average replacement rate among all unemployed workers who are eligible to UI or were eligible to UI earlier during their current unemployment spell. In month t, the effective replacement rate is

$$R(t) = \frac{\sum R_j(t) \cdot N_j(t)}{\sum N_j(t)},$$

where $N_j(t)$ is the number of unemployed workers who are in the j-th week of their unemployment spell and are or were eligible to UI, and $R_j(t)$ is the average UI replacement rate for individuals who are in the j-th week of their unemployment spell.

To compute $\sum R_j(t) \cdot N_j(t)$, we split the sum into active and exhausted claims. A claim is exhausted when a jobseeker has been unemployed longer than the potential duration of benefits, k. Since jobseekers who have exhausted their benefits have a zero replacement rate, the sum is solely driven by active claims:

$$\sum R_j(t) \cdot N_j(t) = \sum_{j \leq k} R_j(t) \cdot N_j(t).$$

In practice we compute this sum as follows:

$$\sum_{j \leq k} R_j(t) \cdot N_j(t) = \overline{R_{j \leq k}}(t) \cdot \left(\sum_{j \leq k} N_j(t) \right),$$

where $\overline{R_{j \leq k}}(t)$ is the average replacement rate for all active claims at time t and $\sum_{j \leq k} N_j(t)$ is the total number of active claims in all UI programs at time t.

The Department of Labor (DOL) provides data for all existing UI programs: regular programs, extended benefit programs, and exceptional federal extensions during recessions. We use the weekly number of active UI claims to compute $\sum_{j \leq k} N_j(t)$. And we use the quarterly average replacement rate among all active claims to compute $\overline{R_{j \leq k}}(t)$. This average replacement rate is computed by the DOL as the ratio of claimants' weekly benefits to claimants' base earnings: it is stable over time, fluctuating between 45.8% and 47.4% with an average value of 46.5%.[29] Unfortunately, this average replacement rate is only available since 1997, so we cannot use it to compute the effective replacement rate for 1990–2014 period. Instead, we take advantage of the stability of the average replacement rate and set $\overline{R_{j \leq k}}(t) = 46.5\%$ for all t.

To compute $\sum N_j(t)$, we need the number of unemployed workers at time t who are eligible to UI or were eligible to UI earlier during their current unemployment spell. Since we do not know the number of unemployed workers who were eligible to UI during their current unemployment spell, we measure $\sum N_j(t)$ by $u(t) \cdot \beta(t)$, where $u(t)$ is the total number of unemployed workers in

[29] This is not surprising: almost all US states define weekly UI benefits as 1/26×base earnings, where base earnings are the highest quarterly earnings in the year prior to becoming unemployed. This amounts to a 50% replacement rate of base earnings.

month t and $\beta(t)$ is the fraction of unemployed workers who are job losers at time t. While quits and new entrants in the labor force are not eligible for UI, job losers who meet minimal criteria are eligible to UI. Hence, the number of job losers who are unemployed is a good approximation of the number of unemployed workers who currently are or have been eligible to UI. We measure $u(t)$ with the number of unemployed workers in CPS data. To compute $\beta(t)$, we use the number of job losers as a percent of total unemployed workers in CPS data. This is the fraction of individuals who entered unemployment through a job loss in the stock of unemployed at time t. Finally, we cap $\sum N_j(t)$ to the number of active claims for these few months. We do this to correct an anomaly that occurs for a few months during the Great Recession: the number of active claims is slightly larger than our estimate of the number of unemployed workers who are or were eligible to UI. This anomaly arises because we only approximately measure the stock of unemployed workers who are or were eligible to UI.

Appendix D. Estimates of UI Statistics in the Literature

We compile existing estimates of various statistics that enter our optimal UI formula.

A. *Matching Elasticity (η)*

The matching elasticity is defined by $1-\eta = d\ln(f(\theta))/d\ln(\theta)$. Empirical evidence suggests that the matching function is Cobb-Douglas (Petrongolo and Pissarides 2001, p. 424). With a Cobb-Douglas matching function $m(e,u,v) = \mu\cdot(e\cdot u)^{\eta}\cdot v^{1-\eta}$, we have $f(\theta)\equiv m/(e\cdot u) = \mu\cdot[v/(u\cdot e)]^{1-\eta}$. Hence, η is the elasticity of the matching function with respect to unemployment.

A vast literature studies the matching function and estimates η. In their survey, Petrongolo and Pissarides (2001, p. 424) conclude that the estimates of η fall between 0.5 and 0.7.

Evidence obtained in US data since the publication of Petrongolo and Pissarides's survey agrees with their assessment. For instance, Shimer (2005, p. 32) estimate $\eta = 0.72$ in CPS data. Rogerson and Shimer (2011, p. 638) estimate $\eta = 0.58$ in JOLTS data. Many of these estimates, however, take the search efforts of workers and firms as constant. The estimates could therefore be biased if the efforts are endogenous—as in our model, where workers' job-search effort is endogenous. Borowczyk-Martins, Jolivet and Postel-Vinay (2013) propose an estimation method that is immune to this bias. On JOLTS data, they find a lower estimate than earlier work: $\eta = 0.3$ (p. 444).

Based on these findings, we set $\eta = 0.6$. Given the uncertainty about the exact value of η, we also consider the cases $\eta = 0.5$ and $\eta = 0.7$ in the sensitivity analysis of Section IV.

B. *Discouraged-Worker Elasticity (ε^f)*

The discouraged-worker elasticity, ε^f, measures how job-search effort responds to labor market conditions. Search effort can be measured either by the time spent searching for a job or by the number of methods used to search for a job.

Two studies measure ε^f using the American Time Use Survey (ATUS), in which search effort is directly measured as the amount of time spent searching for a job. These studies suggest that ε^f is positive. DeLoach and Kurt (2013) find that workers do reduce their search in response to deteriorating labor market conditions. They also find that reductions in household wealth occurring at the same time as increases in unemployment mitigate the discouraged-worker effect, explaining why job search may appear acyclical. Gomme and Lkhagvasuren (2015) find that individual search effort is mildly procyclical. They also show that the search effort of long-term unemployed workers is slightly countercyclical whereas that of short-term unemployed workers is quite procyclical.

Two other studies measure ε^f from CPS data, in which search effort is proxied by the number of job-search methods used. These studies suggest that ε^f is zero or slightly negative. Shimer (2004) finds that labor market participation and search intensity are broadly acyclical, even after controlling for changing characteristics of unemployed workers over the business cycle. This empirical evidence suggests that ε^f is close to zero. Next, Mukoyama, Patterson and Sahin (2014) combine ATUS and CPS data and find that aggregate search effort is countercyclical. Half of the countercyclical movement in search effort, however, is explained by a cyclical shift in the observable characteristics of unemployed workers, and a large share of the remaining countercyclical movement is explained by the fall in housing and stock-market wealth. This evidence suggests that ε^f is slightly negative.

Overall, these studies suggest that the response of search effort to the job-finding rate is small. We therefore set $\varepsilon^f = 0$.

Our calibration $\varepsilon^f = 0$ implies that job search is unresponsive to labor market conditions, but it does not imply that job search is unresponsive to UI. We can link ε^f to ε^m, which measure the response of job search to UI. Let $1/\kappa$ be the elasticity of $\psi'(e)$ with respect to e. Let ε^e_Δ be the elasticity of $e^s(f,\Delta U)$ with respect to ΔU. Let $\Lambda(x) \equiv x/(s+x)$. The elasticity of $\Lambda(x)$ with respect to x is $1-\Lambda(x)$. The effort supply $e^s(f,\Delta U)$ satisfies (6), which can be written

$$e^s \cdot \psi'(e^s) = \Lambda(e^s \cdot f) \cdot (\Delta U + \psi(e^s)). \tag{A11}$$

Differentiating this condition with respect to ΔU yields

$$\varepsilon^e_\Delta + \frac{1}{\kappa} \cdot \varepsilon^e_\Delta = (1-l) \cdot \varepsilon^e_\Delta + \frac{\Delta U}{\Delta U + \psi(e)} + \frac{e \cdot \psi'(e)}{\Delta U + \psi(e)} \cdot \varepsilon^e_\Delta.$$

Equation (A11) implies that $e \cdot \psi'(e) = l \cdot (\Delta U + \psi(e))$. Therefore,

$$\varepsilon^e_\Delta = \kappa \cdot \frac{\Delta U}{\Delta U + \psi(e)}.$$

Since the labor supply satisfies $l^s(\theta,\Delta U) = \Lambda\left(e^s(f(\theta),\Delta U) \cdot f(\theta)\right)$, the elasticity of $l^s(\theta,\Delta U)$ with respect to ΔU is $(1-l) \cdot \varepsilon^e_\Delta$. By definition, ε^m is $l/(1-l)$ times the elasticity of $l^s(\theta,\Delta U)$ with respect to ΔU. Thus,

$$\varepsilon^m = l \cdot \varepsilon^e_\Delta = l \cdot \kappa \cdot \frac{\Delta U}{\Delta U + \psi(e)}. \tag{A12}$$

Next, we differentiate (A11) with respect to f and obtain

$$\varepsilon^f + \frac{1}{\kappa} \cdot \varepsilon^f = (1-l) \cdot (\varepsilon^f + 1) + \frac{e \cdot \psi'(e)}{\Delta U + \psi(e)} \cdot \varepsilon^f.$$

Equation (A11) implies that $e \cdot \psi'(e) = l \cdot (\Delta U + \psi(e))$. Hence,

$$\varepsilon^f = (1-l) \cdot \kappa.$$

Combining this equation with (A12), we find

$$\varepsilon^f = \frac{1-l}{l} \cdot \frac{\Delta U + \psi(e)}{\Delta U} \cdot \varepsilon^m.$$

We infer that ε^f is much smaller than ε^m in normal circumstances because $(1-l)/l$ is close to 0. Thus, the model predicts a weak response of job search to labor market conditions even when the response of job search to UI is significant.

