A Macroeconomic Approach to Optimal Unemployment Insurance: Applications

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Abstract

This paper applies Landais, Michaillat, and Saez's (2016) theory of optimal unemployment insurance (UI) to determine how optimal UI varies over the business cycle in the United States since 1990. The optimal UI replacement rate is the Baily-Chetty rate plus a correction term, which depends on whether the labor market is slack, efficient, or tight, and how UI affects labor market tightness. To implement the optimal UI formula expressed in terms of estimable statistics, we produce new series on US labor market efficiency. We find that the labor market is too slack except in very good times. In addition, empirical evidence suggests that UI increases tightness. Hence, the correction term is sharply countercyclical. Optimal UI is therefore markedly countercyclical. In fact, the cyclicality of optimal UI is fairly close to the cyclicality of actual UI.

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Unemployment insurance (UI) is a key component of social insurance, and whether to increase or decrease the generosity of UI during slumps is an important yet unresolved public policy question. For instance, in the United States, the generosity of UI automatically increases with the unemployment rate, but these automatic increases remain debated. A broad body of work shows that an increase in the generosity of UI leads to a reduction in unemployed workers' search effort. Proponents of increasing UI in slumps argue that the reduction in search effort does not raise the unemployment rate much in slumps because high unemployment is due to a scarcity of jobs, not insufficient search. Proponents of reducing UI in slumps worry that higher UI may lead to higher wages through bargaining and thus lower job creation by firms.[1]

In a companion paper (Landais, Michaillat and Saez 2016), we develop a theory of optimal UI to inform this public policy debate. We show that the optimal replacement rate is the conventional Baily (1978)-Chetty (2006) rate plus a correction term. The correction term measures the effect of UI on welfare through labor market tightness and therefore is the product of two terms: the effect of UI on tightness and the effect of tightness on welfare. In this paper, we apply the theory to explore how the generosity of UI should vary over the business cycle in the United States.[2]

We begin in Section I by extending the static matching model from our companion paper into a richer dynamic matching model that can be brought to the data and used for quantitative applications. In particular, the model allows for partial self-insurance via home production for the unemployed, and a nonpecuniary cost of unemployment. The optimal UI formula carries over almost identically. All the terms in the formula can be expressed in terms of estimable statistics. We discuss how to estimate these statistics in Sections II and III.

An increase in labor market tightness raises welfare when the value of having a job relative to being unemployed is high enough compared to recruitment costs. In Section II, we develop a method that exploits this insight to assess whether labor market tightness is too slack, efficient, or too tight at any point in time. Our method produces a new time series measuring the efficiency of the US labor market since 1990. Such a series had not been constructed before in the search-and-

[1]For an overview of the debate during the Great Recession in the United States, see Robert Barro, "The Folly of Subsidizing Unemployment", Wall Street Journal, 08/30/2015, http://www.wsj.com/articles/SB10001424052748703959704575454431457720188 and "The Wages of Unemployment", Wall Street Journal, 10/17/2013, http://www.wsj.com/articles/SB10001424052702304410204579139451591729392.

[2]Our work complements the important contribution by Kroft and Notowidigdo (2016), who study the fluctuations of the Baily-Chetty replacement rate over the business cycle.

matching literature and is the most important contribution of this paper.[3] Measuring the efficiency of the labor market is a difficult empirical question but it is central for optimal UI, and for a broad range of stabilization policies. Our method should be seen as a blueprint that should be amended as better empirical evidence becomes available.

Our method has two steps: (1) determine the share of labor devoted to recruiting, and (2) determine the utility loss from unemployment. First, using several sources from the Bureau of Labor Statistics (BLS) and Census Bureau, we construct a time series for the share of labor devoted to recruiting covering 1990–2014. This share averages 2.3% and is sharply procyclical as predicted by the matching model. Second, we combine a variety of sources measuring the consumption drop upon unemployment, risk aversion, and the nonpecuniary cost of unemployment. Overall, we find that the US labor market is too slack on average, is much too slack in slumps (especially in 1992, 2001, and 2009), and is too tight only in strong booms (in 1998–2000).

An increase in UI raises labor market tightness when the macroelasticity of unemployment with respect to UI is smaller than the microelasticity. In Section III, we review the evidence on this issue, including several recent studies whose analysis is guided in part by the theory developed in our companion paper. Although there remains significant uncertainty about the estimates, most studies find that the microelasticity is larger than the macroelasticity. Moreover, there is compelling evidence of rat-race channel in several case studies but no clear evidence that an increase in UI raises wages, as happens through the job-creation channel. Based on this evidence, we conclude that an increase in UI raises tightness.

Combining the results from Sections II and III, in Section IV, we apply our optimal UI formula to the United States for 1990–2014. First, we use our optimal formula to estimate the welfare effect of a small deviation from actual UI at each point in time, which provides a direct evaluation of whether actual UI is too high or too low at each point in time. To measure the generosity of the actual UI system, we construct a series of the effective UI replacement rate among all unemployed workers. The series takes into account the potential duration during which eligible unemployed workers can collect UI. The series express variations in UI generosity in the United States in

[3]The literature has never formulated the condition for efficiency on the labor market in terms of the recruiter-producer ratio. The standard condition for efficiency on a matching labor market is the Hosios (1990) condition, which compares the elasticity of the matching function with workers' bargaining power. The bargaining power is hard to measure, explaining why nobody has attempted to assess the efficiency of the labor market before.

a simple yet comprehensive way that fits our model. Our actual UI replacement rates series is countercyclical, indicating that the extensions of UI benefit duration more than compensate for the increase in unemployment duration during recessions. We find that the actual generosity of UI is close to optimal on average and over the business cycle. In particular, the extension of the duration of UI benefits in the wake of the Great Recession seems close to optimal. There are two periods when the UI program seems suboptimal: UI was inefficiently high in the boom preceding the dot-com bubble (1997–2000) and inefficiently low in the recovery following the Great Recession particularly after 2013 when the duration extensions were eliminated while the unemployment rate was still fairly high.

Second, we use our formula to compute the optimal UI replacement rate. As is well known, optimal policy formulas expressed in estimable statistics are only implicit formulas because some of the right-hand-side terms are endogenous to UI (Chetty 2008). Our main innovation is to systematically express these right-hand-side terms as a function of UI using empirical knowledge regarding how each term varies with UI. This allows us to compute the optimal UI replacement rate using solely our optimal UI formula and without having to fully specify an underlying structural model.[4] Overall, we find that the optimal replacement rate is markedly countercyclical and varies between 35% and 52% over the 1990–2014 period. Because these estimates rely on empirical estimates for which there is considerable uncertainty, we provide some sensitivity analysis around the most important parameters. While the generosity of optimal UI varies with the parameters, the finding that optimal UI is sharply countercyclical is robust.

Third, to assess the validity of our formula-based approach, we also simulate a specific matching model and compute optimal UI in this context. We find that over the business cycle, optimal UI from the structural model is very close to the formula-based optimal UI.

I. Optimal Unemployment Insurance in a Dynamic Model

In this section we propose a rich dynamic model of UI that extends the static model from our companion paper (Landais, Michaillat and Saez 2016). To improve the description of the cost of unemployment, the model includes partial self-insurance against unemployment through home

[4]This formula-based approach could be applied to many other optimal policy problems.

production and a nonpecuniary cost of unemployment. The model also includes long-term employment relationships and labor market flows from unemployment to employment and from employment to unemployment. As large flows prevail on the labor market at all times, the dynamic model better describes the real world than the static model. The optimal UI formula that we derive is nearly identical to the formula in our companion paper, even though the presence of labor market flows slightly modifies the derivation. The next sections apply the formula to the United States.

A. The Model

Given that our companion paper details the structure of the model, we keep the presentation short. 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 new worker-firm matches that are 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 function m 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 therefore 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 η as the matching elasticity.

Jobs are destroyed at an exogenous 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, $f(\theta)$, and s 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*) and Michaillat and Saez (2015) show that the employment rate obtained from equation (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 equation (1).

The representative firm employs $l(t)$ workers in total: $n(t)$ workers who produce output and $l(t)-n(t)$ workers who recruit employees by posting vacancies. All workers are paid a real wage $w(t)$. The firm's production function is $y(n(t))$. The function y is differentiable, increasing, and concave. Posting a vacancy requires ρ recruiters. Labor market flows are balanced so $s \cdot l(t) = v(t) \cdot q(\theta(t))$ and the number of vacancies posted by firms is $v(t) = s \cdot l(t)/q(\theta(t))$. Hence the number of recruiters in a firm with $l(t)$ employees is $l(t) \cdot s \cdot \rho / q(\theta(t))$, and the number of producers in the firm is $n(t) = l(t) \cdot (1 - s \cdot \rho / q(\theta(t)))$. The recruiter-producer ratio in the firm therefore is $\tau(\theta(t)) = s \cdot \rho / (q(\theta(t)) - s \cdot \rho)$, and the numbers of employees and producers are related by $l(t) = (1 + \tau(\theta(t))) \cdot n(t)$.

The firm sells its output on a perfectly competitive market. At time t, the firm takes $\theta(t)$ and $w(t)$ as given, and it chooses $l(t)$ to maximize profits $y(l(t)/(1+\tau(\theta(t)))) - w(t) \cdot l(t)$ so that $y'(l(t)/(1+\tau(\theta(t))))/(1+\tau(\theta(t))) = w(t)$. Because we ignore the transitional dynamics of employment, firms maximize a static objective at each instant. The approximation works well as long as the job-destruction rate, s, is much higher than the interest rate; this condition is satisfied in US data where $s \approx 3\%$ per month. The labor demand $l^d(\theta(t), w(t))$ coming out of the profit maximizing first order condition above gives the optimal number of employees for the firm.

The government's UI program provides consumption $c^e(t)$ to employed workers and consumption $c^u(t) < c^e(t)$ to unemployed workers. The generosity of UI is measured by the replacement rate $R(t) = 1 - \Delta c(t)/w(t)$, where $\Delta c(t) \equiv c^e(t) - c^u(t)$. At time t, the government must satisfy the budget constraint $y(n(t)) = (1 - l(t)) \cdot c^u(t) + l(t) \cdot c^e(t)$.

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

Unemployed workers choose $h(t)$ to maximize $U(c^u(t)+h(t))-\lambda(h(t))$. The home-production supply h^s gives the optimal level of home production. It is implicitly defined by the first-order condition of the maximization:

$$\lambda'\left(h^s(c^u(t))\right)=U'\left(c^u(t)+h^s(c^u(t))\right).$$

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

At time t, the representative worker takes $\theta(t)$, $c^e(t)$, $c^u(t)$, and $c^h(t)$ as given, and it chooses $e(t)$ to maximize its expected utility

$$\text{(2)}\quad \frac{e(t)\cdot f(\theta(t))}{s+e(t)\cdot f(\theta(t))}\cdot U(c^e(t))+\frac{s}{s+e(t)\cdot f(\theta(t))}\cdot\left[U(c^h(t))-z-\lambda(h^s(c^u(t)))-\psi(e(t))\right].$$

Effort supply at time t is denoted by $e^s(f(\theta(t)),\Delta U(t))$ and is is implicitly defined by

$$\text{(3)}\quad \psi'(e(t))=\frac{f(\theta(t))}{s+e(t)\cdot f(\theta(t))}\cdot\left(\Delta U(t)+\psi(e(t))\right),$$

$$\text{(4)}\quad \text{where}\quad \Delta U(t)\equiv U(c^e(t))-U(c^h(t))+z+\lambda(h^s(c^u(t))).$$

The utility gain from work is $\Delta U(t)+\psi(e^s(f(\theta(t)),\Delta U(t)))$. The utility gain from work can be expressed as $U(c^e(t))-U(c^h(t))+Z(t)$, where

$$\text{(5)}\quad Z(t)\equiv z+\lambda(h^s(c^u(t)))+\psi(e^s(f(\theta(t)),\Delta U(t)))$$

is the total nonpecuniary cost of unemployment.

The labor supply $l^s(\theta(t),\Delta U(t))$ gives the number of workers who have a job when job search is optimal. It is defined by

$$\text{(6)}\quad l^s(\theta(t),\Delta U(t))=\frac{e^s(f(\theta(t)),\Delta U(t))\cdot f(\theta(t))}{s+e^s(f(\theta(t)),\Delta U(t))\cdot f(\theta(t))}.$$

[5]The nonpecuniary cost of work for employed workers has been normalized to zero; with a nonzero cost of work, we could redefine z as the nonpecuniary cost of unemployment net of the nonpecuniary cost of work.

Finally, the wage is given by a general wage mechanism: $w(t) = w(\theta(t), \Delta U(t))$.

An equilibrium at time t is parameterized by the generosity of UI, $\Delta U(t)$. In equilibrium, tightness equalizes labor supply and demand: $l^s(\theta(t), \Delta U(t)) = l^d(\theta(t), w(\theta(t), \Delta U(t)))$. This equation defines the equilibrium level of tightness as an implicit function of $\Delta U(t)$, denoted $\theta(\Delta U(t))$. Once $\theta(t) = \theta(\Delta U(t))$ is determined, it is simple to determine the equilibrium level of the other variables: $l(t)$ is determined by $l(t) = l^s(\theta(t), \Delta U(t))$, $e(t)$ by $e(t) = e^s(f(\theta(t)), \Delta U(t))$, $n(t)$ by $n(t) = l(t)/(1+\tau(\theta(t)))$, $w(t)$ by $w(t) = w(\theta(t), \Delta U(t))$, and $c^e(t)$ and $c^u(t)$ by the government's budget constraint and (4).

B. The Optimal Unemployment Insurance Formula

At any point in time, the government chooses $\Delta U(t)$ to maximize social welfare, given by (2), subject to the equilibrium constraints. Although the model is dynamic, the government maximizes a static objective at each instant. We achieve this simplification by abstracting from the transitional dynamics of employment. The simplification allows us to describe the optimal UI in the dynamic model with a formula that is almost identical to the one obtained in the static model. To simplify notation, we omit the time index t below.

Optimal UI relies on three statistics: the microelasticity of unemployment with respect to UI

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

the discouraged-worker elasticity

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

and the macroelasticity of unemployment with respect to UI

(9) $$\varepsilon^M = \frac{\Delta U}{1-l} \cdot \frac{dl}{d\Delta U}.$$

In this dynamic model, the optimal UI replacement rate $R = 1 - \Delta c/w$ is given by the formula:

$$
\begin{aligned}
R = &\overbrace{\frac{l}{w} \cdot \frac{\Delta U}{\varepsilon^m} \cdot \left(\frac{1}{U'(c^e)} - \frac{1}{U'(c^h)}\right)}^{\text{Baily-Chetty replacement rate}} \\
&+ \underbrace{\left(1 - \frac{\varepsilon^M}{\varepsilon^m}\right)}_{\text{elasticity wedge}} \cdot \underbrace{\frac{1}{1+\varepsilon^f} \cdot \left[\frac{\Delta U + \psi(e)}{w \cdot \phi} + \left(1 + \varepsilon^f\right) \cdot R - \frac{\eta}{1-\eta} \cdot \frac{\tau(\theta)}{u}\right]}_{\text{efficiency term}},
\end{aligned}
\tag{10}
$$

where $\phi = 1/\left[l/U'(c^e) + (1-l)/U'(c^h)\right]$ is the harmonic mean of workers' marginal consumption utilities. The derivation of the formula is presented in Appendix B.