C. *Microelasticity of Unemployment Duration with Respect to Benefit Level*

The microelasticity of unemployment duration with respect to benefit level is defined by

$$\text{(A13)} \qquad \varepsilon_b^m = -\left.\frac{\partial \ln(e^s \cdot f(\theta))}{\partial \ln(c^u)}\right|_{\theta, c^e}.$$

Landais (2015) provides high-quality estimates of ε_b^m by implementing a regression kink design on CWBH data. Averaging over five US states for 1976–1984, Landais estimates $\varepsilon_b^m = 0.4$ (p. 244). Using similar data but a different identification strategy, Meyer (1990) obtains slightly higher estimates. Depending on the specification, Meyer's estimates of ε_b^m fall between 0.5 and 0.9 (Table V, columns (4)–(5), row "log UI benefit level" and Table VI, columns (6)–(9), row "log UI benefit level"). These two studies rely on older data, but Card et al. (2015) obtain comparable estimates in more recent data. They implement a regression kink design on an administrative dataset from Missouri for 2003–2013 and find that ε_b^m is 0.35 in 2003–2007 and between 0.65 and 0.9 in 2008–2013 (p. 126).

Based on this evidence, we set $\varepsilon_b^m = 0.4$. Since these studies obtain a range of estimates for ε_b^m, we also consider the cases $\varepsilon_b^m = 0.2$ and $\varepsilon_b^m = 0.6$ in the sensitivity analysis of Section IV.

The estimate of ε_b^m is useful to compute the microelasticity of unemployment with respect to UI, ε^m. Using (A13) and $1 - l^s = s/(s + e^s \cdot f(\theta))$, we have

$$\text{(A14)} \qquad \varepsilon_b^m = \frac{1}{l} \cdot \left.\frac{\partial \ln(1-l^s)}{\partial \ln(c^u)}\right|_{\theta, c^e} = -\frac{c^u}{l \cdot (1-l)} \cdot \left.\frac{\partial l^s}{\partial c^u}\right|_{\theta, c^e}.$$

We now consider a change dc^u keeping c^e, and θ constant. By definition, $\Delta U = U(c^e) - U(c^u + h) + z + \lambda(h)$. The change dc^u does not affect c^e but it affects h. Since workers choose h to maximize $U(c^u + h) - \lambda(h)$, however, changes in h resulting from changes in c^u have no impact on ΔU. We conclude that the change dc^u implies a change $d\Delta U = -U'(c^h) \cdot dc^u$. Using (A14) and the definition of ε^m, we obtain

$$\text{(A15)} \qquad \varepsilon_b^m = \frac{c^u}{l \cdot (1-l)} \cdot U'(c^h) \cdot \left.\frac{\partial l^s}{\partial \Delta U}\right|_{\theta} = \frac{c^u \cdot U'(c^h)}{l \cdot \Delta U} \cdot \varepsilon^m.$$

D. Coefficient of Relative Risk Aversion (γ)

A large literature has estimated risk aversion, following a broad range of approaches. We take our estimate of the coefficient of relative risk aversion γ from Chetty (2006). We use this estimate because it comes from data also used to measure the microelasticity of unemployment with respect to UI and the consumption drop upon unemployment. Since the estimate comes from a setting close to ours, the curvature of utility that it measures is relevant for evaluating the effect of UI on welfare (Chetty and Finkelstein 2013, p. 154).

Chetty uses data on labor supply behavior from more than 30 studies and analyzes the risk aversion implied by the impact of wage changes on labor supply. He reports that the mid-point of plausible estimates is 1, with an upper bound of $\gamma = 2$ and a lower bound around $\gamma = 0.2$ (p. 1822, p.1830). Accordingly, we set the relative risk aversion to $\gamma = 1$. Given the uncertainty about the exact value of γ, we also consider the cases $\gamma = 0.5$ and $\gamma = 2$ in the sensitivity analysis of Section IV.

The coefficient of relative risk aversion allows us to link marginal utility to consumption. Indeed, a first-order Taylor expansion of U' around c^e yields $U'(c^h) = U'(c^e) - U''(c^e) \cdot \left(c^e - c^h\right)$. Since $\gamma = -c^e \cdot U''(c^e)/U'(c^e)$, we obtain the following first-order approximation:

$$\text{(A16)} \qquad \frac{U'(c^h)}{U'(c^e)} = 1 + \gamma \cdot \left(1 - \frac{c^h}{c^e}\right).$$

Since the first-order Taylor expansion of $1/(1+x)$ around $x = 0$ is $1 - x$, we obtain another first-order approximation:

$$\text{(A17)} \qquad \frac{U'(c^e)}{U'(c^h)} = 1 - \gamma \cdot \left(1 - \frac{c^h}{c^e}\right).$$

E. Consumption Drop upon Unemployment ($1 - c^h/c^e$)

A large literature documents the drop in consumption upon unemployment in the United States.

A number of studies measure consumption by expenditure on food. Gruber (1997, p. 195) estimates in data from the Panel Study of Income Dynamics (PSID) that food expenditure falls by 7% upon unemployment. Many studies have confirmed this estimate in PSID data. For instance, Stephens (2001, p. 32) finds that food expenditure falls by 9% following a job displacement and Hendren (2016, p. 13) finds that it falls by 8%. Different datasets yield comparable estimates. For instance, in a dataset describing more than 200,000 checking accounts that have received UI benefits, Ganong and Noel (2016, Table 6, column (3)) find that food expenditure falls by 5% while receiving UI.

It is possible that upon unemployment, food consumption falls less than food expenditure. If households spend more time on food production at home when unemployed, they may be able to smooth food consumption despite reducing food expenditures (Aguiar and Hurst 2005).

There are several factors suggesting, however, that the consumption drop used to calibrate our formula should be larger than the drop in food expenditure upon unemployment.

First, food consumption is more inelastic than total consumption to an income change, so the drop of total consumption upon unemployment will be larger than the drop of food consumption.

For instance, Browning and Crossley (2001, p. 19) report that the income elasticity of food consumption is 0.6, which implies that drops in food consumption by 5%, 7%, or 9% would translate into drops in total consumption by $5\%/0.6 = 8\%$, $7\%/0.6 = 12\%$, or $9\%/0.6 = 15\%$. Consistent with this argument, Ganong and Noel (2016, Table 6, column (3)) find that expenditure on all nondurable goods fall by 7% while receiving UI.

Second, it seems that consumption of workers who eventually become unemployed start falling well before they actually lost their job. Hendren (2016, p. 13) finds in PSID data that food expenditure drops by about 3% in the two years before the job loss.

Third, in the United States, UI benefits only last for a limited time (usually 26 weeks). Households who cannot find a job before their benefits expire suffer an additional consumption drop. In the same way that the effective replacement rate plotted in Figure 2 accounts for unemployed workers receiving benefits and unemployed workers whose benefits expired, the consumption drop should incorporate the consumption of unemployed workers receiving benefits and unemployed workers whose benefits expired. Ganong and Noel (2016) find that the consumption drop upon benefit expiration is significant. They show that expenditure on all nondurable goods fall by an additional 10% upon expiration (p. 26); therefore, the expenditure on all nondurable goods for unemployed workers whose benefits expired is $7\% + 10\% = 17\%$ below what it was before the job loss. Ideally, our estimate of consumption drop would be a weighted average of the consumption drop upon unemployment and the consumption drop upon expiration, using the shares of eligible unemployed workers with and without benefits as weight.

To conclude, we set the consumption drop upon unemployment to $1 - c^h/c^e = 12\%$. Given the uncertainty about the exact value of the drop, we also consider the cases $1 - c^h/c^e = 5\%$ and $1 - c^h/c^e = 20\%$ in the sensitivity analysis of Section IV.

Next, we link the consumption drop upon unemployment to the UI replacement rate, R. We have $1 - (c^h/c^e) = 12\%$ when R takes its average value of 42%. Since the consumption of unemployed workers, c^h, depends on R, the ratio c^h/c^e mechanically depends on R.

First, Gruber (1997, p. 195, p. 202) estimates that when the UI benefit rate increases by 10 percentage point from an average value of 43%, the food consumption of an unemployed worker increases by 2.7 percent. The implied elasticity of food consumption with respect to UI benefits therefore is $2.7/(10/0.43) = 0.12$. Once again, we convert the response of food consumption into the response of total consumption. Since the income elasticity of food consumption is 0.6, the elasticity of total consumption with respect to UI benefits is $0.12/0.6 = 0.2$. In other words, $d\ln(c^h)/d\ln(c^u) = 0.2$.

Second, we combine the government's budget constraint, $y = l \cdot c^e + (1-l) \cdot c^u$, with the definition of the replacement rate, $c^u = c^e - (1-R) \cdot w$. We find

$$c^e = y + (1-l) \cdot (1-R) \cdot w$$

Let α be the labor share, defined by $\alpha = w \cdot l/y$. We have

$$\frac{c^e}{w} = \frac{l}{\alpha} + (1-l) \cdot (1-R). \tag{A18}$$

The labor share is determined by the shape of the production function. With a production function $y(n) = n^{\alpha}$, the labor share is α. In Section III, we find that the shape of the production function also determines the elasticity wedge. To obtain an elasticity wedge is 0.4, and we set $\alpha = 0.73$.

To have a labor share consistent with the elasticity wedge, we also set $\alpha = 0.73$. Using $\alpha = 0.73$, $1 - l = 6.1\%$, and $R = 42\%$, we find $c^e/w = 1.32$. In addition, (A18) shows that a change dR in the replacement rate implies a change $dc^e = -w \cdot u \cdot dR$. Here the underlying assumption is that w does not respond to R. The empirical evidence presented in Section III.C supports this assumption.

Third, since $c^u = c^e - (1-R) \cdot w$, equation (A18) implies that

$$\frac{c^u}{w} = \frac{l}{\alpha} - l \cdot (1-R). \tag{A19}$$

Using $\alpha = 0.73$, $l = 0.94$, and $R = 42\%$, we find $c^u/w = 0.74$. Moreover, a small change dR in replacement rate generates a benefit change $dc^u = w \cdot l \cdot dR$.

Using the property that $d(c^h/c^e) = (c^h/c^e) \cdot d\ln(c^h/c^e)$, we find that when the replacement rate changes by dR,

$$d(c^h/c^e) = \frac{c^h}{c^e} \cdot \left[\frac{d\ln(c^h)}{d\ln(c^u)} \cdot dln(c^u) - dln(c^e)\right] \cdot dR = \frac{c^h}{c^e} \cdot \left[\frac{d\ln(c^h)}{d\ln(c^u)} \cdot (1-u) \cdot \frac{w}{c^u} + u \cdot \frac{w}{c^e}\right] \cdot dR. \tag{A20}$$

With $1 - c^h/c^e = 12\%$, $d\ln(c^h)/d\ln(c^u) = 0.2$, $c^u/w = 0.74$, and $c^e/w = 1.32$, we have $d(c^h/c^e) = 0.26 \times dR$ and

$$1 - \frac{c^h}{c^e} = 0.12 - 0.26 \times (R - 0.42). \tag{A21}$$

Finally, we assume that the consumption drop upon unemployment does not respond to labor market conditions. This assumption is motivated by the work of Kroft and Notowidigdo (2016). Using PSID data, they find that the consumption drop does not vary with the unemployment rate.

Appendix E. Calibration of the Optimal UI Formula

We compute the approximate optimal UI formula (19) by calibrating its elements one at a time.

A. *The Utility Cost of Unemployment*

We derive (13). This equation expresses the utility cost of unemployment, K, as a function of UI.

We start by computing the average value of K, achieved when unemployment rate and UI replacement rate take their average values. These average values are $u = 6.1\%$ and $R = 42\%$ (Section II). The cost K is given by (9). Since $Z/(\phi \cdot w) = 0.3$ (Section II), it only remains to calculate $\left(U(c^e) - U(c^h)\right)/(\phi \cdot w)$. We rewrite this term as

$$\frac{U(c^e) - U(c^h)}{\phi \cdot w} = \frac{U(c^e) - U(c^h)}{U'(c^e) \cdot c^e} \cdot \frac{U'(c^e)}{\phi} \cdot \frac{c^e}{w}, \tag{A22}$$

We now analyze the three factors in the right-hand side. First, (A18) implies $c^e/w = 1.32$. Next, using (10) and (A17), we obtain

$$\frac{U'(c^e)}{\phi} = 1 - \gamma \cdot (1-l) \cdot \left(1 - \frac{c^h}{c^e}\right). \tag{A23}$$

With $\gamma = 1$ and $1 - c^h/c^e = 12\%$ (Appendix D), and $1 - l = u = 6.1\%$, we find $U'(c^e)/\phi = 0.99$. Last, a first-order Taylor expansion of U yields $U(c^h) = U(c^e) + U'(c^e) \cdot \left(c^e - c^h\right)$ so

$$\text{(A24)} \qquad \frac{U(c^e) - U(c^h)}{U'(c^e) \cdot c^e} = 1 - \frac{c^h}{c^e}.$$

With $1 - c^h/c^e = 12\%$, we find that $\left(U(c^e) - U(c^h)\right) / \left(U'(c^e) \cdot c^e\right) = 0.12$. Combining these estimates with (A22), we conclude that $\left(U(c^e) - U(c^h)\right) / (\phi \cdot w) = 0.99 \times 1.32 \times 0.12 = 0.16$. This implies that the average utility cost of unemployment is $K = 0.16 + 0.3 = 0.46$.

Next, we explore how K depends on labor market conditions. In Section II, we argue that $Z/(\phi \cdot w)$ does not depend on the unemployment rate. In addition, we argue in Appendix D that the consumption drop upon unemployment does not depend on labor market conditions. Hence, we see from (A24) that $(U(c^e) - U(c^h))/(U'(c^e) \cdot c^e)$ does not depend on labor market conditions. Last, equations (A18) and (A23) show that both c^e/w and $U'(c^e)/\phi$ are affected by employment l, but the effects on K will be small. With $R = 42\%$, $\alpha = 0.73$, and $1 - c^h/c^e = 12\%$, we have $\partial(c^e/w)/\partial l = R + (1-\alpha)/\alpha = 0.8$ so the effect of l on K through c^e/w is less than $0.8 \times 0.12 = 0.1$. Since l moves by less than 5 percentage points around its average value of 94%, changes in l have effects on K through c^e/w of less than $5 \times 0.1 = 0.5$ percentage point. We neglect them. Further, with $1 - c^h/c^e = 12\%$ and $\gamma = 1$, we have $\partial(U'(c^e)/\phi)/\partial l = \gamma \cdot (1 - c^h/c^e) = 0.12$ so the effect of l on K through $U'(c^e)/\phi$ is $0.12 \times 0.12 \times 1.32 = 0.02$. Changes in l therefore have effects on K through $U'(c^e)/\phi$ of less than $5 \times 0.02 = 0.1$ percentage point. We also neglect them. To conclude, labor market conditions have minuscule effects on K, and we neglect them.

Finally, we study how K varies with the UI replacement rate, R. Equation (9) shows that

$$K = \frac{U(c^e) - U(c^u + h) + z + \psi(e) + \lambda(h)}{\phi \cdot w}.$$

As in Appendix D, we assume that R has no effect on w. Further, since h is chosen optimally to maximize $U(c^h) - \lambda(h)$, the change in h caused by R has no first-order effect on K. Hence, we only need to determine how $U(c^u)$, $U(c^e)$, $\psi(e)$, and ϕ respond to R.

We start by determining the response of $U(c^u)$ to R. Equation (A19) shows that a small change dR in replacement rate generates a benefit change $dc^u = w \cdot l \cdot dR$. Accordingly, the effect of dR on $U(c^u + h)$ through c^u is $dU(c^u + h) = U'(c^h) \cdot w \cdot l \cdot dR$ and

$$\text{(A25)} \qquad \frac{dU(c^u + h)}{\phi \cdot w} = l \cdot \frac{U'(c^h)}{\phi} \cdot dR.$$

Using (10) and (A16), we obtain

$$\text{(A26)} \qquad \frac{U'(c^h)}{\phi} = 1 + \gamma \cdot l \cdot \left(1 - \frac{c^h}{c^e}\right).$$

With $l = 1 - u = 0.94$, $\gamma = 1$, and $1 - c^h/c^e = 12\%$, we obtain $U'(c^h)/\phi = 1.11$ and $dU(c^u + h)/(\phi \cdot w) = 0.94 \times 1.11 \times dR = 1.04 \times dR$.

Second, we determine the response of $U(c^e)$ to R. Equation (A18) shows that a small change

dR generates a change $dc^e = -u \times w \times dR$. Accordingly, the effect of dR on $U(c^e)$ satisfies

$$\text{(A27)} \qquad \frac{dU(c^e)}{\phi \cdot w} = -u \cdot \frac{U'(c^e)}{\phi} \cdot dR.$$

With $u = 6.1\%$ and $U'(c^e)/\phi = 0.99$, we obtain $dU(c^e)/(\phi \cdot w) = -0.06 \times dR$.

Next we determine the response of $\psi(e)$ to R. Consider again a small change dR. The associated change $dc^u = w \cdot l \cdot dR$ generates an effort change de determined by the microelasticity of unemployment duration with respect to benefit level: $(de/e) = \varepsilon_b^m \cdot (dc^u/c^u) = \varepsilon_b^m \cdot l \cdot (w/c^u) \cdot dR$. Accordingly, the effect of dR on $\psi(e)$ satisfies

$$\frac{d\psi(e)}{\phi \cdot w} = \frac{\psi'(e)}{\phi \cdot w} \cdot de = -\frac{e \cdot \psi'(e)}{\phi \cdot w} \cdot l \cdot \frac{w}{c^u} \cdot \varepsilon_b^m \cdot dR.$$

Using (6), we rewrite this equation as

$$\text{(A28)} \qquad \frac{d\psi(e)}{\phi \cdot w} = -l^2 \cdot K \cdot \frac{w}{c^u} \cdot \varepsilon_b^m \cdot dR.$$

Equation (A19) implies $c^u/w = 0.74$. With $\varepsilon_b^m = 0.4$ (Appendix D), $l = 0.94$, and $K = 0.46$, we obtain $d\psi(e)/(\phi \cdot w) = -0.22 \times dR$.