The formula is nearly identical to the formula in a static model (formula (23) in our companion paper). There are a few small differences between the two formulas, but they can be resolved once the formulas are expressed with the correct sufficient statistics. First, $U'(c^u)$ is replaced by $U'(c^h)$. This is because the correct sufficient statistic is the marginal utility of consumption for unemployed workers. Second, ΔU is replaced by $\Delta U + \psi(e)$ in the efficiency term. This is because the correct sufficient statistic is the utility gap between employed and unemployed workers. This gap is $\Delta U + \psi(e)$ in the dynamic model because only unemployed workers search for jobs, but ΔU in the static model because all workers initially search for jobs. Third, $\tau(\theta)$ is replaced by $\tau(\theta)/u$. This is because the correct sufficient statistic is the number of workers who search for a job which is u in the dynamic model but 1 in the static model where everybody is initially unemployed.

The formula shows that he optimal replacement rate equals the Baily-Chetty replacement rate plus a correction term. The Baily-Chetty rate is the optimal replacement rate when tightness does not respond to UI. The correction term governs how the Baily-Chetty rate must be adjusted to obtain the optimal replacement rate when tightness responds to UI. The correction term measures the effect of UI on welfare through tightness. It equals the effect of UI on tightness times the effect of tightness on welfare, keeping UI constant. When an increase in UI raises welfare through tightness, the correction term is positive and the optimal replacement rate is above the Baily-Chetty rate. Conversely, when an increase in UI reduces welfare through tightness, the correction term is negative and the optimal replacement rate is below the Baily-Chetty rate.

As in the static model, there are empirical criteria to evaluate the effect of tightness on welfare and the effect of UI on tightness: the effect of tightness on welfare is measured by the efficiency term, and the effect of UI on tightness is measured by the elasticity wedge. In Sections II and III, we measure the efficiency term in US data and discuss the sign of the elasticity wedge. Then in Section IV, we use this empirical evidence to solve formula (10) and determine the optimal UI replacement rate in the United States over the business cycle.

II. The Effect of Labor Market Tightness on Social Welfare

In matching models, labor market tightness may be inefficiently high or inefficiently low. This means that increasing tightness while keeping UI constant can have a positive or negative effect on social welfare. However, as showed in Section I, there is an empirical criterion to evaluate the effect of tightness on welfare. An increase in tightness raises welfare if the efficiency term, defined in formula (10), is positive. Conversely, an increase in tightness lowers welfare if the efficiency term is negative. Combining equations (10), (4), and (5), we find that

$$\text{efficiency term} = \frac{1}{1+\varepsilon^f} \cdot \left[\frac{U(c^e) - U(c^h) + Z}{w \cdot \phi} + \left(1+\varepsilon^f\right) \cdot R - \frac{\eta}{1-\eta} \cdot \frac{\tau(\theta)}{u}\right]. \tag{11}$$

We rely on empirical evidence for the United States to compute the efficiency term over the business cycle. The empirical evidence suggests that the efficiency term is sharply procyclical, and thus that an increase in tightness is much more desirable in slumps than in booms.

In the appendices we review available empirical evidence. In Appendix C we review the literature measuring the utility gain from work and set the utility function to $U(c) = \ln(c)$ (coefficient of relative risk aversion of 1), the consumption drop upon unemployment to $c^h/c^e = 0.81$, and the average marginal utility from wages to $\phi \cdot w = 0.77$. In Appendix D we review the literature estimating labor market elasticities and set the discouraged-worker elasticity to $\varepsilon^f = 0$ and the matching elasticity to $\eta = 0.6$. Last, we measure the unemployment rate u with the unemployment rate constructed by the BLS from the Current Population Survey (CPS). The dashed, red line in Figure 1, Panel A, depicts the unemployment rate for 1990–2014. The unemployment rate averages 6.1% and is countercyclical.

In this section we estimate the statistics of the efficiency term that have not been estimated before: the recruiter-producer ratio (τ), the effective replacement rate (R), and the nonpecuniary cost of unemployment (Z). We construct time series for τ and R for the 1990–2014 period, and we propose an estimate for Z.

A. *The Recruiter-Producer Ratio (τ)*

We first construct three different measures of τ. The first two measures are available for 1990–2014, and the third one for 2001–2014. We then combine the three measures into a single composite measure, which we use to construct the efficiency term.

The first measure of τ is based on the size of the recruiting industry, denoted *rec*. We measure *rec* by the seasonally adjusted monthly number of workers in the recruiting industry computed by the BLS from the Current Employment Statistics (CES) survey. The series is available for 1990–2014. The recruiting industry is the industry with North American Industry Classification System (NAICS) code 56131. Its official name is "employment placement agencies and executive search services". It comprises firms primarily engaged in listing employment vacancies and referring or placing applicants for employment, and firms providing executive search, recruitment, and placement services. This industry comprises 280,700 workers on average.

Of course the employees in the recruiting industry constitute only a small fraction of the workers allocated to recruiting. Hence, we scale up *rec* by a factor 8.4 to measure the total amount of labor devoted to recruiting in the economy. Scaling up allows us to account for the many workers who are not in recruiting industry but who spend a lot of time and effort recruiting for their own firm. The scaling factor of 8.4 is chosen to ensure that the share of labor devoted to recruiting in 1997 is 2.5%, thus matching the evidence from the 1997 National Employer Survey. This survey, conducted by the Census Bureau, gathered data from 4500 establishments on their methods for recruiting applicants. Firms in the survey reported spending 2.5% of their labor costs in recruiting activities (Villena Roldan 2010).

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 seasonally adjusted monthly number of workers in all private industries computed by the BLS from the CES survey. This first measure of τ is the solid, blue line in Figure 1, Panel B.

The second measure of τ is based on the vacancy-filling and job-destruction rates measured in CPS data and data from Barnichon (2010). We use the result from Section I that the recruiter-producer ratio satisfies

$$\tau = \frac{s \cdot \rho}{q - s \cdot \rho}, \tag{13}$$

where q is the vacancy-filling rate, s is the job-destruction rate, and ρ is the flow cost of posting a vacancy, assumed to be constant. Appendix E constructs s from CPS data following the method developed by Shimer (2012). The rate s is the solid, blue line in Figure 2, Panel B. We compute q using $q = f/\theta = [e \cdot f]/[v/u]$. Appendix E constructs the job-finding rate $e \cdot f$ from CPS data following the method of Shimer (2012). Next we construct the vacancy-unemployment ratio v/u. We measure u with the number of unemployed workers constructed by the BLS from the CPS. We measure v with the help-wanted advertising index constructed by Barnichon (2010), scaled up so that its average value for 2001–2014 matches the average number of vacancies measured by the BLS from the Job Opening and Labor Turnover Survey (JOLTS).[6] The rate q is the solid, blue line in Figure 2, Panel A. Finally, we set $\rho = 0.77$ to ensure that the average value of τ in 1997 is 2.5%.[7] This second measure of τ is the dotted, green line in Figure 1, Panel B.

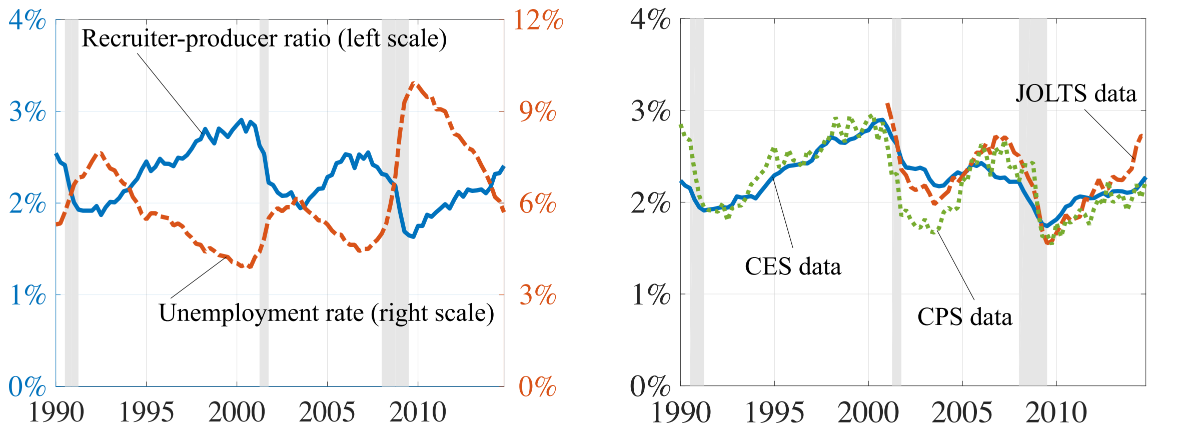
The third measure of τ is based on the vacancy-filling and job-destruction rates measured in the data constructed by the BLS from JOLTS. We use again (13). We measure q by $q = h/v$, where v is the number of vacancies in all nonfarm industries and h is the number of hires in all nonfarm industries. The rate q is the dashed, red line in Figure 2, Panel A. We measure s by the separation rate in all nonfarm industries. The rate s is the dashed, red line in Figure 2, Panel B. Last, we set $\rho = 0.81$ to ensure the average value of τ in 2001 is 2.7%, the same as the average value of the first recruiter-producer ratio.[8] This third measure of τ is the dashed, red line in Figure 1, Panel B.

Despite being constructed from independent sources, all three series of τ displayed in Panel B

[6]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 transform it into a number of vacancies. The average value of the Barnichon index between December 2000 and December 2014 is 80.59. The average number of vacancies in JOLTS data over the same period is 3.707 million. Hence we multiply the Barnichon index by $3.707 \times 10^6/80.59 = 45,996$ to obtain a proxy for the number of vacancies since 1990. We could not use JOLTS data to measure vacancies from 1990 because JOLTS is not available before December 2000.

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

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



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

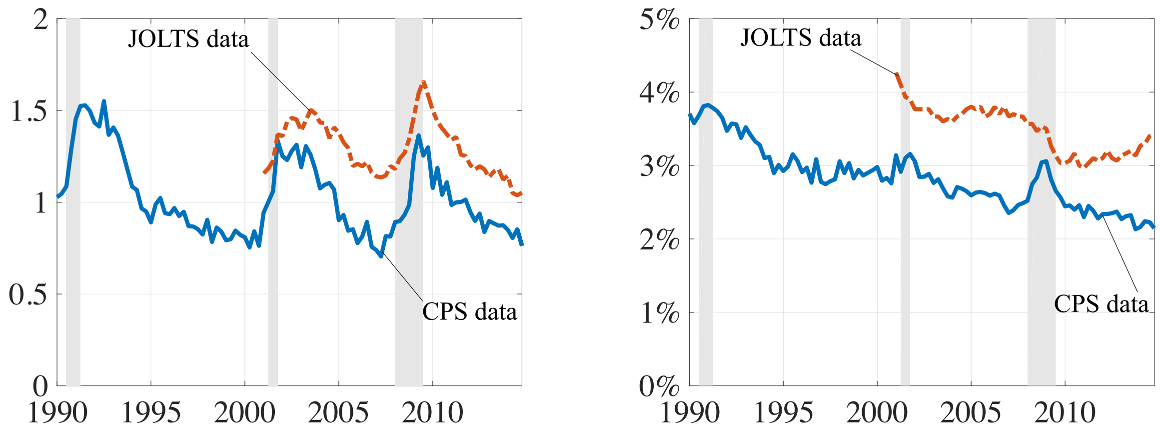
Notes: Panel A: The unemployment rate is the quarterly average of the seasonally adjusted monthly unemployment rate constructed by the BLS from the CPS. The recruiter-producer ratio is a composite measure that combines the three measures in Panel B. Panel B: The recruiter-producer ratio depicted by the solid, blue line is constructed from (12) using data on the size of the recruiting industry (NAICS code 56131). The recruiter-producer ratio depicted by the dotted, green line is constructed from (13) and vacancy-filling and job-destruction rates from CPS data. The recruiter-producer ratio depicted by the dashed, red line is constructed from (13) and vacancy-filling and job-destruction rates from JOLTS data. The recruiter-producer ratios are expressed as quarterly averages of monthly series. The shaded areas represent the recessions identified by the National Bureau of Economic Research (NBER).

of Figure 1 are similar. Consistent with the theory, they are highly procyclical. This observation provides direct evidence that recruiting costs are high when the labor market is tight and low when the labor market is slack. To our knowledge, such direct evidence on recruiting costs over the business cycle is new to the search and matching literature. The first measure, which is directly based on the size of recruiting industry, offers perhaps the most compelling evidence.

Finally, we combine these three basic measures of recruiter-producer ratio to create a composite measure. The composite measure is the average of the first and second measures over the 1990–2000 period, and the average of the three measures over the 2001–2014 period. Figure 1, Panel A, displays this composite measure. It is sharply procyclical, with an average value of 2.3%. The correlation of the composite measure with each of the basic measures is above 0.9.

B. *The Replacement Rate (R)*

The UI program in the United States is much more complex than in our model. In the model, UI indefinitely provides unemployment benefits at a replacement rate R. In the United States,



Panel A. Monthly vacancy-filling rate

Panel B. Monthly job-destruction rate

Figure 2: Vacancy-Filling and Job-destruction Rates in the United States, 1990–2014

Notes: Panel A: The solid, blue line is the vacancy-filling rate constructed as $q = e \cdot f/(v/u)$, where v is the help-wanted advertising index constructed by Barnichon (2010), scaled to match the number of vacancies in JOLTS for 2001–2014; u is the seasonally adjusted number of unemployed persons constructed by the BLS from the CPS; and $e \cdot f$ is the job-finding rate is constructed from CPS data as in Shimer (2012). The dashed, red line is the vacancy-filling rate constructed as $q = h/v$, where v is the number of vacancies in all nonfarm industries and h is the number of hires in all nonfarm industries. Both v and h are seasonally adjusted monthly series constructed by the BLS from JOLTS. Panel B: The solid, blue line is the job-destruction rate constructed from CPS data as in Shimer (2012). The dashed, red line is the seasonally adjusted separation rate in all nonfarm industries constructed by the BLS from JOLTS. The vacancy-filling and job-destruction rates are expressed as quarterly averages of monthly series. The shaded areas represent the recessions identified by the NBER.

weekly unemployment benefits replace around 50% of prior individual weekly wage earnings, up to a maximum level of benefits and only for a limited duration.[9] Furthermore, while the normal duration of benefits is 26 weeks, the duration is adjusted when labor market conditions worsen. 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. During the Great Recession, the Emergency Unemployment Compensation program extended total duration up to 99 weeks.[10]

As a simple model cannot possibly capture all aspects of the UI program, we summarize the generosity of the UI program with an effective replacement rate. This effective replacement rate gives the average replacement rate among all jobseekers who have lost their jobs and are eligible or have been eligible to UI at some point during their current spell.[11] The effective replacement rate is

[9] Almost all US states define weekly UI benefits as 1/26$\times$base earnings, where base earnings is the highest quarterly earnings in the year prior to becoming unemployed. This amounts to a 50% replacement rate of base earnings.

[10] See Marinescu (2016, Section 2) for more details about the UI program in the United States.