Last, the response of $1/(\phi \cdot w)$ to R is exactly zero under log utility and minuscule otherwise. Indeed,

$$\frac{1}{\phi \cdot w} = \frac{1}{w} \cdot \left[\frac{1-u}{U'(c^e)} + \frac{u}{U'(c^h)}\right].$$

A change dR leads to changes $dc^e/w = -u \cdot dR$ and $dc^u/w = (1-u) \cdot dR$. Hence, it leads to a change

$$d\left(\frac{1}{\phi \cdot w}\right) = (1-u) \cdot u \cdot \left[\frac{U''(c^e)}{(U'(c^e))^2} - \frac{U''(c^h)}{(U'(c^h))^2}\right] \cdot dR = \gamma \cdot (1-u) \cdot u \cdot \left[\frac{1}{c^e \cdot U'(c^e)} - \frac{1}{c^h \cdot U'(c^h)}\right] \cdot dR.$$

With constant-relative-risk-aversion utility $U(c) = \left(c^{1-\gamma} - 1\right)/(1-\gamma)$, $c \cdot U'(c) = c^{1-\gamma}$ and

$$d\left(\frac{1}{\phi \cdot w}\right) = \frac{\gamma \cdot (1-u) \cdot u}{(c^h)^{1-\gamma}} \cdot \left[\left(\frac{c^h}{c^e}\right)^{1-\gamma} - 1\right] \cdot dR \approx (1-u) \cdot u \cdot \frac{\gamma \cdot (\gamma - 1)}{(c^h)^{1-\gamma}} \cdot \left(1 - \frac{c^h}{c^e}\right) \cdot dR.$$

With $\gamma = 1$, this is exactly 0. With other values of γ around 1 (say 0.5 or 2), the response of $1/(\phi \cdot w)$ to R remains minuscule because $u \cdot (1 - c^h/c^e) = 0.006$. Hence, we neglect this response.

Collecting all the results, and using the fact that $K = 0.46$ when $R = 42\%$, we obtain

$$\text{(A29)} \qquad K = 0.46 - (1.04 + 0.06 + 0.22) \cdot (R - 0.42) = 0.46 - 1.32 \times (R - 0.42).$$

B. The Elasticity Wedge

We derive (16). The equation relates the elasticity wedge to labor market conditions.

The average value of the elasticity wedge is 0.4 (Section III). This average value is achieved when the ratio τ/u takes its average value of 0.38 (Section II). Our aim is to determine how the elasticity wedge varies when τ/u deviates from its average value. Some empirical evidence discussed in Section III.E indicates that the elasticity wedge is higher when the labor market is depressed and τ/u is low. Unfortunately, the evidence is insufficient to quantify the response of the elasticity wedge to τ/u. Because of the lack of direct evidence, we resort to an indirect, structural approach. We compute the elasticity wedge in the job-rationing model of Michaillat (2012) and use the response predicted by the model. The model is described in Section IV.D.

The elasticity of $1+\tau(\theta)$ with respect to θ is $\eta\cdot\tau(\theta)$. From (20), we infer that the elasticity of $l^d(\theta,a)$ with respect to θ is $-\eta\cdot\tau(\theta)\cdot\alpha/(1-\alpha)$. By definition, ε^M is $l/(1-l)$ times the elasticity of l with respect to ΔU. Since $l=l^d(\theta,a)$ in equilibrium, we infer that

$$\varepsilon^M = -\frac{l}{1-l}\cdot\eta\cdot\frac{\alpha}{1-\alpha}\cdot\tau(\theta)\cdot\frac{\Delta U}{\theta}\cdot\frac{d\theta}{d\Delta U}.$$

We substitute the expression for $(\Delta U/\theta)\cdot(d\theta/d\Delta U)$ from (A8) into this equation and obtain

$$\varepsilon^M = \frac{\eta}{1-\eta}\cdot\frac{\alpha}{1-\alpha}\cdot\frac{1}{1+\varepsilon^f}\cdot\frac{\tau(\theta)}{u}\cdot\left(\varepsilon^m-\varepsilon^M\right).$$

Dividing this equation by ε^m and rearranging yields the elasticity wedge:

$$1-\frac{\varepsilon^M}{\varepsilon^m} = 1\Big/\left(1+\frac{\eta}{1-\eta}\cdot\frac{\alpha}{1-\alpha}\cdot\frac{1}{1+\varepsilon^f}\cdot\frac{\tau(\theta)}{u}\right). \tag{A30}$$

This equation describes the elasticity wedge as a function of τ/u. The derivative of this function is

$$\frac{d(1-\varepsilon^M/\varepsilon^m)}{d(\tau/u)} = -\left(1-\frac{\varepsilon^M}{\varepsilon^m}\right)^2\cdot\frac{\eta}{1-\eta}\cdot\frac{\alpha}{1-\alpha}\cdot\frac{1}{1+\varepsilon^f}. \tag{A31}$$

Next, we calibrate the production-function parameter α so that the average value of the elasticity wedge is 0.4. In (A30), we set $\eta=0.6$ and $\varepsilon^f=0$ (Appendix D) and $\tau/u=0.38$. We then need $\alpha=0.73$ to obtain an average elasticity wedge of 0.4.

Finally, we use these results to linearize the elasticity wedge around its average value. Equation (A31) shows that with $\eta=0.6$, $\varepsilon^f=0$, and $\alpha=0.73$, the average value of the derivative $d(1-\varepsilon^M/\varepsilon^m)/d(\tau/u)$ is 0.65. Hence, we linearize the elasticity wedge as follows:

$$1-\frac{\varepsilon^M}{\varepsilon^m} = 0.4-0.65\times\left(\frac{\tau}{u}-0.38\right).$$

C. The Baily-Chetty Replacement Rate

We compute equation (17), which gives the Baily-Chetty replacement rate as a function of UI.

We begin by reworking the expression of the Baily-Chetty replacement rate in equation (11). Using (A17), we rewrite the Baily-Chetty replacement rate as

$$\gamma\cdot\frac{l\cdot\Delta U}{\varepsilon^m\cdot\phi\cdot w}\cdot\frac{\phi}{U'(c^e)}\cdot\left(1-\frac{c^h}{c^e}\right).$$

Then, equation (A12) implies that

$$\text{(A32)} \qquad \frac{l \cdot \Delta U}{\varepsilon^m \cdot \phi \cdot w} = \frac{1}{\kappa} \cdot \frac{\Delta U + \psi(e)}{\phi \cdot w} = \frac{1}{\kappa} \cdot K,$$

where $1/\kappa$ is the elasticity of $\psi'(e)$ with respect to e. Hence, we rewrite the Baily-Chetty replacement rate as

$$\text{(A33)} \qquad \frac{\gamma}{\kappa} \cdot K \cdot \frac{\phi}{U'(c^e)} \cdot \left(1 - \frac{c^h}{c^e}\right).$$

Equations (A21) and (A29) give $1 - c^h/c^e$ and K. Appendix D shows that $\gamma = 1$. There only remains to estimate κ and $\phi/U'(c^e)$.

To compute κ, we use equation (A15), which gives

$$\frac{\varepsilon^m \cdot \phi \cdot w}{l \cdot \Delta U} = \frac{\phi}{U'(c^h)} \cdot \frac{w}{c^u} \cdot \varepsilon_b^m.$$

Combining this equation with (A32), we obtain

$$\text{(A34)} \qquad \kappa = K \cdot \frac{\phi}{U'(c^h)} \cdot \frac{w}{c^u} \cdot \varepsilon_b^m.$$

With $K = 0.46$, $U'(c^h)/\phi = 1.11$ (equation (A26)), $c^u/w = 0.74$ (equation (A19)), and $\varepsilon_b^m = 0.4$ (Appendix D), we find $\kappa = 0.22$.

Equation (A23) shows that on average $\phi/U'(c^e) = 1/0.99 = 1.01$ and that $\phi/U'(c^e)$ does not respond much to changes in labor market conditions and UI. Indeed, the equation shows that $\partial(U'(c^e)/\phi)/\partial l = \gamma \cdot (1 - c^h/c^e) = 1 \times 0.12 = 0.12$ and $\partial(U'(c^e)/\phi)/\partial R = \gamma \cdot u \cdot \partial(1 - c^h/c^e)/\partial R = 1 \times 0.061 \times 0.26 = 0.016$ (we use estimates from Appendix D). The effect of R is obviously tiny. Since employment l moves by less than 0.05 around its average value of 0.94, changes in l have effects on $\phi/U'(c^e)$ of at most $0.05 \times 0.12 = 0.006$, which are minuscule compared to the average value of $U'(c^e)/\phi$. In sum, we set $\phi/U'(c^e) = 1.01$ and assume it is constant.

Combining all the evidence with (A33), we find that the Baily-Chetty replacement rate is

$$4.6 \times [0.46 - 1.32 \times (R - 0.42)] \times [0.12 - 0.26 \times (R - 0.42)].$$

The Baily-Chetty replacement rate does not depend on labor market conditions. This property arises from the observation that the consumption drop upon unemployment does not depend on labor market conditions and from the supply-side structure of the matching model—in particular, job-search behavior is not affected much by labor market conditions.

One related property can be seen in (A34): the microelasticity of unemployment duration with respect to benefit level, ε_b^m, does not depend much on labor market conditions. Is this realistic? Landais (2015) estimates how ε_b^m varies with labor market conditions and finds that the state unemployment rate has an effect on ε_b^m that is small and not significantly different from zero (online appendix: p. 17 and Table A5). Schmieder, von Wachter and Bender (2012) obtain a similar result using administrative data from Germany.[30] Card et al. (2015) is the only study finding that ε_b^m changes with the unemployment rate: their estimate of ε_b^m in Missouri is much larger when unemployment was high (2008–2013) than when it was low (2003–2007). Part of the variation, however, is explained by to the extremely long duration of benefits after the Great Recession, which affect benefit exhaustion rates. At the end, the property that ε_b^m does not respond much to labor market conditions seems realistic.

D. The Variation of τ/u with UI

We compute (18). This equation relates the ratio τ/u to the UI replacement rate, R.

We begin by computing the semielasticity $d\ln(\tau)/dR$. Equation (2) implies that

$$\frac{d\ln(\tau)}{d\ln(\theta)} = \eta \cdot (1+\tau).$$

Moreover, equation (A8) shows that

$$\frac{d\ln(\theta)}{d\ln(\Delta U)} = -\left(1-\frac{\varepsilon^M}{\varepsilon^m}\right)\cdot\frac{\varepsilon^m}{(1-\eta)\cdot(1-u)\cdot(1+\varepsilon^f)}.$$

Last, $\Delta U = U(c^e) - U(c^u+h) + z + \lambda(h)$. Since z is constant and h is chosen optimally to minimize ΔU, R affects ΔU only through c^u and c^e. Consider a small change dR in replacement rate. This change leads to changes dc^u and dc^e in consumption and dl in employment. Equations (A19) and (A18) imply that

$$dc^u = w\cdot l\cdot dR + \left(\frac{1-\alpha}{\alpha}+R\right)\cdot dl$$
$$dc^e = -w\cdot u\cdot dR + \left(\frac{1-\alpha}{\alpha}+R\right)\cdot dl.$$

(As in Appendix D, we assume that R does not affect w.) Hence, the change dR leads to a change

$$\begin{aligned} d\Delta U &= U'(c^h)\cdot\left\{\left(\frac{U'(c^e)}{U'(c^h)}-1\right)\cdot\left(\frac{1-\alpha}{\alpha}+R\right)\cdot dl - \left(u\cdot\frac{U'(c^e)}{U'(c^h)}+l\right)\cdot w\cdot dR\right\} \\ &= -U'(c^h)\cdot\left\{\gamma\left(1-\frac{c^h}{c^e}\right)\cdot\left(\frac{1-\alpha}{\alpha}+R\right)\cdot dl + \left[1-\gamma\cdot u\cdot\left(1-\frac{c^h}{c^e}\right)\right]\cdot w\cdot dR\right\}. \end{aligned}$$

This expression can be simplified with a few numerical approximations. With $\gamma = 1$, $u = 0.061$, and $1-c^h/c^e = 0.12$ (Appendix D and Section II), the term $\gamma\cdot u\cdot(1-c^h/c^e)$ is less than 0.01 so it can be neglected. In addition, the change dl has to be much smaller than dR in the range of R that we consider. Since the term in front of dl is one order of magnitude smaller than the term in front of dR, we neglect the entire term attached to dl. Accordingly, the effect of dR on ΔU simplifies to

[30] Schmieder, von Wachter and Bender (2012) use variations in the potential duration of benefits by age and a regression discontinuity design to estimate the microelasticity of unemployment duration with respect to the potential duration of benefits. They replicate the estimation across labor markets with different unemployment rates. Their estimates are broadly constant when the unemployment rate fluctuates (p. 732 and Figure VI, panel A).

$d\Delta U = -U'(c^h) \cdot w \cdot dR$.

Combining these results, we infer

$$\frac{d\ln(\tau)}{dR} = \frac{d\ln(\tau)}{d\ln(\theta)} \cdot \frac{d\ln(\theta)}{d\ln(\Delta U)} \cdot \frac{d\ln(\Delta U)}{dR} = \frac{\varepsilon^m \cdot U'(c^h) \cdot w}{(1-u) \cdot \Delta U} \cdot \left(1 - \frac{\varepsilon^M}{\varepsilon^m}\right) \cdot \frac{\eta}{1-\eta} \cdot \frac{1+\tau}{1+\varepsilon^f}.$$

Next, we compute the semielasticity $d\ln(u)/dR$. The definition of ε^M implies $d\ln(u)/d\ln(\Delta U) = -\varepsilon^M$. Since $d\Delta U/dR = -U'(c^h) \cdot w$, we infer

$$\frac{d\ln(u)}{dR} = \frac{d\ln(u)}{d\ln(\Delta U)} \cdot \frac{d\ln(\Delta U)}{dR} = \frac{\varepsilon^m \cdot U'(c^h) \cdot w}{(1-u) \cdot \Delta U} \cdot (1-u) \cdot \frac{\varepsilon^M}{\varepsilon^m}.$$

Combining these results and using (A15), we obtain

$$\text{(A35)} \quad \frac{d(\tau/u)}{dR} = \frac{\tau}{u} \cdot \left[\frac{d\ln(\tau)}{dR} - \frac{d\ln(u)}{dR}\right] = \frac{\tau}{u} \cdot \frac{\varepsilon_b^m \cdot w}{c^u} \cdot \left[\left(1 - \frac{\varepsilon^M}{\varepsilon^m}\right) \cdot \frac{\eta}{1-\eta} \cdot \frac{1+\tau}{1+\varepsilon^f} - (1-u) \cdot \frac{\varepsilon^M}{\varepsilon^m}\right].$$

Finally, we use the derivative (A35) to obtain a linear relationship between the ratio τ/u and the replacement rate R around their observed values, $\hat{\tau}/\hat{u}$ and $\hat{R}$. First, we set $\eta = 0.6$, $\varepsilon^f = 0$, and $\varepsilon_b^m = 0.4$ (Appendix D); $1 - \varepsilon^m/\varepsilon^m = 0.4$ (Section III); $\tau = 2.3\%$ and $u = 6.1\%$ (Section II); and $c^u/w = 0.74$ (equation (A19)). Under this calibration, $d(\tau/u)/dR = 0.01$. This calibration describes the average labor market and UI program, so 0.01 is the average value of $d(\tau/u)/dR$; it is not the value at $\hat{\tau}/\hat{u}$ and $\hat{R}$. But using the derivative at $\hat{\tau}/\hat{u}$ and $\hat{R}$ instead of the average derivative would only add second-order terms to the linear relationship; we opt to neglect them. Accordingly, we obtain

$$\frac{\tau}{u} = \frac{\hat{\tau}}{\hat{u}} + 0.01 \times \left(R - \hat{R}\right).$$

Appendix F. Sensitivity Analysis

We describe the formulas used to compute the alternative optimal replacement rates in the sensitivity analysis of Figure 8. We derive these formulas by following the steps of the derivation of the baseline formula, given by (19). To avoid repetition, however, we do not provide the entire derivations here: we only describe the steps that are modified by the changes in calibration.

A. *Elasticity Wedge* $(1 - \varepsilon^M/\varepsilon^m)$

With a generic elasticity wedge $1 - \varepsilon^M/\varepsilon^m$, the optimal UI formula becomes

$$\begin{aligned} R = {} & 4.6 \times [0.46 - 1.32 \times (R - 0.42)] \times [0.12 - 0.26 \times (R - 0.42)] \\ & + \left[1 - \frac{\varepsilon^M}{\varepsilon^m}\right] \times \left[0.88 - 0.32 \times (R - 0.42) - 1.5 \times \frac{\tau}{u}\right], \\ \text{where} \qquad & \frac{\tau}{u} = \frac{\hat{\tau}}{\hat{u}} + 0.21 \times \left[1.53 \times \left(1 - \frac{\varepsilon^M}{\varepsilon^m}\right) - 0.94 \times \frac{\varepsilon^M}{\varepsilon^m}\right] \times \left(R - \hat{R}\right). \end{aligned}$$

To obtain the replacement rates in panel A, we solve this formula with $1-\varepsilon^M/\varepsilon^m = -0.4$ and $1-\varepsilon^M/\varepsilon^m = 0$.

B. Microelasticity of Unemployment Duration with respect to Benefit Level (ε_b^m)

The microelasticity ε_b^m influences the calibration of the microelasticity of unemployment with respect to UI, ε^m. Indeed, (A34) implies that with a generic microelasticity ε_b^m, the parameter κ that determines the microelasticity ε^m satisfies

$$\kappa(\varepsilon_b^m) = 0.56 \times \varepsilon_b^m.$$

In addition, the microelasticity ε_b^m affects the utility cost of unemployment. Indeed, (A28) implies that with a generic microelasticity ε_b^m, $d\psi(e)/(\phi \cdot w) = -\varepsilon_b^m \times 0.55 \times dR$. As a consequence,

$$K(R, \varepsilon_b^m) = 0.46 - [1.11 + 0.55 \times \varepsilon_b^m] \times (R - 0.42).$$

Finally, the microelasticity ε_b^m affects the ratio τ/u. Equation (A35) implies that with a generic microelasticity ε_b^m,

$$\frac{\tau}{u}(R, \varepsilon_b^m) = \frac{\hat{\tau}}{\hat{u}} + \varepsilon_b^m \times 0.03 \times \left(R - \hat{R}\right).$$

With a generic microelasticity ε_b^m, the optimal UI formula therefore becomes

$$\begin{aligned} R = & \frac{1.01}{\kappa(\varepsilon_b^m)} \times [K(R, \varepsilon_b^m)] \times [0.12 - 0.26 \times (R - 0.42)] \\ & + \left[0.4 - 0.65 \times \left(\frac{\tau}{u}(R, \varepsilon_b^m) - 0.38\right)\right] \times \left[K(R, \varepsilon_b^m) + R - 1.5 \times \frac{\tau}{u}(R, \varepsilon_b^m)\right]. \end{aligned}$$

To obtain the replacement rates in panel B, we solve this formula with $\varepsilon_b^m = 0.6$ and $\varepsilon_b^m = 0.2$.