[11] Only job losers are eligible to UI. Previously non-employed people who are actively looking for a job are counted

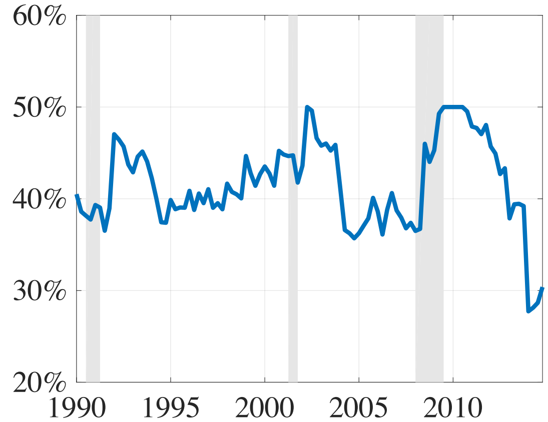


Figure 3: Effective UI Replacement Rate in the United States, 1990–2014

Notes: The effective UI replacement rate is constructed in Appendix F. The shaded areas represent the recessions identified by the NBER.

constructed as the average replacement rate times the ratio of the total number of UI beneficiaries to the total number of unemployed workers who became unemployed through job loss. Appendix F describes the construction of this replacement rate. Our effective replacement rate depends on 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 plotted in Figure 3. While the actual replacement rate for UI recipients is always 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). The effective replacement rate rises after the three recessions of the 1990–2014 period due to state and federal extensions that increase the potential duration of benefits when unemployment rises. Benefit duration expansions more than compensated for the increased duration of unemployment during recessions. After the recession of 2001 and the Great Recession of 2008–2009, the effective replacement rate increased to 50%.[12] The replacement rate fell sharply after the UI extensions expired in January 1st, 2014 while the unemployment rate was still fairly high, leading to a replacement rate of less than 30%, the lowest in the period 1990–2015.

as unemployed but are not eligible.

[12]We cap the replacement rate at 50%. During the Great Recession, the number of UI recipients slightly exceeded the number of unemployed workers who entered unemployment by losing their job.

C. The Nonpecuniary Costs of Unemployment (Z)

The nonpecuniary cost of unemployment is defined by (5). It measures the difference between the well-being of an unemployed and that of an employed worker, keeping consumption constant. It is high if unemployment has a high mental or physical health cost, and if home production or job search are costly. It is low if employment is costly or if unemployed workers enjoy leisure.

Di Tella, MacCulloch and Oswald (2003) find that being unemployed is very costly. Using the US General Social Survey (GSS) for 1972–1994, and controlling for income and other personal characteristics, they find that becoming unemployed is equivalent to dropping from the top to the bottom income quartile, or from becoming divorced (Di Tella, MacCulloch and Oswald 2003, Table 5). Using the Euro-barometer survey, which covers twelve European countries for 1975–1992, they are able to quantify the cost of unemployment. They find that falling unemployed is as bad as losing \$3,500 of income a year (Di Tella, MacCulloch and Oswald 2003, p.819). The average GDP per capita across the nations and years in the sample is \$7,809, and the average unemployment rate is 8.6% (Di Tella, MacCulloch and Oswald 2003, Table 6). With a labor share of 0.7 in these countries, the average wage per worker is $0.7 \times \$7809/(1-0.086) = \$5980$. Since the average marginal utility from \$1 in the population is ϕ, they find $Z = (3500/5980) \times w \times \phi = 0.59 \times w \times \phi$. Other studies using well-being surveys find even larger estimates of Z.[13]

Psychological research shows that people get used to many traumatic events, returning to a normal level of well-being after an initial period of adaptation.[14] However, this adaptation does not seem to occur with unemployment. People seem to remain unhappy for a long time after becoming unemployed, and people who experience several spells of unemployment do not seem to get used to it.[15] Hence, we assume that Z is independent of the duration and frequency of individual unemployment spells.

One potential issue with the estimate from Di Tella, MacCulloch and Oswald (2003) is that it relies on reported well-being and not observed choices. The study by Borgschulte and Martorell

[13] Using the GSS for 1972–1998, Blanchflower and Oswald (2004) find that falling unemployed is as bad as losing approximately \$60,000 of income a year, when the average yearly income in their sample ranges from \$4,261 in 1973 to \$20,457 in 1998. Hence their results suggests a huge nonpecuniary cost of unemployment: $Z \geq 3 \times w \times \phi$. Using the German Socio-Economic Panel for 1984–1989, Winkelmann and Winkelmann (1998) also find that the nonpecuniary cost of unemployment is much larger than the pecuniary cost.

[14] Kahneman et al. (2004, p.429).

[15] See for instance Winkelmann and Winkelmann (1998) and Lucas et al. (2004).

(2016) addresses this limitation. They use military personnel records linked to post-service civilian earnings to measure how enlisted service members choosing to reenlist or exit the military value an increase in the local unemployment rate by one percentage point. They find that servicemen are willing to accept a reduction in re-enlistment earnings of more than 1.5% to avoid the increase in unemployment. With log utility, this implies that $0.01 \times \left[\ln(c^e/c^h) + Z\right] = 0.015 \times \phi \times w$. Using $c^h/c^e = 0.81$ and $\phi \cdot w = 0.77$, we find $Z = (1.5 - 0.21/0.77) \times \phi \times w = 1.2 \times \phi \times w$. Therefore, even a conservative estimate of Z drawn from the work of Borgschulte and Martorell is larger than the estimate from Di Tella, MacCulloch and Oswald (2003).

The evidence presented here suggests that workers suffer a possibly large nonpecuniary cost of unemployment. This evidence sharply contrasts with the typical calibration in matching models. In these models, unemployed workers enjoy some utility from the consumption of UI benefits and additional utility from leisure. Including utility from leisure is equivalent to setting $Z < 0$.[16] But the calibration $Z < 0$ has never been justified on empirical grounds. It is usually introduced to increase the rigidity of Nash bargained wages and generate larger business cycle fluctuations.[17] To reach a compromise between the typical calibration in matching models and the evidence above, we set $Z = 0.3 \times \phi \times w$. This is the mid-point between $Z = 0$ in Shimer (2005) and the estimate $Z = 0.6 \times \phi \times w$ from Di Tella, MacCulloch and Oswald (2003). In addition, we will consider the cases $Z = 0$ and $Z = 0.6 \times \phi \times w$ in the sensitivity analysis of Section IV.

D. Summary and Discussion

The new evidence collected in this section, together with existing evidence summarized in the appendices, allows us to determine the value of the term $\left[U(c^e) - U(c^h) + Z\right]/(\phi \cdot w)$ in the efficiency term (11) when R is at its average value of 0.42. We find that $\left[U(c^e) - U(c^h) + Z\right]/(\phi \cdot w) = [\ln(1/0.81)]/0.77 + 0.3 = 0.57$. The utility gain from finding a job is 0.57 times the marginal utility of a full wage. Hence, the utility replacement rate of the UI program is $1 - 0.57 = 0.43$.

However, the consumption drop upon unemployment, job-search effort, and home production inevitably depends on the replacement rate R. So the entire term $\left[U(c^e) - U(c^h) + Z\right]/(\phi \cdot w)$

[16]For instance, the calibration in Shimer (2005) implies $Z = 0$. The calibrations in Hall and Milgrom (2008) and Hagedorn and Manovskii (2008) imply $Z < 0$.

[17]Nash bargained wages are too flexible to generate realistic labor market fluctuations unless unemployed workers enjoy a very high and fixed utility from leisure (Shimer 2005; Hagedorn and Manovskii 2008).

depends on R. And the effective replacement rate varies over the business cycle, as documented by Figure 3. We therefore need to determine how $\left[U(c^e)-U(c^h)+Z\right]/(\phi\cdot w)$ depends on R.[18]

We link $\left[U(c^e)-U(c^h)+Z\right]/(\phi\cdot w)$ to R in Appendix G. Two variables respond strongly to R: the consumption of unemployed workers, c^u, and the job-search effort, e which affects Z as seen in equation (5). Using empirical evidence on how UI affects c^u and job search effort e, we find that $\left[U(c^e)-U(c^h)+Z\right]/(\phi\cdot w)=0.57-1.74\times(R-0.42)$. The utility gain from work falls with R as both the consumption drop upon unemployment and the job-search effort decrease with R.

We can now compute the efficiency term for 1990–2014. With $\left[U(c^e)-U(c^h)+Z\right]/(\phi\cdot w)=0.57-1.74\times(R-0.42)$, $\varepsilon^f=0$, and $\eta=0.6$, the efficiency term (11) is

$$0.99-0.74\times(R-0.42)-1.5\times\frac{\tau}{u}. \tag{14}$$

We plug into expression (14) the times series for R plotted in Figure 3 and the times series for τ and u plotted in Figure 1, Panel A. We obtain the efficiency term displayed in Figure 4.

In normal times, the efficiency term is somewhat positive: its average value over 1990–2014 is 0.39. In bad times, the efficiency term is very positive: it reaches 0.61 in 1992, right after the 1990–1991 recession, 0.49 in 2003, in the wake of the 2001 recession, and 0.69 in 2009, at the end of the Great Recession. The efficiency term is only negative in very good times: it is negative between 1999 and 2001 with a trough at -0.15 in 2000.

The exact level of the efficiency term is sensitive to the value of several statistics for which our estimates are somewhat imprecise. The main takeaway of the exercise is therefore not what the average level of the efficiency term is, but rather that the efficiency term is subject to sharp countercyclical fluctuations over the business cycle. These fluctuations are driven by the significant fluctuations of τ/u, illustrated on Figure 1. What these fluctuations imply is that an increase in tightness yields a much larger welfare gain in bad times than in normal or good times.

In theory, fluctuations can be efficient or inefficient in matching models. The measure of the efficiency term developed in this section directly addresses this question. As far as we know, this

[18]While we account for the link between utility gain from work and UI, we abstract from the link between utility gain from work and labor market conditions. This choice is motivated by the recent work of Kroft and Notowidigdo (2016). Using data from the Panel Study of Income Dynamics (PSID) for 1968–1997, they find that the consumption drop upon unemployment does not vary significantly with the unemployment rate. We have also found that job-search effort does not respond to labor market conditions.

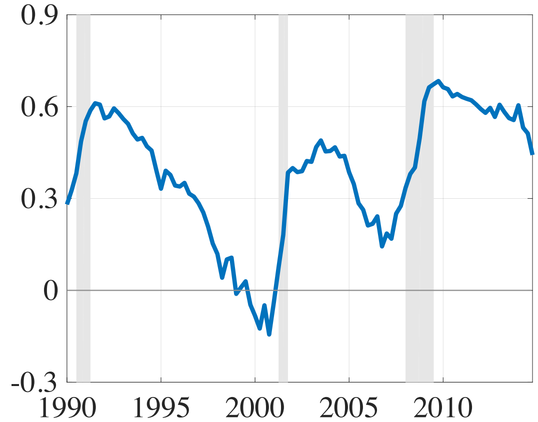


Figure 4: Efficiency Term in the United States, 1990–2014

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.

is the first empirical method that can be used to assess the efficiency of labor market fluctuations. Our findings of a markedly countercyclical efficiency term suggest that labor market fluctuations are inefficient. The finding suggests that the amount of slack on the labor market is inefficiently high in bad times, closer to efficient in normal times, and maybe inefficiently low in good times.

Whether labor market fluctuations are efficient or not has critical implications for the conduct of numerous policies. The implication is that more should be done to stabilize the labor market over the business cycle. For instance, Michaillat and Saez (2014, 2015, 2016) apply the same matching framework to study optimal monetary policy, optimal debt policy, and optimal government purchases. In all these cases, the optimal policy depends on the gap between actual tightness and efficient tightness, and the policies should be used to bring tightness closer to its efficient level when the efficiency term is nonzero.

III. The Effect of Unemployment Insurance on Labor Market Tightness

In theory, an increase in UI can lower tightness through a job-creation channel or raise tightness through a rat-race channel (Landais, Michaillat and Saez 2016). However, as discussed in Section I, there is an empirical criterion to evaluate if an increase in UI raises or lowers tightness. An increase in UI raises tightness if the macroelasticity of unemployment with respect to UI, ε^M, is smaller than the microelasticity of unemployment with respect to UI, ε^m. Conversely, an increase in UI lowers tightness if ε^M is larger than ε^m.

In this section, we review empirical evidence on the wedge between macroelasticity and microelasticity, $1-\varepsilon^M/\varepsilon^m$. The evidence suggests that the elasticity wedge is positive, with an estimate for the United States around $1-\varepsilon^M/\varepsilon^m = 0.4$. This evidence implies that the macroelasticity is smaller than the microelasticity and thus that an increase in UI raises tightness. The evidence also provides support for the rat-race channel.

A. *Estimates of the Elasticity Wedge*

The ideal experiment to estimate the elasticity wedge is a design with 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. The treatment is to offer higher or longer UI benefits. Nontreated jobseekers in nontreated markets are a pure control group. Nontreated jobseekers in treated markets are affected only by the change in tightness in their labor market. Hence, the elasticity wedge can be estimated by comparing the unemployment durations of nontreated jobseekers in nontreated markets to that of nontreated jobseekers in treated markets. Here we discuss the few studies that aim to estimate the elasticity wedge on US data.

In an early study, Levine (1993) finds that the decrease in the search effort of jobseekers eligible for UI induced by an increase in UI has a positive effect on the job-finding probability of jobseekers ineligible for UI in the same labor market. This result is obtained using microdata from the CPS and National Longitudinal Survey of Youth, as well as state-level data on unemployment and UI recipients. This finding implies a positive elasticity wedge. Moreover, he finds that an increase in UI has a positive effect on the unemployment rate of workers eligible for UI, a negative effect on the unemployment rate of workers ineligible for UI, and an insignificant effect on the aggregate unemployment rate.[19] This suggests that the macroelasticity is 0 and the elasticity wedge is 1.

In a recent study, Marinescu (2016) follows another route to assess the sign and magnitude of the elasticity wedge: she directly estimates the effect of a change in UI on labor market tightness. The changes in UI that she considers are the long UI extensions implemented in the US from 2007 to 2011. Using detailed information on vacancies and job applications from CareerBuilder.com, a major online job board, she estimates the effect of the UI increase on aggregate search effort,

[19]See Levine (1993, Table 5, columns 1–4). The main issue is that UI eligibility is not randomly assigned.

measured by the number of job applications sent, and vacancies. At the state level, she finds that the increase in UI reduces job applications but has no effect on vacancies. Since tightness is the ratio of vacancies to aggregate search effort, the increase in UI raises tightness, and the elasticity wedge is positive. Marinescu computes an elasticity wedge of $1-\varepsilon^M/\varepsilon^m = 0.4$.[20]

Johnston and Mas (2016) analyze an unexpected reduction in benefit duration in Missouri in 2011. First, using a regression discontinuity design on state-level administrative data, they find that a one-month reduction in potential duration of benefits decreases the average spell of nonemployment by 10 days, which translates into a microelasticity of unemployment with respect to maximum benefit duration of $\varepsilon^m_D = 0.65$.[21] Then, using state-level administrative data and a difference-in-differences estimator taking other US states as a control, they find a reduction in unemployment rate of 0.8–0.9 percentage points.[22] Since the macro effect of UI is commensurate to the micro effect, they conclude that the elasticity wedge is zero.

In sum, a median estimate of the elasticity wedge in the United States is around $1-\varepsilon^M/\varepsilon^m = 0.4$. This is the estimate from Marinescu (2016). It is higher than the estimate of 0 from Johnston and Mas (2016) but lower than the estimate of 1 from Levine (1993). In addition, we will consider the cases $1-\varepsilon^M/\varepsilon^m = 0.2$ and $1-\varepsilon^M/\varepsilon^m = 0.6$ in the sensitivity analysis of Section IV.

This estimate is consistent with the evidence available for other countries. Lalive, Landais and Zweimüller (2015) estimate the elasticity wedge in Austrian data. They use a natural experiment that offers the desired design: the Regional Extended Benefit Program implemented in 1988–1993. The treatment was an increase in benefit duration from 52 to 209 weeks for eligible unemployed workers in a subset of regions. They find that noneligible unemployed workers in treated labor markets experienced significantly lower unemployment duration as a result of the program. This result implies that the elasticity wedge is positive. They report an estimate of $1-\varepsilon^M/\varepsilon^m = 0.21$.[23]

[20] See Marinescu (2016, p.31).