C. Nonpecuniary Cost of Unemployment (Z)

The cost Z affects the utility cost of unemployment: equations (9) and (A28) show that with a generic cost Z, we have

$$K(R, Z) = 0.16 + \frac{Z}{\phi \cdot w} - \left[1.10 + 0.48 \times \left(0.16 + \frac{Z}{\phi \cdot w}\right)\right] \times (R - 0.42).$$

In addition, (A34) implies that with a generic cost Z, the parameter κ satisfies

$$\kappa(Z) = 0.49 \times \left(0.16 + \frac{Z}{\phi \cdot w}\right).$$

With a generic cost Z, the optimal UI formula therefore becomes

$$R = \frac{1.01}{\kappa(Z)} \times [K(R,Z)] \times [0.12 - 0.26 \times (R - 0.42)] \\ + \left[0.4 - 0.65 \times \left[\frac{\hat{\tau}}{\hat{u}} - 0.38 + 0.01 \times \left(R - \hat{R}\right)\right]\right] \times \left[K(R,Z) + R - 1.5 \times \frac{\tau}{u}\right].$$

To obtain the replacement rates in panel C, we solve this formula with $Z = 0$ and $Z = 0.6 \cdot \phi \cdot w$.

D. *Matching Elasticity (η)*

The elasticity η affects the ratio τ/u: equation (A35) implies that with a generic elasticity η,

$$\frac{\tau}{u}(R,\eta) = \frac{\hat{\tau}}{\hat{u}} + 0.21 \times \left[0.41 \times \frac{\eta}{1-\eta} - 0.56\right] \times \left(R - \hat{R}\right).$$

The elasticity η also affects the efficiency term. Overall, with a generic elasticity η, the optimal UI formula becomes

$$R = 4.6 \times [0.46 - 1.32 \times (R - 0.42)] \times [0.12 - 0.26 \times (R - 0.42)] \\ + \left[0.4 - 0.65 \times \left(\frac{\tau}{u}(R,\eta) - 0.38\right)\right] \times \left[0.88 - 0.32 \times (R - 0.42) - \frac{\eta}{1-\eta} \times \frac{\tau}{u}(R,\eta)\right].$$

To obtain the replacement rates in panel D, we solve this formula with $\eta = 0.7$ and $\eta = 0.5$.

E. *Coefficient of Relative Risk Aversion (γ)*

The risk aversion γ affects the Baily-Chetty replacement rate, as showed by (A33). It also affects on the utility cost of unemployment. First, (A25) and (A26) imply that with a generic risk aversion γ, we have $dU(c^u + h)/(\phi \cdot w) = (0.94 + 0.10 \times \gamma) \times dR$, which yields

$$K(R,\gamma) = 0.46 - (1.22 + 0.10 \times \gamma) \times (R - 0.42).$$

Equation (A23) implies that γ also affects K through $U'(c^e)/\phi$ and $dU(c^e)/(\phi \cdot w)$, but these effects are negligible. Moreover, γ affects the parameter κ: equation (A34) implies that with a generic risk aversion γ, we have

$$\kappa(\gamma) = \frac{0.25}{1 + 0.11 \times \gamma}.$$

In sum, with a generic risk aversion γ, the optimal UI formula becomes

$$R = \gamma \times \frac{1.01}{\kappa(\gamma)} \times [K(R,\gamma)] \times [0.12 - 0.26 \times (R - 0.42)] \\ + \left[0.4 - 0.65 \times \left[\frac{\hat{\tau}}{\hat{u}} - 0.38 + 0.01 \times \left(R - \hat{R}\right)\right]\right] \times \left[K(R,\gamma) + R - 1.5 \times \frac{\tau}{u}\right].$$

To obtain the replacement rates in panel E, we solve this formula with $\gamma = 0.5$ and $\gamma = 2$.

F. Consumption Drop Upon Unemployment ($1 - c^h/c^e$)

The consumption drop is a function of the UI replacement rate, as showed by (A21). We denote by c^h/c^e the consumption ratio for a generic replacement rate R and by $\overline{c^h/c^e}$ the consumption ratio when the replacement rate takes the average value of $\overline{R} = 42\%$. Equation (A20) implies that $d(c^h/c^e) = 0.30 \times \overline{c^h/c^e} \times dR$. Hence, the consumption drop upon unemployment satisfies

$$1 - \frac{c^h}{c^e} = 1 - \overline{c^h/c^e} - 0.30 \times \overline{c^h/c^e} \times (R - 0.42).$$

The consumption drop also affects the utility cost of unemployment. First, using (A22) and (A24), we find that at $R = \overline{R}$,

$$K\left(\overline{R}, \overline{c^h/c^e}\right) = 1.61 - 1.31 \times \overline{c^h/c^e}.$$

(Equation (A23) shows that $\overline{c^h/c^e}$ affects K through $U'(c^e)/\phi$, but the effect is negligible.) In addition, (A25), (A26), and (A28) imply that

$$\frac{dU(c^u + h)}{\phi \cdot w} = \left[1.82 - 0.88 \times \overline{c^h/c^e}\right] \times dR,$$
$$\frac{d\psi(e)}{\phi \cdot w} = -0.48 \times \left[K\left(\overline{R}, \overline{c^h/c^e}\right)\right] \times dR.$$

(Equation (A23) shows that $\overline{c^h/c^e}$ also affects K through $dU(c^e)/(\phi \cdot w)$, but the effect is negligible.) Hence, we find that

$$K\left(R, \overline{c^h/c^e}\right) = K\left(\overline{R}, \overline{c^h/c^e}\right) - \left[1.82 + 0.48 \times K\left(\overline{R}, \overline{c^h/c^e}\right) - 0.88 \times \overline{c^h/c^e}\right] \times (R - 0.42).$$

Last, the consumption drop affects the parameter κ: (A26) and (A34) imply that with a generic consumption ratio $\overline{c^h/c^e}$, we have

$$\kappa\left(\overline{c^h/c^e}\right) = 0.54 \times \frac{K\left(\overline{R}, \overline{c^h/c^e}\right)}{1.94 - 0.94 \times \overline{c^h/c^e}}.$$

In sum, with a generic consumption drop $1 - \overline{c^h/c^e}$, the optimal UI formula becomes

$$R = \frac{1.01}{\kappa\left(\overline{c^h/c^e}\right)} \times \left[K(R, \overline{c^h/c^e})\right] \times \left[1 - \overline{c^h/c^e} - 0.30 \times \overline{c^h/c^e} \times (R - 0.42)\right]$$
$$+ \left[0.4 - 0.65 \times \left[\frac{\hat{\tau}}{\hat{u}} - 0.38 + 0.01 \times \left(R - \hat{R}\right)\right]\right] \times \left[K(R, \overline{c^h/c^e}) + R - 1.5 \times \frac{\tau}{u}\right].$$

(Equation (A23) implies that $\overline{c^h/c^e}$ also affects the Baily-Chetty replacement rate through $U'(c^e)/\phi$, but the effect is negligible.) To obtain the replacement rates in panel F, we solve this formula with $1 - \overline{c^h/c^e} = 0.05$ and $1 - \overline{c^h/c^e} = 0.2$.

Table A1: Parameter Values in the Simulation Model

	Description	Source
$s = 2.8\%$	Monthly job-separation rate	CPS, 1990–2014
$\eta = 0.6$	Matching elasticity	Petrongolo and Pissarides (2001)
$\mu = 0.60$	Matching efficacy	Matches $\theta = 0.43$
$\rho = 0.80$	Matching cost	Matches $\tau = 2.3\%$
$\alpha = 0.73$	Production function: concavity	Matches $1 - \varepsilon^M/\varepsilon^m = 0.4$
$\omega = 0.73$	Real wage level	Matches $u = 6.1\%$
$\zeta = 0.5$	Real wage rigidity	Michaillat (2014)
$\gamma = 1$	Relative risk aversion	Chetty (2006)
$\sigma = 0.17$	Disutility from home production: convexity	Matches $d\ln(c^h)/d\ln(c^u) = 0.2$
$\xi = 1.43$	Disutility from home production: level	Matches $1 - c^h/c^e = 12\%$
$\kappa = 0.22$	Disutility from job search: convexity	Matches $\varepsilon^m_b = 0.4$
$\delta = 0.33$	Disutility from job search: level	Matches $e = 1$
$z = -0.14$	Disutility from unemployment	Matches $Z = 0.3 \times \phi \times w$

Appendix G. Calibration of the Simulation Model

We calibrate the job-rationing model simulated in Section IV. The parameter values used in the simulations are summarized in Table A1. For the calibration, we normalize average technology to $a = 1$ and average job-search effort to $e = 1$.

First, we use a concave production function:

$$y(n) = a \cdot n^{\alpha},$$

where the parameter a measures technology and the parameter α measures diminishing marginal returns to labor. We set $\alpha = 0.73$ to be consistent with $1 - \varepsilon^M/\varepsilon^m = 0.4$ (Appendix E).

Next, we use a constant-relative-risk-aversion specification for the utility from consumption:

$$U(c) = \frac{c^{1-\gamma} - 1}{1-\gamma},$$

where the parameter γ is the coefficient of relative risk aversion. We set $\gamma = 1$ (Appendix D), which implies that $U(c) = \ln(c)$.

Then, we calibrate the parameters related to matching. We use a Cobb-Douglas matching function:

$$m(e \cdot u, v) = \mu \cdot (e \cdot u)^{\eta} \cdot v^{1-\eta},$$

where the parameter μ measures the matching efficacy and the parameter η is the matching elasticity. We set $\eta = 0.6$ (Appendix D). With this matching function, $f(\theta) = \mu \cdot \theta^{1-\eta}$ and $q(\theta) = \mu \cdot \theta^{-\eta}$.

We set the job-separation rate to its average value for 1990–2014: $s = 2.8\%$ (Appendix B).

To calibrate the matching efficacy, we rewrite (1) as

$$\mu = \theta^{\eta-1} \cdot \frac{s \cdot (1-u)}{u \cdot e}.$$

We use the number of vacancies constructed in Section II.A from the Barnichon (2010) data. The average number of vacancies is 3.80 million for 1990–2014. And the average number of unemployed workers in CPS data for 1990–2014 is 8.82 million. Since the average job-search effort is normalized 1, the average tightness for 1990–2014 is $\theta = 3.80/(1 \times 8.82) = 0.43$. With $s = 2.8\%$, $\theta = 0.43$, $\eta = 0.6$, $e = 1$, and $u = 6.1\%$ (Section II), we get $\mu = 0.60$.

To calibrate the matching cost, we exploit (2), which implies

$$\rho = \mu \cdot \theta^{-\eta} \cdot \frac{\tau}{s \cdot (1+\tau)}.$$

With $\mu = 0.6$, $s = 2.8\%$, $\theta = 0.43$, and $\tau = 2.3\%$ (Section II), we obtain $\rho = 0.80$.

We now calibrate the parameters related to wages. We use a partially rigid wage schedule:

$$w(a) = \omega \cdot a^{1-\zeta},$$

where the parameter ω governs the wage level and the parameter ζ governs wage rigidity. Following Michaillat (2014), we set the wage rigidity to $\zeta = 0.5$.

Then we calibrate the wage level. We use (20) and the equilibrium condition $l^d(\theta, a) = l = 1-u$, which imply

$$\omega = a^{\zeta} \cdot \alpha \cdot (1-u)^{\alpha-1} \cdot (1+\tau)^{-\alpha}.$$

With $a = 1$, $\tau = 2.3\%$, $\alpha = 0.73$, and $u = 6.1\%$, we obtain $\omega = 0.73$.

We now compute the consumption levels implied by the calibration. The definition of the replacement rate implies $c^e - c^u = w \cdot (1-R)$. The government's budget constraint imposes $(1-u) \cdot c^e + u \cdot c^u = a \cdot n^{\alpha}$. Solving this linear system of two equations with $a = 1, w = 0.73$, $R = 42\%$ (Section II), $u = 6.1\%$, $\tau = 2.3\%$, $n = (1-u)/(1+\tau) = 0.92$, and $\alpha = 0.73$, we obtain $c^e = 0.97$ and $c^u = 0.54$. As $1 - c^h/c^e = 12\%$ (Appendix D), we find $c^h = 0.85$ and $h = c^h - c^u = 0.31$.

These consumption levels allow us to calibrate other statistics. The average marginal utility ϕ satisfies $1/\phi = (1-u) \cdot (c^e)^{\gamma} + u \cdot (c^h)^{\gamma}$. With $\gamma = 1$, $u = 6.1\%$, $c^e = 0.97$, and $c^h = 0.85$, we find $\phi = 1.04$. We set the total nonpecuniary cost from unemployment to $Z = 0.3 \times \phi \times w$ (Section II). With $\phi = 1.04$ and $w = 0.73$, we obtain $Z = 0.23$. Finally, with log utility, $Z = 0.23$, $c^e = 0.97$, and $c^h = 0.85$, we find that the utility gain from work is $U(c^e) - U(c^h) + Z = \ln(c^e/c^h) + Z = 0.36$.

We assume that the disutility from home production is a convex power function:

$$\lambda(h) = \xi \cdot \frac{h^{1+\sigma}}{1+\sigma},$$

where the parameter ξ governs the level of disutility and the parameter σ governs the convexity of the disutility function. Equation (4) implies that

$$\xi \cdot h^{\sigma} = (c^u + h)^{-\gamma}. \tag{A36}$$

We implicitly differentiate this equation with respect to c^u and obtain

$$\frac{dh}{dc^u} = -\frac{\gamma \cdot (h/c^h)}{\sigma + \gamma \cdot (h/c^h)}$$

$$\text{and} \qquad \frac{dc^h}{dc^u} = 1 + \frac{dh}{dc^u} = \frac{\sigma}{\sigma + \gamma \cdot (h/c^h)}.$$

Since $c^h = 0.85$, $c^u = 0.54$ and $d\ln(c^h)/d\ln(c^u) = 0.2$ (Appendix D), we infer that $dc^h/dc^u = 0.2 \times (0.85/0.54) = 0.31$. Furthermore, $h/c^h = 0.35$ and $\gamma = 1$. We conclude that $\sigma = 0.17$. Using (A36), $\gamma = 1$, $c^u = 0.54$, $h = 0.31$, and $\sigma = 0.17$, we find $\xi = 1.43$.

We assume that the disutility from search effort is a convex power function:

$$\psi(e) = \delta \cdot \frac{\kappa}{1+\kappa} \cdot e^{(1+\kappa)/\kappa},$$

where the parameter δ governs the level of disutility and the parameter κ governs the convexity of the disutility function. We set $\kappa = 0.22$ to be consistent with $\varepsilon_b^m = 0.4$ (Appendix E). To calibrate δ, we use equation (6). With $e = 1$, the equation implies

$$\delta = (1-u) \cdot \Big(U(c^e) - U(c^h) + Z \Big).$$

With $u = 6.1\%$ and $U(c^e) - U(c^h) + Z = 0.36$, we find $\delta = 0.33$.

Last, we calibrate the disutility from unemployment, z. We target $Z = z + \psi(e) + \lambda(h) = 0.23$. On average $\lambda(h) = \lambda(0.31) = 0.31$ and $\psi(e) = \psi(1) = 0.06$, so we set $z = -0.14$.

Appendix H. Additional Simulation Results

We discuss additional results obtained in the simulations of Section IV. The simulations compare three UI programs: in the first, the replacement rate remains constant at 42%, the average US value; in the second, the replacement rate is the Baily-Chetty replacement rate, described in formula (11); and in the third, the replacement rate is the optimal replacement rate, given by formula (11). Under each UI program, we simulate equilibria spanning the business cycle.

Figure A2 displays the additional results. The first three panels describe the labor market conditions. When technology increases from 0.96 to 1.03 and UI remains constant, the unemployment rate falls from 10% to 4.5%. The unemployment rate responds when the UI replacement rate adjusts from its original level of 42% to the Baily-Chetty and optimal levels; however, these responses are small. The range of fluctuations of the unemployment rate in the simulations is consistent with the range observed in the United States (Figure 1, panel A).

As the unemployment rate falls, the recruiter-producer ratio increases from 1% to 3.7%. This is because when technology varies, it shifts the labor demand, which generates negative comovements between tightness and unemployment (Michaillat and Saez 2015). Hence, the tightness θ is procyclical, which makes the recruiter-producer ration $\tau(t)$ procyclical. The range of fluctuations of the recruiter-producer ratio in the simulations is comparable, albeit somewhat wider, to the range observed in the United States (Figure 1).

Finally, since u is countercyclical and τ is procyclical, the ratio $\tau(\theta)/u$ is procyclical. As a