[21] Johnston and Mas (2016) measure the microelasticity of unemployment duration with respect to maximum benefit duration. In practice this microelasticity is nearly identical to the microelasticity of unemployment with respect to maximum benefit duration, ε^m_D. On the one hand, average unemployment duration is $1/(e\cdot f(\theta))$ because unemployed workers find a job at rate $e\cdot f(\theta)$. On the other hand, unemployment is $u = s/(s+e\cdot f(\theta)) \approx s/(e\cdot f(\theta))$; the approximation is valid in US data because $u \ll 1$ and thus $s \ll e\cdot f(\theta)$. Accordingly, the microelasticities of unemployment and unemployment duration are approximately equal, and the microelasticity of unemployment duration can be used to measure ε^m_D. To compute this elasticity, we use the facts that the potential duration of benefits before the reform was 57 weeks (p.8) and the average duration of unemployment was 29.3 weeks (Table 1). We thus have $\varepsilon^m_D = ((10/7)/29.3)/((30/7)/57) = 0.65$.

[22] See Johnston and Mas (2016, Table 5, columns (1)–(3), row Missouri$\times$post).

[23] See Lalive, Landais and Zweimüller (2015, p.3567).

The elasticity wedge could also in principle be measured by estimating separately the microelasticity and macroelasticity and comparing their magnitudes. This indirect approach has the advantage of being conceptually simple. But it suffers from the drawback that elasticities are nonstructural constructs that need not be stable across contexts or policy variations. In fact, the fairly broad range of microelasticity estimates obtained in the literature suggests that the microelasticity may not be stable across contexts. Moreover, the macroelasticity can fluctuate significantly over the business cycle. Therefore, as Johnston and Mas (2016) do, one needs to identify and estimate the micro and macro responses to the same UI change, in the same context, to measure the elasticity wedge properly. Measures of the elasticity wedge obtained by comparing estimates of microelasticity and macroelasticity obtained separately are not really compelling.

An implication is that estimates of the macroelasticity obtained in isolation, without a corresponding estimate of the microelasticity, are not sufficient to draw normative conclusions. For instance, Hagedorn et al. (2013) use the large extensions in benefit duration implemented in the United States in the 2009–2012 period and compare border counties across states with different benefit durations. They find a macroelasticity of unemployment with respect to maximum benefit duration of $\varepsilon_D^M = 0.39$.[24] Their macroelasticity estimate falls in the range of microelasticity estimates in the literature. Hence, it does not provide conclusive evidence about the sign of the elasticity wedge, which is the relevant statistic for policy.[25]

B. *Evidence on the Rat-Race and Job-Creation Channels*

The elasticity wedge summarizes the overall effect of UI on tightness. In matching models, UI affects tightness through two channels: the rat-race channel, which raises tightness, and the job-creation channel, which lowers tightness. A number of papers study these two effects in isolation, thus providing additional evidence on the effect of UI on tightness. Overall, the absence of evidence of job-creation channels together with the evidence of rat-race channels corroborates direct

[24] Hagedorn et al. (2013) find that permanently increasing the benefits from 26 to 99 weeks would increase the average unemployment rate from 5 to 10.5% (p.14). Therefore, the estimated macroelasticity of unemployment with respect to benefit duration is $[(10.5-5)/5]\,/\,[(99-26)/26] = 0.39$.

[25] With a microelasticity $\varepsilon_D^m = 0.65$ as in Johnston and Mas (2016), the macroelasticity $\varepsilon_D^M = 0.39$ implies a large positive elasticity wedge: $1-\varepsilon_D^M/\varepsilon_D^m = 0.4$. With a microelasticity $\varepsilon_D^m = 0.43$ as in the classic study by Katz and Meyer (1990, Table 4), the macroelasticity $\varepsilon_D^M = 0.39$ implies a small positive elasticity wedge: $1-\varepsilon_D^M/\varepsilon_D^m = 0.09$. With a microelasticity $\varepsilon_D^m = 0.22$ as in the recent work of Rothstein (2011, Table 5, columns 3–5) with data from the Great Recession, the macroelasticity $\varepsilon_D^M = 0.39$ could imply a negative elasticity wedge: $1-\varepsilon_D^M/\varepsilon_D^m = -0.77$.

evidence suggesting that the elasticity wedge is positive.

Numerous papers measure the effect of an increase in job-search effort by some jobseekers, induced for example by placement programs, on the job-finding probability of other jobseekers.[26] If higher job-search effort by some leads to lower job-finding probability for others, then the rat-race channel is present. Crepon et al. (2013) offer a compelling identification by analyzing a large randomized field experiment in France. Some young educated jobseekers are treated by receiving job placement 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. Interpreting the treatment as an increase in search effort from e^C for control jobseekers to e^T for treated jobseekers, the results translate into an elasticity wedge $1-\varepsilon^M/\varepsilon^m = 0.4$.[27]

The best way to measure the job-creation channel is to investigate whether a more generous UI raises wages. Several studies use administrative data to determine the effect of more generous UI benefits on re-employment wage. Most studies find no effect or slightly negative effects on wages (for example, Card, Chetty and Weber 2007; Johnston and Mas 2016). Marinescu (2016) explores the effect of more generous UI benefits on the wages advertised by firms on CareerBuilder.com. She finds no effect. The absence of significant effects of UI on re-employment or advertised wages suggests that the job-creation effect is likely to be small.[28]

C. Variations of The Elasticity Wedge With Unemployment

In addition to the evidence presented so far, there is evidence that the elasticity wedge is much higher in slumps than in booms. Using longitudinally matched CPS data, Valletta (2014) uncov-

[26] See Card, Kluve and Weber (2010) for a survey.

[27] 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 increase in the job-finding probability of treated jobseekers in treated areas compared to control jobseekers in control areas is only $\left[e^T\cdot f^T\right] - \left[e^C\cdot f^C\right] = 5.7 - 2.1 = 3.6\%$. Since ε^m is proportional to $\left[e^T - e^C\right]\cdot f^T$ and ε^M is proportional to $\left[e^T\cdot f^T\right] - \left[e^C\cdot f^C\right]$, the implied elasticity wedge is $1-\varepsilon^M/\varepsilon^m = 1 - 3.6/5.7 = 0.4$.

[28] By inducing longer unemployment durations, more generous benefits could have a negative effect on wages if the duration of unemployment affects the productivity of unemployed workers or is interpreted by employers as a negative signal of productivity, as in the field experiment conducted by Kroft, Lange and Notowidigdo (2013). It is difficult to disentangle this negative effect from the positive effect of UI on wages through bargaining, which is the relevant effect for our analysis. Using administrative data for Germany, Schmieder, von Wachter and Bender (2016) attempt such a decomposition. They control for the duration of the unemployment spell and find a negative effect of UI on wages through longer unemployment durations but zero effect through wage bargaining. Lalive, Landais and Zweimüller (2015) use the same method and find a positive but tiny effect of UI through wage bargaining in Austria.

ers spillover effects of UI extensions on unemployed workers ineligible for UI during the Great Recession (2007–2011). He finds those ineligible for UI have higher job-finding rates when UI duration is longer, but the spillover effect is only present in states with high unemployment (Table 6, column 2). This suggests that the elasticity wedge is close to zero when unemployment is low but positive when unemployment is high.

This evidence from the United States is consistent with evidence from European countries. Lalive, Landais and Zweimüller (2015) finds that the elasticity wedge is significantly larger in labor markets in which tightness is initially low. Crepon et al. (2013) also find that the rat-race channel is stronger in areas and periods with higher unemployment.[29]

Direct evidence is unavailable to quantify the fluctuations of the elasticity wedge precisely. We therefore rely on slightly more structural evidence to build a time series for the elasticity wedge. The job-rationing model of Michaillat (2012) is consistent with a positive elasticity wedge and the rat-race channel. We therefore compute a closed-form expression for the wedge in the job-rationing model of Michaillat (2012) and use empirical evidence to evaluate the expression over time. Appendix H shows that in the job-rationing model, the elasticity wedge is

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

To compute the elasticity wedge, we first need to calibrate the parameter $\alpha<1$. The production function in the job-rationing model is $y(n)=a\cdot n^{\alpha}$, so the parameter α describes diminishing marginal returns to labor. The magnitude of the elasticity wedge is determined by α. Hence, we calibrate α to match $1-\varepsilon^M/\varepsilon^m=0.4$ on average. In equation (15) we set $1-\varepsilon^M/\varepsilon^m=0.4$, $\eta=0.6$, $\tau=2.3\%$, $u=6.1\%$, and $\varepsilon^f=0$. We obtain $\alpha=0.73$.

To construct a time series for the elasticity wedge, we use the time series for u and τ displayed in Figure 1, Panel A, and keep the other statistics constant at $\eta=0.6$, $\alpha=0.73$, and $\varepsilon^f=0$. We obtain the time series in Figure 5. By construction, the elasticity wedge is 0.4 on average. The wedge is sharply countercyclical. This is because in (15), the unemployment rate u is countercyclical and the recruiter-producer ratio τ is procyclical. At the end of the 1990–1991 recession, the wedge reached 0.5. And at the end of the Great Recession, it reached 0.6. On the other hand, the

[29] See Lalive, Landais and Zweimüller (2015, online appendix: Table 9) and Crepon et al. (2013, Table VI, Table X).

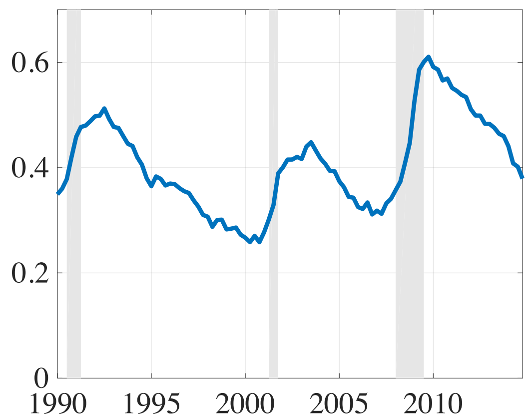


Figure 5: Elasticity Wedge in the United States, 1990–2014

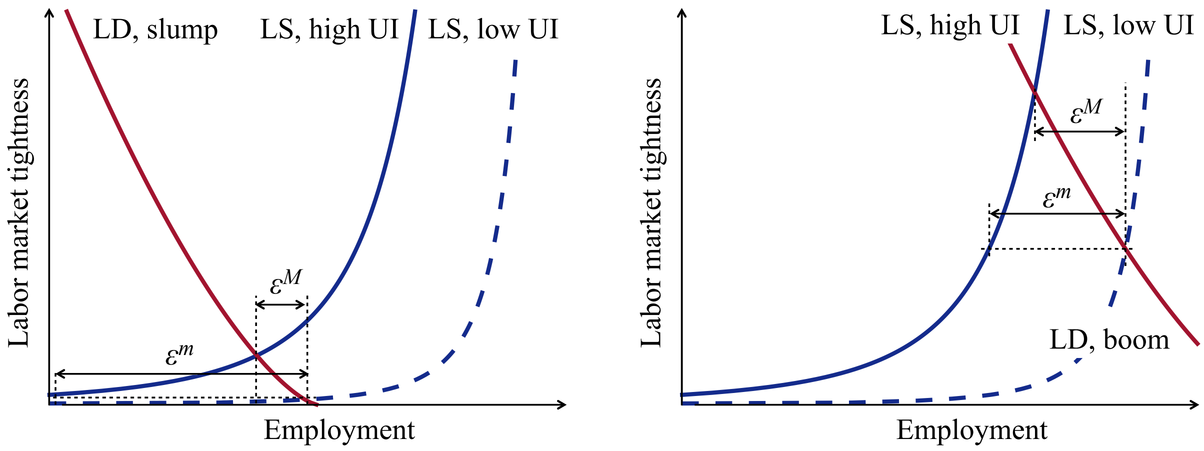
Notes: The elasticity wedge is constructed using (15). The elasticity wedge is positive when the macroelasticity of unemployment with respect to UI is smaller than the microelasticity of unemployment with respect to UI; it is negative when the macroelasticity is larger than the microelasticity. A positive elasticity wedge indicates that an increase in UI raises labor market tightness. The shaded areas represent the recessions identified by the NBER.

wedge fell to 0.25 in the boom of 2000.

Figure 5 shows that the elasticity wedge is higher in slumps than in booms. This result implies that the rat-race channel is stronger in slumps than in booms. The mechanism generating this property in the job-rationing model is described in Figure 6. The wedge between ε^M and ε^m depends on the slope of the labor supply relative to the slope of the labor demand. In a slump (Panel A), the labor supply is flat at the equilibrium point because the matching process is congested by search efforts; hence, ε^M is much lower than ε^m. Conversely, in a boom (Panel B), the labor supply is steep at the equilibrium point because the matching process is congested by the large number of vacancies; hence, ε^M is close to ε^m. 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 congestions fluctuate over the business cycle.

D. Summary and Discussion

Direct estimates of the elasticity wedge suggest that the elasticity wedge is positive, with an estimate for the United States around $1-\varepsilon^M/\varepsilon^m = 0.4$. The absence of evidence in favor of the job-creation channel, coupled with convincing evidence in favor of the rat-race channel, corroborates the finding that the elasticity wedge is positive. Since the elasticity wedge is positive, an



Panel A. High elasticity wedge in a slump

Panel B. Low elasticity wedge in a boom

Figure 6: Countercyclicality of the Elasticity Wedge in the Job-Rationing Model

Notes: The elasticity wedge is $1 - \varepsilon^M/\varepsilon^m$. A slump is an equilibrium with low technology, and a boom is an equilibrium with high technology.

increase in the generosity of UI raises the labor market tightness. This property of UI implies that the Baily-Chetty formula is invalid as soon as tightness is inefficiently high or low.

In addition, the empirical finding of a positive elasticity wedge has important implications for the underlying mechanics of the labor market. As explained in our companion paper, different matching models make different predictions regarding the sign of the elasticity wedge, and evidence on this sign can validate or falsify these models. The standard model of Pissarides (2000) predicts a negative elasticity wedge. It is therefore inconsistent with the empirical evidence. The fixed-wage model of Hall (2005*a*) predicts zero elasticity wedge and is inconsistent with all the empirical evidence except that in Johnston and Mas (2016). In contrast, the job-rationing model of Michaillat (2012) predicts a positive elasticity wedge. It is therefore the only model consistent with the empirical evidence. Furthermore, the job-rationing model is the only model that can generate the rat-race channel observed in several studies. Overall, the empirical evidence on the elasticity wedge suggests that the job-rationing model is better suited to describe the labor market.

IV. Applications of the Optimal Unemployment Insurance Formula

The results from Section II imply that an increase in tightness yields much larger welfare gain in bad times than in good times. The results from Section III imply that an increase in UI raises tightness. These results imply that the optimal UI replacement rate is much more countercyclical than the Baily-Chetty replacement rate. In this section, we go one step further and combine the empirical evidence from Sections II and III with formula (10) to solve for the optimal UI replacement rate in the United States since 1990. We find that the optimal replacement rate is sharply countercyclical: it varies between 35% and 52% over the 1990–2014 period. Of course, UI is more generous in bad times in the United States. We find that the cyclicality of the optimal replacement rate is fairly close to the cyclicality of the effective replacement rate in the United States.

A. *The Welfare Effect of a Small Change in Unemployment Insurance*

In this subsection, we evaluate formula (10) at the current UI policy, as in Chetty (2008). If the formula holds, we infer that the current replacement rate R is optimal. If the replacement rate R is larger than the left-hand side, we infer that the current R is too high. If the replacement rate R is smaller than the left-hand side, we infer that the current R is too low.