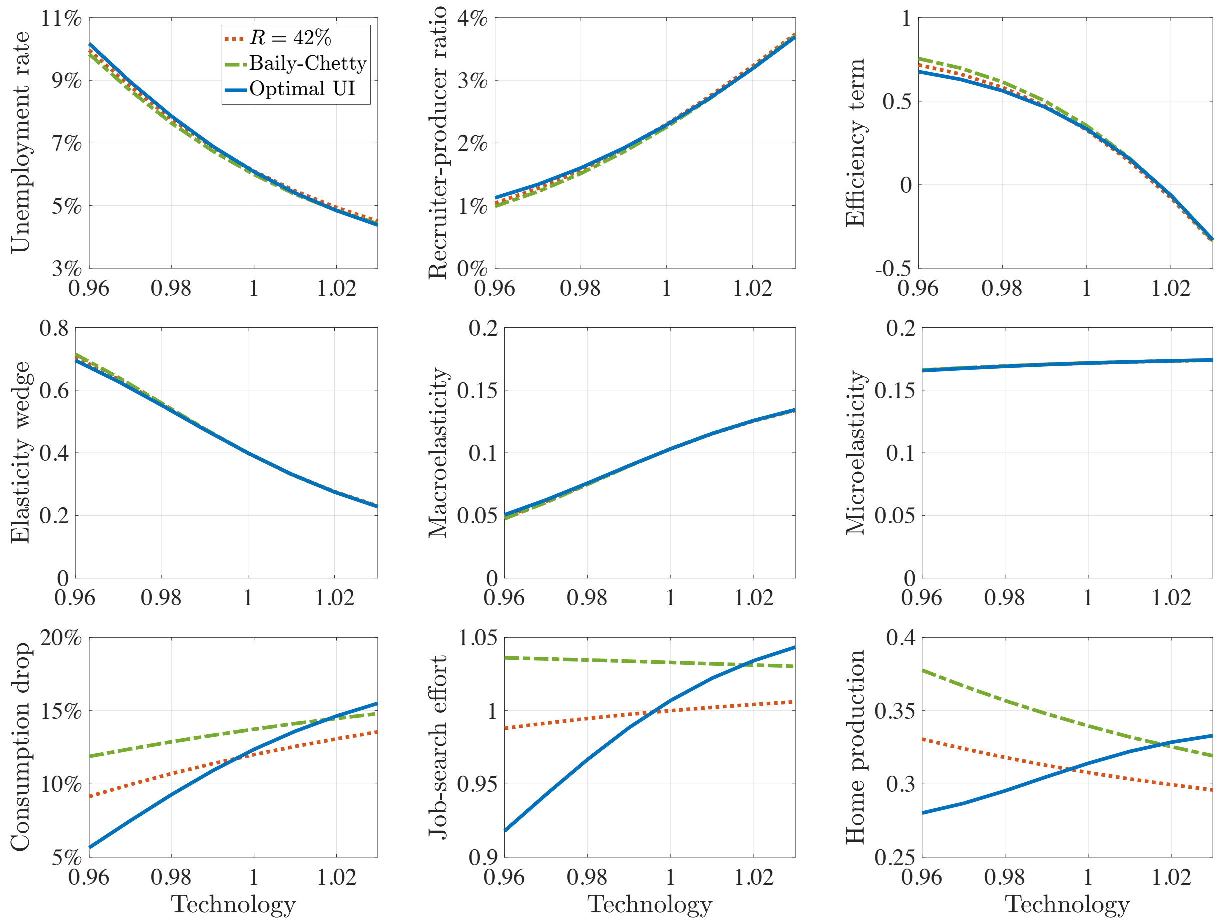


Figure A2: Additional Simulation Results

Notes: This figure complements Figure 10 in Section IV. The figure depicts equilibria under a constant replacement rate of $R = 42\%$ (dotted, red line), the Baily-Chetty replacement rate (dashed, green line), and the optimal UI replacement rate (solid, blue line). The optimal replacement rate is computed using formula (11) and the Baily-Chetty replacement rate using the expression in (11). The equilibria are parametrized by various levels of technology. The results are obtained by simulating the job-rationing model of Michaillat (2012) under the calibration in Appendix G.

consequence, the efficiency term is countercyclical: it is above 0.5 for high unemployment rates, around 0.3 on average, and below -0.3 for low unemployment rates. The fluctuations of the efficiency term in the simulations are consistent with those in Figure 3.

The next three panels display the microelasticity (ε^m), macroelasticity (ε^M), and elasticity wedge ($1 - \varepsilon^M/\varepsilon^m$). On average, the elasticity wedge is positive, equal to 0.4. The elasticity wedge is countercyclical but always positive: as the unemployment rate falls, it decreases from 0.71 to 0.23. Section III.E explains why the elasticity wedge is countercyclical and provides empirical evidence. The fluctuations of the elasticity wedge in the simulations are consistent with those in Figure 5.

In the simulations, the elasticity wedge varies because the macroelasticity of unemployment with respect to UI does. Indeed, as the unemployment rate falls, the macroelasticity increases from 0.05 to 0.13 . Hence, UI has a weaker influence on unemployment in slumps and a stronger influence in booms; this property arises because of job rationing. Unlike the macroelasticity, the microelasticity of unemployment with respect to UI is broadly constant around 0.17 in all labor market conditions. Hence, UI has the same effect on job-search effort in slumps and booms.

The next panel shows that the consumption drop upon unemployment is procyclical: as the unemployment rate falls, the consumption drop rises from 9% to 14% when $R = 42\%$, from 12% to 15% under Baily-Chetty UI, and from 6% to 16% under optimal UI. Under optimal UI, the consumption drop is procyclical because the replacement rate is countercyclical. Under constant and Baily-Chetty UI, the consumption drop is procyclical because home production is countercyclical. This happens because unemployed workers receive lower UI benefits in bad times due to the (weakly) lower replacement rate and lower output in the economy. With lower benefits, the marginal value of home production is higher, so home production is higher.

Figure 10 in Section IV shows that the optimal UI program is quite generous in bad times, with a replacement rate above 50%. This result is striking because, as showed in the last two panels of Figure A2, the optimal UI program has significant disincentives effects at the micro level. These disincentive effects, arising from moral hazard, reduce job search and home production: in bad times, both job search and home production are about 10% below their average levels.

References

Aguiar, Mark, and Erik Hurst. 2005. "Consumption versus Expenditure." *Journal of Political Economy*, 113(5): 919–948.

Barnichon, Regis. 2010. "Building a Composite Help-Wanted Index." *Economics Letters*, 109(3): 175–178.

Borowczyk-Martins, Daniel, Grégory Jolivet, and Fabien Postel-Vinay. 2013. "Accounting for endogeneity in matching function estimation." *Review of Economic Dynamics*, 16(3): 440–451.

Browning, Martin, and Thomas F. Crossley. 2001. "Unemployment Insurance Benefit Levels and Consumption Changes." *Journal of Public Economics*, 80(1): 1–23.

Card, David, Andrew Johnston, Pauline Leung, Alexandre Mas, and Zhuan Pei. 2015. "The Effect of Unemployment Benefits on the Duration of Unemployment Insurance Receipt: New Evidence from a Regression Kink Design in Missouri, 2003-2013." *American Economic Review*, 105(5): 126–130.

Chetty, Raj. 2006. "A New Method of Estimating Risk Aversion." *American Economic Review*, 96(5): 1821–1834.

Chetty, Raj, and Amy Finkelstein. 2013. "Social Insurance: Connecting Theory to Data." In *Handbook of Public Economics*. Vol. 5, , ed. Alan J. Auerbach, Raj Chetty, Martin Feldstein and Emmanuel Saez, 111–193. Amsterdam:Elsevier.

DeLoach, Stephen, and Mark Kurt. 2013. "Discouraging Workers: Estimating the Impacts of Macroeconomic Shocks on the Search Intensity of the Unemployed." *Journal of Labor Research*, 34(4): 433–454.

Ganong, Peter, and Pascal Noel. 2016. "How Does Unemployment Affect Consumer Spending?" http://scholar.harvard.edu/files/ganong/files/ganong_jmp_unemployment_spending.pdf.

Gomme, Paul, and Damba Lkhagvasuren. 2015. "Worker Search Effort as an Amplification Mechanism." *Journal of Monetary Economics*, 75: 106–122.

Gruber, Jonathan. 1997. "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review*, 87(1): 192–205.

Hendren, Nathaniel. 2016. "Knowledge of Future Job Loss and Implications for Unemployment Insurance." *American Economic Review*, forthcoming.

Kroft, Kory, and Matthew J. Notowidigdo. 2016. "Should Unemployment Insurance Vary With the Unemployment Rate? Theory and Evidence." *Review of Economic Studies*, 83(3): 1092–1124.

Landais, Camille. 2015. "Assessing the Welfare Effects of Unemployment Benefits Using the Regression Kink Design." *American Economic Journal: Economic Policy*, 7(4): 243–278.

Landais, Camille, Pascal Michaillat, and Emmanuel Saez. 2016. "A Macroeconomic Approach to Optimal Unemployment Insurance: Theory." *American Economic Journal: Economic Policy*, forthcoming.

Meyer, Bruce. 1990. "Unemployment Insurance and Unemployment Spells." *Econometrica*, 58(4): 757–782.

Michaillat, Pascal. 2012. "Do Matching Frictions Explain Unemployment? Not in Bad Times." *American Economic Review*, 102(4): 1721–1750.

Michaillat, Pascal. 2014. "A Theory of Countercyclical Government Multiplier." *American Economic Journal: Macroeconomics*, 6(1): 190–217.

Michaillat, Pascal, and Emmanuel Saez. 2015. "Aggregate Demand, Idle Time, and Unemployment." *Quarterly Journal of Economics*, 130(2): 507–569.

Mukoyama, Toshihiko, Christina Patterson, and Aysegul Sahin. 2014. "Job Search Behavior over the Business Cycle." Federal Reserve Bank of New York Staff Report 689.

Petrongolo, Barbara, and Christopher A. Pissarides. 2001. "Looking into the Black Box: A Survey of the Matching Function." *Journal of Economic Literature*, 39(2): 390–431.

Rogerson, Richard, and Robert Shimer. 2011. "Search in Macroeconomic Models of the Labor Market." In *Handbook of Labor Economics*. Vol. 4A, , ed. Orley C. Ashenfelter and David Card, 619–700. Amsterdam:Elsevier.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender. 2012. "The Effects of Extended Unemployment Insurance Over the Business Cycle: Evidence from Regression Discontinuity Estimates over Twenty Years." *Quarterly Journal of Economics*, 127(2): 701–752.

Shimer, Robert. 2004. "Search Intensity." http://sites.google.com/site/robertshimer/intensity.pdf.

Shimer, Robert. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." *American Economic Review*, 95(1): 25–49.

Shimer, Robert. 2012. "Reassessing the Ins and Outs of Unemployment." *Review of Economic Dynamics*, 15(2): 127–148.

Stephens, Melvin. 2001. "The Long-Run Consumption Effects Of Earnings Shocks." *Review of Economics and Statistics*, 83(1): 28–36.