Given what we have already done, assessing formula (10) at the current UI policy is not difficult. We computed the efficiency term and elasticity wedge in the previous sections. The last thing to do is compute the Baily-Chetty replacement rate over time. Computing the Baily-Chetty replacement rate is standard in the literature and particularly simple given what we have already done. The key parameters are the consumption drop upon unemployment (discussed above), the coefficient of relative risk aversion (set to one as discussed above), and the elasticity ε_R^m of unemployment duration with respect to the UI replacement rate R (we set $\varepsilon_R^m = 0.4$).[30] We therefore relegate the calculations to Appendix I. Collecting all the evidence, we conclude that

$$\text{Baily-Chetty replacement rate} = \frac{0.57 - 1.74 \times (R - 0.42)}{0.44} \times [0.19 - 0.5 \times (R - 0.42)]\,. \tag{16}$$

We now assess formula (10) at the current UI policy. To do so, we compute the Baily-Chetty replacement rate with (16) and the times series for R plotted in Figure 3. We compute the correction term using the efficiency term plotted in Figure 4 and the elasticity wedge plotted in Figure 5. The line plotted in Figure 7 shows the difference between the right-hand side and the left-hand

[30] Appendix A discusses the link between the microelasticity ε^m used in the theoretical model of Section I and the elasticity ε_R^m traditionally estimated in empirical studies. Appendix D explains our calibration assumption $\varepsilon_R^m = 0.4$.

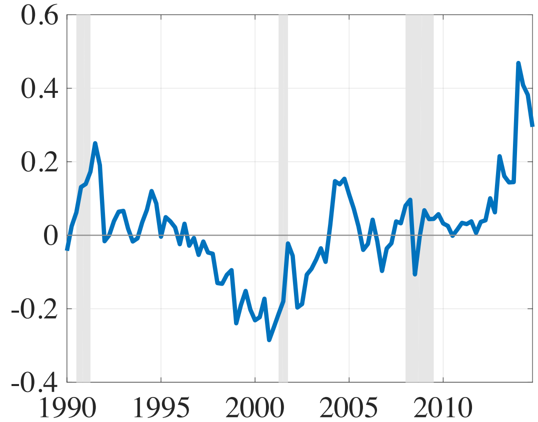


Figure 7: Welfare Effect of a Small UI Increase in the United States, 1990–2014

Notes: The welfare effect of a small increase in UI equals the Baily-Chetty replacement rate + the elasticity wedge $\times$ the efficiency term - R. The Baily-Chetty replacement rate is constructed using (16). The elasticity wedge is constructed using (15) and depicted in Figure (5). The efficiency term is constructed using (14) and depicted in Figure (4). The replacement rate R is constructed in Appendix F and depicted in Figure (3). When the welfare effect is positive, the current UI replacement rate is too low. When the welfare effect is negative, the current UI replacement rate is too high. The shaded areas represent the recessions identified by the NBER.

side of formula (10). When it is positive, a small increase in UI raises welfare, so the current replacement rate is too low. When it is negative, a small increase in UI reduces welfare, so the current replacement rate is too high.

We find that the average of the line plotted in 7 is zero, which means that the effective replacement rate in the United States is optimal on average. There are three periods between 1990 and 2014 when UI seems suboptimal. First, it seems that UI was not generous enough after the 1990–1991 recession. Second, it seems that UI was too generous in 1997–2001, during the pronounced boom associated with the dot-com bubble. Finally, while the increase in UI enacted during the Great Recession was close to optimal, it seems that UI was much too low after 2013. Since unemployment duration markedly increased after the Great Recession but the duration of benefits was cut back to normal levels at the end of 2013, many unemployed workers were left without benefits, driving down the effective generosity of UI. As a result, UI is much too low in 2014.

B. The Optimal Unemployment Insurance Replacement Rate

It seems that the generosity of UI in the United States, while close to optimal on average, is sometimes inadequate (Figure 7). In this subsection, we use formula (10) to solve for the optimal

UI replacement rate at any point in time. To do so, we need to link the statistics in formula (10) with the replacement rate R. This allows us to resolve the endogeneity of the right-hand-side terms of formula (10) with R, without having to fully specify the underlying structural model.

Using the work done above, we rewrite formula (10) as follows:

$$
\begin{aligned}
R = {} & \frac{1}{0.44} \times [0.57 - 1.74 \times (R - 0.42)] \times [0.19 - 0.5 \times (R - 0.42)] \\
& + \left[1 - \frac{\varepsilon^M}{\varepsilon^m}\right] \times \left[0.99 - 0.74 \times (R - 0.42) - 1.5 \times \frac{\tau}{u}\right].
\end{aligned}
\tag{17}
$$

Using this formula and our series for $1 - \varepsilon^M/\varepsilon^m$ and τ/u, we solve for R during the 1990–2014 period. The resulting optimal replacement rate is displayed on Figure 8.

Figure 8 displays both the optimal replacement rate (in solid blue line) and the actual US replacement rate (in dashed red line). The first thing to notice is that the average of the actual US replacement rate is the same as the average of the optimal replacement rate: 42%. This means that the average generosity of UI in the United States is correctly chosen (if all our calibration assumptions are right).

UI is close to optimal not only on average but also when the unemployment rate rises. The nominal replacement rate does not vary in the United States, but the effective replacement rate is higher when the unemployment rate is higher because UI benefits have a longer duration. Our analysis suggests that the increase in the effective replacement rate in the United States is close to optimal when the unemployment rate is high after recessions. For instance, after the 1990–1991 recession the effective replacement rate rises to 47%, which is also the level of the optimal replacement rate. And after the Great Recession the effective replacement rate rises to 50%, which is the close to the optimal replacement rate of 52%. An exception is the 2001 recession, when the effective replacement rate was too high.

Figure 8 reinforces the findings from Figure 7 that UI was too generous during the dot-com bubble but insufficiently generous in the aftermath of the Great Recession. At the peak of the boom in 2000, the optimal replacement rate falls to 34%, but the actual replacement rate remains around 45%. On the other hand, after the Great Recession, the actual replacement rate falls drastically to 28%, but the optimal replacement rate is much higher, around 40%.

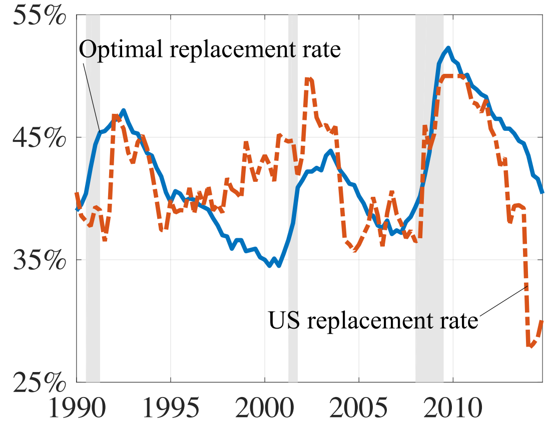


Figure 8: Optimal UI Replacement Rate in the United States, 1990–2014

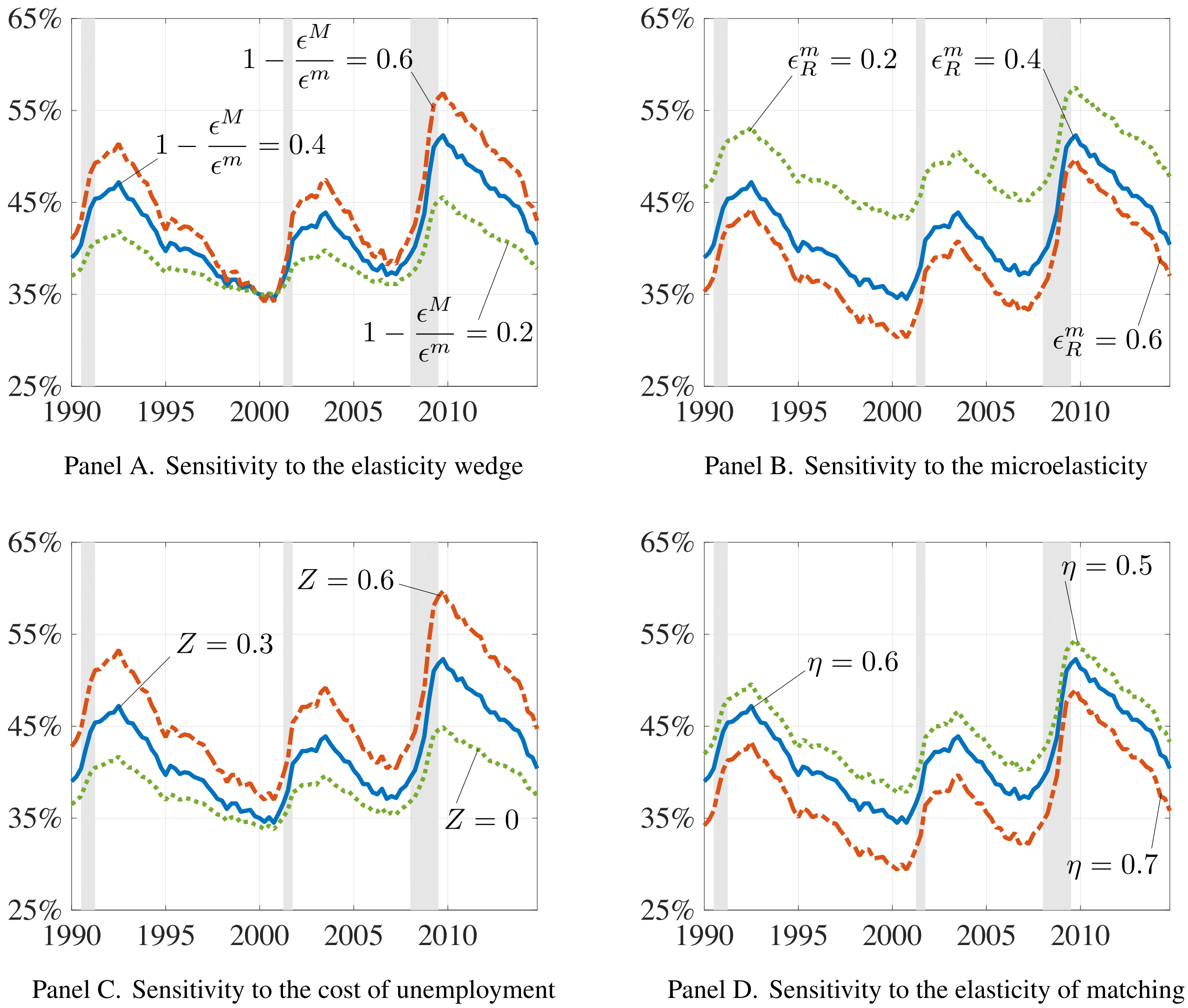
Notes: The optimal UI replacement rate is constructed by solving formula (17). The actual UI replacement rate in the United States is constructed in Appendix F. The shaded areas represent the recessions identified by the NBER.

C. *Sensitivity Analysis*

There is considerable uncertainty for the estimates of several statistics used in our analysis. Hence, we explore the sensitivity of the results to the value of four key statistics that enter our optimal UI formula: the elasticity wedge $1-\varepsilon^M/\varepsilon^m$, the microelasticity of unemployment duration with respect to benefits ε_R^m, the nonpecuniary cost of unemployment Z, and the matching elasticity η.

The Elasticity Wedge ($1-\varepsilon^M/\varepsilon^m$). The elasticity wedge matters because it is a key factor in the correction term. In Figure 9, Panel A, we compute the optimal replacement rate using formula (10) and alternative values for the average elasticity wedge. The dashed, red line shows the optimal replacement rate with a high average elasticity wedge of $1-\varepsilon^M/\varepsilon^m=0.6$. The dotted, green line shows the optimal replacement rate with a low average elasticity wedge of $1-\varepsilon^M/\varepsilon^m=0.2$. Finally, the solid, blue line is the benchmark from Figure 8, constructed with an average elasticity wedge of $1-\varepsilon^M/\varepsilon^m=0.4$.

We find that when the elasticity wedge is higher, the fluctuations of optimal replacement rate are wider. With a low elasticity wedge of 0.2, the optimal replacement rate increases by only 11 percentage points (from 35% to 46%) between the strongest boom (in 2000) and the strongest slump (in 2009). On the other hand, with a high elasticity wedge of 0.6, the optimal replacement rate increases by 23 percentage points (from 34% to 57%) between the strongest boom and



Panel A. Sensitivity to the elasticity wedge

Panel B. Sensitivity to the microelasticity

Panel C. Sensitivity to the cost of unemployment

Panel D. Sensitivity to the elasticity of matching

Figure 9: Optimal UI Replacement Rate in the United States, 1990–2014, for Different Values of Key Statistics

Notes: The optimal UI replacement rate is constructed by solving formula (17). The shaded areas represent the recessions identified by the NBER.

slump. A higher elasticity wedge leads to more volatility in the optimal replacement rate because it accentuates the volatility of the correction term.

The Microelasticity of Unemployment Duration With Respect to Benefits (ε^m_R). The microelasticity ε^m_R determines the microelasticity of unemployment with respect to UI, ε^m, which is a key element of the Baily-Chetty replacement rate. In Figure 9, Panel B, we compute the optimal replacement rate using formula (10) and alternative values for ε^m_R. The dotted, green line shows the optimal replacement rate with a low microelasticity $\varepsilon^m_R = 0.2$. The dashed, red line shows the optimal replacement rate with a high microelasticity $\varepsilon_R^m = 0.6$. Finally, the solid, blue line is the benchmark from Figure 7, constructed with $\varepsilon_R^m = 0.4$.

We find that when the microelasticity is higher, the average optimal replacement rate is lower and the fluctuations of the optimal replacement rate are wider. With a low microelasticity of $\varepsilon_R^m = 0.2$, the optimal replacement rate is 49% on average, with a minimum of 43% and a maximum of 58% over the 1990–2014 period. With a high microelasticity of $\varepsilon_R^m = 0.6$, the optimal replacement rate is only 39% on average, with a minimum of 30% and a maximum of 50% over the 1990–2014 period. While the microelasticity plays a very important role in booms, its influence is much more limited in slumps. The gap between the optimal replacement rates corresponding to $\varepsilon_R^m = 0.2$ and $\varepsilon_R^m = 0.6$ is 13 percentage points in the 2000 boom but only 8 percentage point in the 2009 slump. A higher microelasticity leads to a lower optimal replacement rate because it reduces the Baily-Chetty replacement rate. It leads to a more volatile optimal replacement rate because, by reducing the Baily-Chetty replacement rate, it makes the correction term a more important determinant of the optimal replacement rate; and the correction term is very volatile while the Baily-Chetty replacement rate is fairly stable.

The Nonpecuniary Cost of Unemployment (Z). The nonpecuniary cost matters because it determines the level of the efficiency term, and the efficiency term is a key factor in the correction term in our optimal UI formula. In Figure 9, Panel C, we compute the optimal replacement rate using formula (10) and alternative values for the nonpecuniary cost Z. The dotted, green line shows the optimal replacement rate with a low cost $Z = 0$. In that case, the cost of unemployment solely comes from lower consumption. The dashed, red line shows the optimal replacement rate with a high cost $Z = 0.6 \times \phi \times w$. Finally, the solid, blue line is the benchmark from Figure 7 with $Z = 0.3 \times \phi \times w$.

We find that when the nonpecuniary cost of unemployment is higher, the optimal replacement rate is always higher. With a low nonpecuniary cost of $Z = 0$, the optimal replacement rate is 38% on average, with a minimum of 34% and a maximum of 45% over the 1990–2014 period. With a high nonpecuniary cost of $Z = 0.6 \times \phi \times w$, the optimal replacement rate is 47% on average, with a minimum of 73% and a maximum of 60% over the 1990–2014 period. Furthermore, in our calibration, the value of nonpecuniary cost of unemployment makes a difference especially in slumps; in booms, the value of nonpecuniary cost of unemployment does not matter much. The gap between the optimal replacement rates corresponding to $Z = 0$ and $Z = 0.6 \times \phi \times w$ is 15 percentage points in the 2009 slump but only 3 percentage point in the 2000 boom.

The Matching Elasticity (η). The matching elasticity influences the level and volatility of the efficiency term. In Figure 9, Panel D, we compute the optimal replacement rate using formula (10) and alternative values for η. The dotted, green line shows the optimal replacement rate with a low elasticity $\eta = 0.5$. The dashed, red line shows the optimal replacement rate with a high elasticity $\eta = 0.7$. Finally, the solid, blue line is the benchmark from Figure 7, constructed with $\eta = 0.6$.

We find that when η is higher, the average optimal replacement rate is lower and the fluctuations of the optimal replacement rate are slightly wider. With a low elasticity of $\eta = 0.5$, the optimal replacement rate is 45% on average, with a minimum of 38% and a maximum of 54% over the 1990–2014 period. With a high elasticity of $\eta = 0.7$, the optimal replacement rate is 37% on average, with a minimum of 29% and a maximum of 49% over the 1990–2014 period. A higher elasticity leads to a lower optimal replacement rate because it increases the term $[\eta/(1-\eta)] \cdot (\tau/u)$ and thus reduces the efficiency term. It leads to a more volatile optimal replacement rate because it amplifies the fluctuations of τ/u.

Summary. The values of the elasticity wedge, microelasticity, nonpecuniary cost of unemployment, and matching elasticity have a significant influence on the level and volatility of the optimal UI replacement rate. However, the specific value of these four statistics does not affect our conclusions about the cyclicality of optimal UI (of course, the elasticity wedge needs to be positive). In all the scenarios considered in Figure 9, the optimal replacement rate is countercyclical.

D. Accuracy of the Formula Implementation

We now simulate a specific matching model to verify that the implementation of formula (10) described in Figure 8 is accurate. Given that most statistics depend on R and the business cycle, it is important to verify that their movements are either small enough to be neglected or are well-captured by our linear approximations.

The matching model used for the simulations is the job-rationing model developed by Michaillat (2012). We choose this model because it generates a positive elasticity wedge. It is therefore consistent with the empirical evidence presented in Section III, whereas other common matching models are not. Furthermore, because real wages are somewhat rigid in this model, technology shocks lead tightness to be sometimes inefficiently low and sometimes inefficiently high. Hence, the model is also in line with the empirical evidence presented in Section II.

To obtain the job-rationing model, we specialize the generic model proposed in Section I. First, we specify a concave production function: $y(n(t)) = a(t) \cdot n(t)^{\alpha}$. The exogenous variable $a(t) > 0$ measures the technology of the firm at time t, and the parameter $\alpha \in (0,1)$ captures decreasing marginal returns to labor. Second, we specify a wage mechanism that is independent of UI and partially rigid with respect to technology: $w(t) = \omega \cdot a(t)^{1-\gamma}$. The parameter $\gamma \in (0,1]$ measures the rigidity of wages with respect to technology. If $\gamma = 0$, wages are flexible: they are proportional to technology. If $\gamma = 1$, wages are fully rigid: they do not respond to technology.

Taking $a(t)$ and $\theta(t)$ as given, the firm chooses $l(t)$ to maximize profits

$$a(t) \cdot \left[\frac{l(t)}{1+\tau(\theta(t))}\right]^{\alpha} - \omega \cdot a(t)^{1-\gamma} \cdot l(t).$$

The labor demand $l^d(\theta(t), a(t))$ gives the optimal number of workers employed by the firm:

$$l^d(\theta(t), a(t)) = \left(\frac{\alpha}{\omega}\right)^{\frac{1}{1-\alpha}} \cdot a(t)^{\frac{\gamma}{1-\alpha}} \cdot (1+\tau(\theta(t)))^{-\frac{\alpha}{1-\alpha}}. \tag{18}$$

The labor demand is decreasing in tightness because when tightness is higher, hiring workers requires more recruiters and is therefore less profitable. The labor demand is increasing in technology because when technology is higher, the wage-technology ratio is lower by wage rigidity, so hiring workers is more profitable. The labor demand is independent of UI because wages are.

We calibrate the job-rationing model to match the empirical evidence presented in Sections II and III and in this section. The calibration is standard, so we relegate it to Appendix J. We represent the business cycle as a succession of steady-state equilibria in which technology takes different values: a slump is an equilibrium with low technology and high unemployment; a boom is an equilibrium with high technology and low unemployment.[31] We compute a collection of steady-

[31] Technology shocks are a conventional and convenient way to generate business cycles in matching models. Michaillat and Saez (2015) show that these models can also accommodate other types of shocks, particularly aggre-

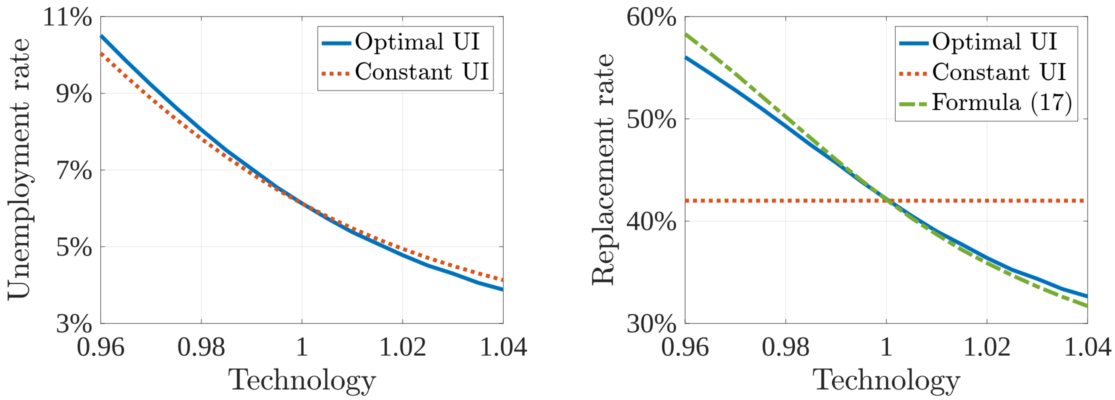


Figure 10: Simulations of Optimal UI over the Business Cycle

Notes: This figure compares the equilibria where the UI replacement rate is constant at $R = 42\%$ to those where the UI replacement rate is set optimally using formula (10). The simulation model is the job-rationing model of Michaillat (2012). The model is described in Section IV.D and calibrated in Appendix J. In the two panels, the equilibria are parameterized by various levels of technology. On the right panel, the dashed green line displays the replacement rate given by formula (17) and the solid blue line the replacement rate given by formula (10).

state equilibria spanning all the stages of the business cycle. We compare equilibria in which the UI replacement rate remains constant at 42%, the average US value, to equilibria in which the UI replacement rate is optimal.

Figure 10 displays the results of the simulations. When technology increases from 0.96 to 1.04 and UI remains constant, the unemployment rate falls from 9.4% to 4.2%. 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. As the unemployment rate u falls, the labor market tightness θ increases and the ratio $\tau(\theta)/u$ increases.

Through the mechanism described in (15), the elasticity wedge is countercyclical in the simulations. The elasticity wedge is sharply countercyclical because the macroelasticity of unemployment with respect to UI is sharply procyclical while the microelasticity is broadly acyclical. In slumps, the macroelasticity is low because of job rationing: firms are not looking to hire workers, so the increase in job search triggered by a reduction in UI has very little effect on unemployment.

As $\tau(\theta)/u$ is very procyclical, the efficiency term is also very countercyclical: it is very positive for high unemployment rates, mildly positive on average, and just below zero for low unemployment rates. These sharp fluctuations arise because business cycle fluctuations are inefficient.

gate demand shocks. For our analysis, what matters is that shocks to the labor demand drive business cycles—whether these are aggregate demand or technology shocks is unimportant.

The combined fluctuations of the efficiency term and elasticity wedge imply that the correction term fluctuates sharply over the business cycle. The correction term is very positive with high unemployment rates and somewhat negative for low unemployment rates. As the Baily-Chetty replacement rate is stable over the business cycle, the optimal replacement is quite countercyclical: it falls from 56% to 33% when technology increases from 0.96 to 1.04.

The unemployment rate responds to the adjustment of the replacement rate from its original level of 42% to its optimal level. In particular, in slumps the optimal replacement rate is well above 42% so the unemployment rate increases above its original level. However, because the macroelasticity is low in slumps, the large adjustment of UI has a limited effect on unemployment. When technology is 0.96, the increase in replacement rate from 42% to 56% only raises the unemployment rate from 10.1% to 10.5%.

Finally, Figure 10 compares the optimal replacement rate, given by (10), to the approximately optimal replacement rate, given by (17). Despite the various approximations made to derive formula (17), the formula is remarkably accurate. The two formulas deviate by at most 2 percentage point. This simulation results therefore suggest that the method developed in Section IV.B is extremely accurate and could be used to compute optimal UI replacement rates based solely on observable sufficient statistics. Resorting to simulations of structural models may be unnecessary.

V. Conclusion

This paper applies the theory of optimal UI developed in our companion paper (Landais, Michaillat and Saez 2016) to explore how the generosity of UI should vary over the business cycle. The optimal UI replacement rate is the conventional Baily-Chetty rate plus a correction term. We empirically measure the correction term in the United States for 1990–2014, and find that it is sharply countercyclical. This result suggests that the optimal UI replacement rate is much more countercyclical than the Baily-Chetty replacement rate.

We develop a method to compute the optimal UI replacement rate based solely on observable sufficient statistics. Using statistics for the United States, we find that the optimal replacement rate broadly oscillates from 35% to 55% when the unemployment rate oscillates between 4% to 10%. Furthermore, we find that the fluctuations of the effective replacement rate in the United States are close to optimal. In particular, the long extensions of UI benefits enacted in the United States when the unemployment rate rises lead to increases in the effective replacement rate that nearly match the increases of the optimal replacement rate.

Beyond its implication for optimal UI, the empirical evidence presented in this paper has implications for our understanding of the labor market. First, the empirical evidence in Section III suggests that the macroelasticity of unemployment with respect to UI is smaller than the microelasticity. This evidence indicates that the job-rationing model of Michaillat (2012) is better suited than other common matching models to describe the labor market. This empirical finding has several policy ramifications. In common matching models, policies that stimulate labor supply (such as job-search monitoring or job-placement support) are effective to reduce unemployment in slumps, whereas policies that stimulate labor demand (such as public employment) are ineffective. In the job-rationing model, these results are reversed: policies that stimulate labor supply are ineffective to reduce unemployment in slumps, whereas policies that stimulate labor demand are effective (Michaillat 2012, 2014). The finding of a positive wedge between macroelasticity and microelasticity therefore implies that policies stimulating labor demand should be favored to reduce unemployment in slumps.

Second, the empirical evidence in Section II suggests that the efficiency term is markedly countercyclical: it is positive in slumps but negative in booms. This finding has macroeconomic implications. It supports the view that unemployment is inefficiently high in slumps and inefficiently low in booms and therefore implies that more effort should be done to stabilize the macroeconomy.

Third, the measure of the efficiency term obtained here could be applied to a broad range of stabilization problems. For instance, the work of Michaillat and Saez (2014, 2015, 2016) on optimal monetary policy, debt policy, and government purchases shows that an estimate of the efficiency term is required to determine the optimal response of these stabilization policies to macroeconomic shocks. The reason is that the efficiency term gives a direct measure of the unemployment gap (the gap between actual and efficient unemployment rates), which determines the need for stabilization.

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Appendix A. Elasticities in the Matching Model

This appendix computes the microelasticity of unemployment with respect to UI, the discouraged-worker elasticity, and the microelasticity of unemployment duration with respect to the replacement rate in the matching model of Section I. We use these results throughout the paper.

The Microelasticity of Unemployment With Respect to UI (ε^m). Let $1/\kappa \equiv (e/\psi'(e)) \cdot \psi''(e)$ be the elasticity of $\psi'(e)$ with respect to e. Let $\varepsilon^e_\Delta \equiv (\Delta U/e) \cdot (\partial e^s/\partial \Delta U)$ be the elasticity of effort supply with respect to the utility gain from work. Let $L(x) \equiv x/(s+x)$. The elasticity of $L(x)$ with respect to x is $1 - L(x)$. The effort supply $e^s(f, \Delta U)$ satisfies equation (3), which can be written as

(A1) $$e^s \cdot \psi'(e^s) = L(e^s \cdot f) \cdot (\Delta U + \psi(e^s)).$$

Differentiating this condition with respect to ΔU yields

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

In equilibrium, $e \cdot \psi'(e)/(\Delta U + \psi(e)) = l$. Therefore,

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

Since the labor supply satisfies $l^s(\theta, \Delta U) = L(e^s(f(\theta), \Delta U) \cdot f(\theta))$, 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, $\varepsilon^m = l \cdot \varepsilon^e_\Delta$ and we obtain

(A2) $$\varepsilon^m = l \cdot \kappa \cdot \frac{\Delta U}{\Delta U + \psi(e)}.$$

The Discouraged-Worker Elasticity (ε^f). We differentiate (A1) with respect to f and obtain

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

In equilibrium, $e \cdot \psi'(e)/(\Delta U + \psi(e)) = l$. Hence, by rearranging the terms in this equation, we obtain $\varepsilon^f = u \cdot \kappa$. Combining this equation with (A2), we infer

(A3) $$\varepsilon^f = \frac{u}{1-u} \cdot \frac{\Delta U + \psi(e)}{\Delta U} \cdot \varepsilon^m.$$

The Microelasticity of Unemployment Duration With Respect to the Replacement Rate (ε^m_R). The microelasticity of unemployment duration with respect to the replacement rate is

(A4) $$\varepsilon^m_R \equiv -\left.\frac{\partial \ln(e^s \cdot f(\theta))}{\partial \ln(R)}\right|_{\theta, c^e, w}.$$

We link ε^m to ε^m_R. Using (A4) and $1-l^s = s/(s+e^s\cdot f(\theta))$, we have

$$\text{(A5)} \qquad \varepsilon^m_R = \frac{1}{l}\cdot\left.\frac{\partial \ln(1-l^s)}{\partial \ln(R)}\right|_{\theta,c^e,w} = -\frac{R}{l\cdot(1-l)}\cdot\left.\frac{\partial l^s}{\partial R}\right|_{\theta,c^e,w}.$$

We now consider a change dR keeping c^e, θ, and w constant. As we have seen in Section II, the change dR implies a utility change $d\Delta U = -U'(c^h)\cdot w\cdot dR$. Using (A5), we infer that

$$\text{(A6)} \qquad \varepsilon^m_R = \frac{R}{l\cdot(1-l)}\cdot U'(c^h)\cdot w\cdot\left.\frac{\partial l^s}{\partial \Delta U}\right|_{\theta} = \frac{R\cdot w\cdot U'(c^h)}{l\cdot\Delta U}\cdot\varepsilon^m.$$

Appendix B. The Optimal UI Formula

This appendix derives formula (10). The formula characterizes optimal UI in the dynamic model of Section I. The derivation of the formula closely follows the derivations in our companion paper (Landais, Michaillat and Saez 2016), so we only present the main steps and the calculations that are different. The differences arise because the model is dynamic and not static, and because we introduce home production and a nonpecuniary cost of unemployment.

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, given by (6), can be written as $l^s(\theta,\Delta U) = L(e^s(f(\theta),\Delta U)\cdot f(\theta))$, where the function L is defined by $L(x) = x/(s+f(x))$. Given that the elasticity of $L(x)$ with respect to x is $1-L(x)$, the elasticity of the labor supply with respect to tightness is

$$\text{(A7)} \qquad \frac{\theta}{l}\cdot\left.\frac{\partial l^s}{\partial\theta}\right|_{\Delta U} = u\cdot(1+\varepsilon^f)\cdot(1-\eta).$$

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

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

$$\frac{\partial SW}{\partial \theta} = u \cdot \frac{l}{\theta} \cdot (1-\eta) \cdot (\Delta U + \psi(e)) + U'(c^h) \cdot \frac{\partial c^u}{\partial \theta}. \tag{A8}$$

The factor u in the first term appears because the environment is dynamic, as in (A7). 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 (A7) implies that $\partial l^s / \partial \theta = u \cdot (l/\theta) \cdot (1-\eta) \cdot (1+\varepsilon^f)$. Second, with home production, the derivative of

$$c^e(c^u, \Delta U) = U^{-1}\left(U(c^u + h^s(c^u)) - z - \lambda(h^s(c^u)) + \Delta U\right) \tag{A9}$$

with respect to c^u is $\partial c^e / \partial c^u = U'(c^h)/U'(c^e)$. 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

$$u \cdot \frac{l}{\theta} \cdot (1-\eta) \cdot (1+\varepsilon^f) \cdot (w - \Delta c) - \frac{l}{\theta} \cdot \eta \cdot \tau(\theta) \cdot w = \left[\frac{l}{U'(c^e)} + \frac{1-l}{U'(c^h)}\right] \cdot U'(c^h) \cdot \frac{\partial c^u}{\partial \theta}, \tag{A10}$$

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

Combining (A8) and (A10), we recompute equation (10) from our companion paper:

$$\left.\frac{\partial SW}{\partial \theta}\right|_{\Delta U} = u \cdot \frac{l}{\theta} \cdot (1-\eta) \cdot \phi \cdot w \cdot \left[\frac{\Delta U + \psi(e)}{\phi \cdot w} + R \cdot \left(1 + \varepsilon^f\right) - \frac{\eta}{1-\eta} \cdot \frac{\tau(\theta)}{u}\right], \tag{A11}$$

where ϕ is the harmonic mean of workers' marginal consumption utilities:

$$\frac{1}{\phi} = \frac{l}{U'(c^e)} + \frac{1-l}{U'(c^u)}.$$

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

$$\frac{\partial SW}{\partial \Delta U} = l + U'(c^h) \cdot \frac{\partial c^u}{\partial \Delta U}. \tag{A12}$$

Next we recompute equation (17) from our companion paper. Using the work that we have done to obtain (A10), we find

$$\frac{1-l}{\Delta U} \cdot \varepsilon^m \cdot (w - \Delta c) - \frac{l}{U'(c^e)} = \left(\frac{l}{U'(c^e)} + \frac{1-l}{U'(c^h)} \cdot\right) \cdot U'(c^h) \cdot \frac{\partial c^u}{\partial \Delta U}. \tag{A13}$$

Combining (A12) and (A13), we recompute equation (11) from the companion paper:

$$\text{(A14)} \qquad \left.\frac{\partial SW}{\partial \Delta U}\right|_{\theta} = u \cdot \frac{\phi \cdot w}{\Delta U} \cdot \varepsilon^m \cdot \left[R - \frac{l}{w} \cdot \frac{\Delta U}{\varepsilon^m} \cdot \left(\frac{1}{U'(c^e)} - \frac{1}{U'(c^h)}\right)\right].$$

The last step before obtaining the optimal UI formula is to link the elasticity wedge to the equilibrium response of tightness to UI. Using (A7), we find that

$$\text{(A15)} \qquad \varepsilon^M = \varepsilon^m + l \cdot (1-\eta) \cdot \left(1 + \varepsilon^f\right) \cdot \frac{\Delta U}{\theta} \cdot \frac{d\theta}{d\Delta U}.$$

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 (A11) and (A14) and the derivative $d\theta/d\Delta U$ implied by (A15), we obtain formula (10).

Appendix C. The Utility Gain from Work

In this appendix we survey available empirical evidence and provide estimates for the coefficient of relative risk aversion, consumption drop upon unemployment, and the average marginal utility from wages. We use this empirical evidence to derive the expression (14) for the efficiency term and the expression (16) for the Baily-Chetty replacement rate.

The Utility Function (U). In a setting closely related to ours, Chetty (2006) finds that the impact of wage changes on labor supply implies an upper bound on the coefficient of relative risk aversion close to one. We therefore take a coefficient of relative risk aversion equal to 1 so that the consumption utility is $U(c) = \ln(c)$. A coefficient of 1 is on the low side compared to estimates of risk aversion obtained in other settings, implying a relatively low optimal replacement rate.

The Consumption Drop Upon Unemployment (c^h/c^e). We begin by reviewing evidence on the average consumption drop upon unemployment. Several studies have documented the drop in consumption upon unemployment in the United States using measures of food consumption. Using the PSID for 1968–1987, Gruber (1997) estimates that the drop for food consumption upon unemployment is 7%. Estimates are roughly consistent across studies: Stephens (2001) finds that food consumption falls by 9% following a job displacement, and Aguiar and Hurst (2005) find that in unemployment food consumption is lower by 5%.

As emphasized by Browning and Crossley (2001), total consumption is more elastic than food consumption to an income change so the drop of total consumption is larger than 7%. Using the Consumer Expenditure Survey for 1972–1973, Hamermesh (1982) estimates that the income elasticity of food consumption at home is 0.24 while that of food consumption away from home is 0.82. Furthermore, in the consumption basket of an unemployed worker the share of food consumption at home is 0.164 while that of food consumption away from home is 0.041. Hence the income elasticity of food consumption for unemployed workers is $0.24 \times [0.164/(0.164+0.41)] + 0.82 \times [0.041/(0.164+0.41)] = 0.36$. As a consequence, we expect the drop of total consumption upon unemployment to be $7\%/0.36 = 19\%$ so that $c^h/c^e = 0.81$.

The Average Marginal Utility from Wages ($\phi \cdot w$). With log utility, we have $1/(\phi \cdot w) = (c^e/w) \cdot \left[l + u \cdot (c^h/c^e)\right]$. A useful result is that $1/(\phi \cdot w) \approx c^e/w$ because $u = 0.06$, $l = 0.94$, and $c^h/c^e = 0.81$ so $l + u \cdot (c^h/c^e) = 0.99$. The resource constraint imposes that $y = l \cdot c^e + u \cdot c^u$. Let α be the labor share: $y = w \cdot l/\alpha$. Furthermore, $c^u = c^e - (1-R) \cdot w$. Hence, we have $c^e/w = (l/\alpha) + u \cdot (1-R)$. Combining these results, we obtain $1/(\phi \cdot w) = \left[l + u \cdot (c^h/c^e)\right] \cdot [(l/\alpha) + u \cdot (1-R)]$. In the class of models considered here, the labor share is determined by the shape of the production function. With a production function $y(n) = n^\alpha$, the labor share is exactly α. We will see in Section III that the parameter α in the production function also determines the elasticity wedge $1 - \varepsilon^M/\varepsilon^m$. We will find that a reasonable estimable of the elasticity wedge is 0.4, and that this implies $\alpha = 0.73$. To have a labor share consistent with the evidence on the elasticity wedge, we set $\alpha = 0.73$. On average we also have $u = 0.06$, $l = 0.94$, $R = 0.42$, and $c^h/c^e = 0.81$. Hence we set $\phi \cdot w = 0.77$.

We have found that $\phi \cdot w$ depends on the unemployment rate and replacement rate. However, as $u \ll l$ and the variations in u are small compared to l, the variations in u, l, R, and c^h/c^e are small compared to l. Hence, we neglect the response of $\phi \cdot w$ to u and R.

Appendix D. Elasticities Describing Job Search and Matching

In this appendix we survey available empirical evidence and provide estimates for the elasticities describing search and matching: the matching elasticity, the discouraged-worker elasticity, and the microelasticity of unemployment duration with respect to the replacement rate. We use this empirical evidence throughout the paper.

The 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 approximately Cobb-Douglas (Petrongolo and Pissarides 2001). With a Cobb-Douglas matching function, $m(e,u,v) = \mu \cdot (e \cdot u)^\eta \cdot v^{1-\eta}$ so that $f(\theta) \equiv m/(e \cdot u) = \mu \cdot [v/(u \cdot e)]^{1-\eta}$. Hence, η corresponds to the elasticity of the matching function with respect to unemployment.

A vast empirical literature studies the matching function and estimates η. We rely on the estimates found in that literature. In their survey, Petrongolo and Pissarides (2001, p.424) conclude that the estimates of η fall between 0.5 and 0.7. We set our estimate to the mid-point of plausible values: $\eta = 0.6$.

Evidence collected since the publication of Petrongolo and Pissarides's survey tend to reinforce their conclusion. For instance, Shimer (2005, p.32) estimate $\eta = 0.72$ in CPS data for 1951–2003. Rogerson and Shimer (2011, p.638) estimate $\eta = 0.58$ in JOLTS data for 2001–2009. Borowczyk-Martins, Jolivet and Postel-Vinay (2013, Table 1, columns 2 and 3) estimate $\eta = 0.59$ and $\eta = 0.67$ with first-difference estimators in JOLTS data for 2000–2012.

However, many of the estimates in the literature assume that search efforts of workers and firms are constant. If these efforts are endogenous (as in our model where job-search effort is endogenous), the estimates of η could be biased. Borowczyk-Martins, Jolivet and Postel-Vinay (2013) propose an estimation method that is immune to this bias. On JOLTS data for 2000–2012, their proposed estimate is $\eta = 0.3$, so lower than previous estimates.

Given the uncertainty about the exact value of η, we will consider the cases $\eta = 0.5$ and $\eta = 0.7$ in the sensitivity analysis of Section IV.

The Discouraged-Worker Elasticity (ε^f). The elasticity ε^f measures how 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 mainly from the CPS, 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) analyzes the CPS over the 1994–2004 period and 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) jointly analyze the ATUS and CPS over the 1994–2011 period 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 therefore suggests that ε^f is slightly negative.

Overall, these empirical studies suggest that the response of search effort to the job-finding rate is quite weak. Therefore, we simply 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. In our dynamic matching model the discouraged-worker elasticity satisfies (A3). The elasticity ε^m measures the response of search effort to UI and the elasticity ε^f the response of search effort to labor market conditions. This equation indicates that ε^f is much smaller than ε^m in normal circumstances because $u/(1-u)$ 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.

The Microelasticity of Unemployment Duration With Respect to the Replacement Rate (ε^m_R). For the United States, one of the most compelling estimates of ε^m_R comes from the work of Landais (2015). An advantage of this study is that it combines modern econometric techniques (a regression kink design) and a large administrative dataset that covers several US states. One drawback is the data are from the late 1970s and early 1980s. Landais finds the following estimates. For Louisiana, ε^m_R is between 0.18 and 0.75 (Table 2, column (1), rows ε_B). For Idaho, ε^m_R is between 0.05 and

0.75 (online appendix: Table B2, column (1), rows ε_B). For Missouri, ε_R^m is between 0.08 and 0.37 (online appendix: Table B3, column (1), rows ε_B). For New Mexico, ε_R^m is between 0.31 and 0.38 (online appendix: Table B4, column (1), rows ε_B). For Washington, ε_R^m is between 0.37 and 0.68 (online appendix: Table B5, column (1), rows ε_B). Overall, Landais finds that ε_R^m is between 0.05 and 0.75, with an average estimate of 0.4.

A large body of work has estimated the microelasticity ε_R^m, and provides strong evidence that UI increases unemployment durations. (See Krueger and Meyer (2002) for a comprehensive survey.) An estimate of 0.4 is in the range of plausible estimates, albeit toward the low end. For instance, in a classic study using the same data as Landais but a different identification strategy, Meyer (1990, Table VI, columns (6)–(9)) finds an elasticity $\varepsilon_R^m = 0.6$. Using more recent administrative data than Meyer and Landais, Card et al. (2015) also find evidence that is consistent with an estimate of 0.4. They implement a regression kink design on administrative data from Missouri for 2003–2013 and find that ε_R^m is between 0.37 and 0.88 (Card et al. 2015, Table 1, column (2)).

While they are not directly comparable as they look at variations in UI duration, not UI level, the recent studies by Rothstein (2011) and Farber and Valletta (2013) find smaller microelasticities than previous studies. These two studies look at the effect of the large extensions in UI benefit duration enacted during the Great Recession. One potential issue is that they do not have access to administrative data but must rely on Current Population Survey data, which tend to be noisy.

Based on this evidence, we set $\varepsilon_R^m = 0.4$. However, given that the evidence in Card et al. (2015) points to a larger ε_R^m while the evidence in Rothstein (2011) and Farber and Valletta (2013) points to a smaller ε_R^m, we will consider the cases $\varepsilon_R^m = 0.2$ and $\varepsilon_R^m = 0.6$ in the sensitivity analysis of Section IV.

Appendix E. Job-Finding and Job-Destruction Rates in CPS Data

In this appendix we follow the method developed by Shimer (2012) to compute job-finding and job-destruction rates in CPS data for the 1990–2014 period. We use these rates to construct one of the measures of recruiter-producer ratio plotted in Figure 1, Panel B.

We assume that unemployed workers find a job according to a Poisson process with arrival rate $e(t)\cdot f(t)$. Under this assumption, the monthly job-finding rate satisfies $e(t)\cdot f(t) = -\ln(1-F(t))$, where $F(t)$ is the monthly job-finding probability. We construct $F(t)$ as follows:

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

where $u(t)$ is the number of unemployed persons at time t and $u^s(t)$ is the number of short-term unemployed persons at time t. We measure $u(t)$ and $u^s(t)$ in the data constructed by the BLS from the CPS. 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). Using the time series for $F(t)$, we construct the time series for $e(t)\cdot f(t)$.

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

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

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 the data constructed by the BLS from the CPS, and we use the series for $e(t) \cdot f(t)$ constructed above. We solve the equation for each t to construct the time series $s(t)$.

Appendix F. The Effective UI Replacement Rate in the United States

This appendix describes the construction of the effective UI replacement rate plotted in Figure 3. The time series for the effective replacement rate summarizes the evolution over time of the generosity of the UI program in the United States. While this synthetic measure cannot possibly capture all the intricacies of the UI program in the United States, it captures the relevant variations in the generosity of the UI policy over the business cycle and in particular the variations in the potential duration that job seekers can collect benefit during an unemployment spell.

Our effective replacement rate aims at capturing the average replacement rate among all jobseekers who have lost their jobs and are eligible or have been eligible to UI at some point during their current spell. Our effective replacement rate therefore will depend on 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.

In practice, we create our replacement rate series based on the following approach. In each month t, the effective replacement rate R^t in the cross-section of unemployed is defined as:

$$R^t = \frac{\sum r_j^t \cdot N_j^t}{\sum N_j^t},$$

where j indexes the week since the start of an unemployment spell. N_j^t is the number of unemployed individuals who, in month t, are in the j-th week of their unemployment spell. r_j^t is the replacement rate on the UI benefits collected by individuals who are in the j-th week of their unemployment spell at time t. To compute the numerator, we split it into active claims and exhaustees. Exhaustees are unemployed who have been unemployed longer than the potential duration of benefits k. Because individuals who have exhausted their benefits have a replacement rate $r_{j>k}^t = 0$, the numerator is solely driven by active claims:

$$R^t = \frac{\overbrace{\sum_{j\leq k} r_j^t \cdot N_j^t}^{\text{Active claims}} + \overbrace{\sum_{j>k} 0 \cdot N_j^t}^{\text{Exhaustees}}}{\sum N_j^t} = \frac{\sum_{j\leq k} r_j^t \cdot N_j^t}{\sum N_j^t}.$$

In practice we compute the numerator using

$$\sum_{j\leq k} r_j^t \cdot N_j^t = \widetilde{r_{j\leq k}^t} \cdot \underbrace{\sum_{j\leq k} N_j^t}_{\text{Total active claims}},$$

where $\sum_{j\leq k} N_j^t$ is the total number of active claims in all UI programs, and $\widetilde{r_{j\leq k}^t}$ is the average replacement rate for all active claims.

The Bureau of Labor Statistics has a comprehensive historical record of all active UI claims in the United States at the weekly level since 1986. It is available from http://www.ows.doleta.gov/unemploy/DataDashboard.asp. The advantage of this record is that it contains information for all existing UI programs: regular programs (State UI, UCFE, UCX), extended benefit programs (EB) and federal extensions during recessions (EUC1990, TEUC and EUC08).

To compute $\widetilde{r^t_{j\leq k}}$, the average replacement rate for active claims we use the replacement rate reports available from the BLS at: http://www.oui.doleta.gov/unemploy/ui_replacement_rates.asp The replacement rate reports from the BLS use the Unemployment Insurance Benefit Accuracy Measurement data, stored in the UI database. This data is a sample of active claims. The reports give an estimate of the average replacement rate among active claims computed as the ratio of claimants' weekly benefit amount to the claimants' base earnings. This average replacement rate is extremely stable over time and very close to 50%. 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.

To compute the denominator, we need an estimate of $\sum N^t_j$, the sum of unemployed at time t who are eligible or have been eligible at some point during their spell. In practice, we estimate $\sum N^t_j = u^t \cdot \beta^t$, where u^t is the total number of unemployed and β^t is the fraction of individuals who are job losers among the unemployed. While quits and new entrants (or re-entrants) in the labor market are not eligible for UI, job losers who meet minimal criteria become eligible for UI after being displaced. In practice, we believe job losers offer a good approximation of the population of individuals who are eligible or have been eligible at some point during their spell.

For unemployment u^t, we use seasonally adjusted number of unemployed workers, 16 years and over, computed by the BLS from CPS data. For β^t, we use the number of job losers as a percent of total unemployed workers computed from by the BLS from the CPS. This is the fraction of individuals who entered unemployment through a job loss in the stock of unemployed at time t.

The advantage of using these series is that they are readily available from the BLS. A more rigorous treatment of eligibility to UI might be made using the micro data from the March supplement of the CPS, but in practice, most of the variables necessary to compute rigorously eligibility using UI state rules are missing or can only be crudely approximated in the March CPS.

Note that, while in theory, the number of eligible (in the denominator) is always larger or equal to the number of active claims, ($\sum N^t_j \geq \sum_{j\leq k} N^t_j$), for a few months during the Great Recession, the number of active claims is slightly larger than our estimates of the stock of eligible. This is due to the fact that our estimate of the the stock of eligible is an approximation using job losers from the CPS. To control for this, we cap the number of eligible estimated from the CPS to the number of active claims for these few months.

Appendix G. Variations of the Utility Gain from Work with UI

This appendix studies how the utility gain from work, $(\Delta U + \psi(e))/(\phi \cdot w)$, varies with UI. We use this empirical evidence to derive the expression (14) for the efficiency term and the expression (16) for the Baily-Chetty replacement rate.

We abstract from the response of the term $1/(\phi \cdot w)$ to R because this response is very small. Recall that $\Delta U = U(c^e) - U(c^u + h) + z + \lambda(h)$. We assume that z is independent of R. And since

h is chosen optimally to minimize ΔU, the change in h caused by R has no first-order effect on ΔU. Finally, the response of c^e to R is bound to be small since the response of UI taxes to R is necessarily small. So we only need to find how c^u and e respond to R.

We start by determining the response of c^u to R. Consider a small change dR in replacement rate. By definition, $c^u = c^e - (1-R) \cdot w$ and the change dR implies a consumption change $dc^u = w \cdot dR$ (we neglect the effect of R on c^e and w). Accordingly, the effect of dR on $\Delta U/(\phi \cdot w)$ is $d\Delta U/(\phi \cdot w) = -U'(c^h) \cdot dc^u/(\phi \cdot w) = -U'(c^h) \cdot w \cdot dR/(\phi \cdot w)$. Using log utility and $1/(\phi \cdot w) \approx c^e/w$, we obtain $d\Delta U/(\phi \cdot w) = -c^e/c^h \times dR = -1.23 \times dR$.

Next we determine the response of e to R. A change dR also generates a change de in job-search effort. This response is given by the microelasticity of unemployment duration with respect to the replacement rate: $de = (e/R) \cdot \varepsilon^m_R \cdot dR$. Hence, the increase in the disutility of job search after an increase dR is $d\psi(e) = \psi'(e) \cdot de = -\psi'(e) \cdot (e/R) \cdot \varepsilon^m_R \cdot dR$. Using (3), we rewrite the utility change: $d\psi(e)/(\phi \cdot w) = -l \cdot [(\Delta U + \psi(e))/(\phi \cdot w)] \cdot (\varepsilon^m_R/R) \cdot dR$. In addition, we have found above that $\varepsilon^m_R = 0.4$, $l = 0.94$, $R = 0.42$, and $(\Delta U + \psi(e))/(\phi \cdot w) = 0.57$. Hence, $d\psi(e)/(\phi \cdot w) = -0.94 \times 0.57 \times 0.4 \times dR/0.42 = -0.51 \times dR$.

Collecting the empirical evidence, and using the fact that $(\Delta U + \psi(e))/(\phi \cdot w) = 0.57$ when $R = 0.42$, we conclude that

$$\text{(A16)} \qquad \frac{\Delta U + \psi(e)}{\phi \cdot w} = 0.57 - (1.23 + 0.51) \cdot (R - 0.42) = 0.57 - 1.74 \times (R - 0.42).$$

Appendix H. The Elasticity Wedge in the Job-Rationing Model

This appendix derives the expression (15) for the elasticity wedge of the job-rationing model introduced in Section IV.D.

The elasticity of $1 + \tau(\theta)$ with respect to θ is $\eta \cdot \tau(\theta)$. From (18), 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 (A15) 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:

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

Appendix I. The Baily-Chetty Replacement Rate

This appendix derives the expression (16) for the Baily-Chetty replacement rate.

With log utility and $1/(\phi \cdot w) = c^e/w$, we rewrite the Baily-Chetty replacement rate as

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

We first compute $1 - (c^h/c^e)$. We have found in Section II that on average $1 - (c^h/c^e) = 0.19$ and that c^h/c^e does not depend on labor market conditions. However, c^h/c^e mechanically varies when R varies because c^h responds to R. We have $c^u = c^e - (1-R) \cdot w$ so a change dR implies a consumption change $dc^u = w \cdot dR$. In addition, Gruber (1997) estimates that when the replacement rate increases by 1 percentage point from an average value of 58%, the food consumption of an unemployed worker increases by 0.27 percent. The implied elasticity of food consumption to UI benefits therefore is $0.27/(1/0.58) = 0.16$. Using again the estimate from Hamermesh (1982) to convert the response of food consumption into the response of total consumption, we infer that $d\ln(c^h)/d\ln(c^u) = 0.16/0.36 = 0.44$. That is, increasing unemployment benefits by 1% increases total consumption when unemployed by 0.44%. So a change dR leads to a change $dc^h = (c^h/c^u) \times 0.44 \times dc^u$ and $dc^h/c^e = (c^h/c^e) \times (w/c^u) \times 0.44 \times dR$. We have $c^h/c^e = 0.81$. Furthermore, $c^u/w = c^e/w - (1-R)$. and we have found that on average $R = 0.42$ and $c^e/w = 1.3$, so $c^u/w = 1.3 - 0.58 = 0.72$. We conclude that $dc^h/c^e = 0.81/0.72 \times 0.44 \times dR = 0.5 \times dR$ and

$$1 - \frac{c^h}{c^e} = 0.19 - 0.5 \times (R - 0.42).$$

Next, we compute ε^m and determine how ε^m responds to labor market conditions and UI. In the matching model, ε^m can be expressed as a function of other statistics. As showed in Appendix A, $\varepsilon^m/(l \cdot \Delta U) = \kappa/(\Delta U + \psi(e))$, where $1/\kappa$ is the elasticity of $\psi'(e)$ with respect to e. We assume that $\psi'(e)$ is isoelastic so κ is constant. we obtain

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

The expression for $(\Delta U + \psi(e))/(\phi \cdot w)$ is given by (A16). The last step is to compute the constant κ. We use the microelasticity of unemployment duration with respect to the replacement rate, ε^m_R. With log utility, (A6) implies that ε^m and ε^m_R are related by

$$\frac{\varepsilon^m}{l \cdot \Delta U} = \frac{c^e}{w} \cdot \frac{c^h}{c^e} \cdot \frac{1}{R} \cdot \varepsilon^m_R.$$

With $c^h/c^e = 0.81$, $R = 0.42$, $c^e/w = 1.3$, and $\varepsilon^m_R = 0.4$, we find that $\varepsilon^m/(l \cdot \Delta U) = 1.3 \times 0.4 \times 0.81/0.42 = 1$. Hence, on average, $\kappa = 1 \times [\Delta U + \psi(e)] = 0.57/1.3 = 0.44$.

Collecting all the evidence, we conclude that the Baily-Chetty replacement rate is

$$\frac{1}{0.44} \times [0.57 - 1.74 \times (R - 0.42)] \times [0.19 - 0.5 \times (R - 0.42)].$$

Table A1: Functional Forms and Parameter Values in the Simulation Model

	Description	Source
	Panel A. Functional forms	
$U(c) = \ln(c)$	Utility from consumption	Chetty (2006)
$m(eu,v) = \mu(eu)^{\eta} v^{1-\eta}$	Matching function	Petrongolo and Pissarides (2001)
$\psi(e) = \delta \frac{\kappa}{1+\kappa} e^{\frac{1+\kappa}{\kappa}}$	Disutility from job-search effort	–
$\lambda(h) = \xi \frac{h^{1+\sigma}}{1+\sigma}$	Disutility from home production	–
$y(n) = an^{\alpha}$	Production function	–
$w = \omega a^{1-\gamma}$	Wage schedule	–
	Panel B. Parameter values	
$s = 2.8\%$	Monthly job-destruction rate	CPS, 1990–2014
$\eta = 0.6$	Matching elasticity	Petrongolo and Pissarides (2001)
$\mu = 0.61$	Matching efficacy	Matches targets
$\rho = 0.79$	Matching cost	Matches $\tau = 2.3\%$
$\kappa = 0.44$	Disutility from search: convexity	Matches $\varepsilon^m_R = 0.4$
$\delta = 0.41$	Disutility from search: level	Matches targets
$\sigma = 0.52$	Disutility from home production: convexity	Matches $d\ln(c^h)/d\ln(c^u) = 0.44$
$\xi = 2.7$	Disutility from home production: level	Matches targets
$z = -0.1$	Nonpecuniary unemployment cost	Matches $Z = 0.3\phi w$
$\alpha = 0.73$	Production function: concavity	Matches $1 - \varepsilon^M/\varepsilon^m = 0.4$
$\omega = 0.73$	Real wage level	Matches $u = 6.1\%$
$\gamma = 0.5$	Real wage rigidity	Michaillat (2014)

Appendix J. Calibration of the Simulation Model

This appendix calibrates the job-rationing model used for simulations in Section IV.D. The functional forms and parameter values used for the simulations are summarized in Table A1.

Before starting the calibration, we impose some normalizations. First, we set the average technology to $a = 1$. Second, we target an average job-search effort of $e = 1$ and a disutility from search effort of $\psi(1) = 0$.

First, as in Section II, we set the consumption utility to $U(c) = \ln(c)$, the matching function to $m(e \cdot u, v) = \mu \cdot (e \cdot u)^{\eta} \cdot v^{1-\eta}$ with $\eta = 0.6$, the production-function parameter to $\alpha = 0.73$.

Next we calibrate the parameters related to matching. We use the job-destruction rate constructed in Appendix E from CPS data. We set the job-destruction rate to its average value for 1990–2014: $s = 2.8\%$. To calibrate the matching efficacy, we exploit the relationship $u \cdot e \cdot f(\theta) = s \cdot (1-u)$, which implies $\mu = s \cdot \theta^{\eta-1} \cdot (1-u)/(u \cdot e)$. 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 $s = 2.8\%$, $\theta = 0.43$, $\eta = 0.6$, $u = 6.1\%$, and $e = 1$, we get $\mu = 0.61$. To calibrate the matching cost, we exploit the relationship $\tau = \rho \cdot s/[\mu \cdot \theta^{-\eta} - \rho \cdot s]$, which implies $\rho = \mu \cdot \theta^{-\eta} \cdot \tau/[s \cdot (1+\tau)]$. With $\mu = 0.61$, $s = 2.8\%$, $\theta = 0.43$, and $\tau = 2.3\%$, we obtain $\rho = 0.79$.

Then we calibrate the parameters of the wage schedule. To calibrate the wage level, we exploit the relationship $\alpha \cdot n^{\alpha-1} = \omega \cdot a^{-\gamma} \cdot (1+\tau)$. With $a = 1$, $\tau = 2.3\%$, $\alpha = 0.73$, and $n = (1-u)/(1+\tau) = 0.920$, we obtain $\omega = 0.73$. Following Michaillat (2014), we set the wage rigidity to $\gamma = 0.5$.

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 resource constraint imposes $(1-u) \cdot c^e + u \cdot c^u = a \cdot n^{\alpha}$. Solving this linear system of two equations with $w = \omega = 0.73$, $R = 0.42$, $u = 6.1\%$, $a = 1$, $n = 0.920$, and $\alpha = 0.73$, we obtain $c^e = 0.97$ and $c^u = 0.54$. As $c^h/c^e = 0.81$, we find $c^h = 0.78$ and $h = c^h - c^u = 0.24$.

We assume that the disutility from search effort is isoelastic: $\psi(e) = \delta \cdot \kappa \cdot e^{(1+\kappa)/\kappa}/(1+\kappa)$. We set $\kappa = 0.44$ to be consistent with $\varepsilon^m_R = 0.4$. To calibrate δ, we use equation (3). With $e = 1$, $u = 6.1\%$, and $\Delta U + \psi(e) = 0.44$, this equation implies $\delta = 0.94 \times 0.44 = 0.41$.

We assume that the disutility from home production is $\lambda(h) = \xi \cdot h^{1+\sigma}/(1+\sigma)$. The optimality condition $\lambda'(h) = U'(c^h)$ implies that $\xi \cdot h^{\sigma} = 1/(c^u + h)$. We implicitly differentiate this equation with respect to c^u and obtain $dh/dc^u = -1/(1+\sigma \cdot c^h/h)$. This implies $dc^h/dc^u = 1 + dh/dc^u = \sigma/\left(\sigma + h/c^h\right)$. Since $c^h/c^u = 1.44$ and $d\ln(c^h)/d\ln(c^u) = 0.44$, we infer that $dc^h/dc^u = (c^h/c^u) \cdot (d\ln(c^h)/d\ln(c^u)) = 0.63$. Combining this fact with $h/c^h = 0.31$ and the expression for dc^h/dc^u, we find $\sigma = 0.52$. Since $\xi = 1/(c^h \cdot h^{\sigma})$ and $c^h = 0.78$, $h = 0.24$, and $\sigma = 0.52$, we find $\xi = 2.7$.

Last, we calibrate the pure nonpecuniary cost from unemployment, z. We target $Z = z + \psi(e) + \lambda(h) = 0.3 \times 0.77 = 0.23$. As $\lambda(h) = 0.20$ and $\psi(e) = 0.41 \times 0.44/(1.44) = 0.12$ in the average state, we set $z = -0.1$.

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