w o r k i n g
p a p e r

10 17

The Ins and Outs of Unemployment in the Long Run: A New Estimate for the Natural Rate?

by Murat Tasci

FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 10-17 October 2010

The Ins and Outs of Unemployment in the Long Run: A New Estimate for the Natural Rate?

by Murat Tasci

In this paper, we present a simple, reduced form model of comovements in real activity and unemployment flows and use it to uncover the trend changes in these flows, which determine the trend in the unemployment rate. We argue that this trend rate has several key features that are reminiscent of a "natural rate." We show that the natural rate, measured this way, has been relatively stable in the last decade, even after the last recession hit the U.S. economy. This relatively muted change was due to two opposing trend changes: On one hand, the trend in the job-finding rate, after being relatively stable for decades, declined by a significant margin in the last decade, pushing trend unemployment up. On the other hand, the separation rate has somewhat offset this effect with a continued secular decline since the early 1980s. We also show that, contrary to business-cycle frequency movements, most of the low-frequency variation in the unemployment rate could be accounted for by changes in the trend of separation rates, not job-finding rates. The notable exception is the last decade, when clear trend changes in both flows imply opposing effects on the trend unemployment rate and slower worker reallocation in the U.S. economy.

JEL classication: E24, E32, J64
Keywords: unemployment, natural rate, job-finding rate, separation rate, labor market search.

The author is grateful to Saeed Zaman for his able research assistance.

Murat Tasci is a research economist at the Federal Reserve Bank of Cleveland. He can be reached at murat.tasci@clev.frb.org.

1 Introduction

This paper lays out a simple, reduced form model that is useful in understanding the comovement between real economic activity and flows into and out of unemployment. We argue that, in light of the large body of literature on the search theory of unemployment, it is important to understand these flows, separation, and the job-finding rate in order to understand the long-run behavior of the unemployment rate[1]. We also show that one can construct an unemployment rate trend based on these flows, which can be interpreted as the rate of unemployment in the long run, with which the actual unemployment rate would converge if the trends in these flows persist. It essentially provides us with a time-varying trend estimate for the unemployment rate. We argue that this trend rate has several key features that are reminiscent of a "natural rate"; hence we use the term interchangeably with unemployment trend from here onward. We show that, measured this way, the natural rate has been relatively stable in the last decade, even after the last recession hit the US economy. Underlying this relatively muted change are two offsetting trends in the flows; the trend in the job-finding rate, after being relatively stable for decades, declined by a significant margin in the last decade, pushing trend unemployment up. However, since the early 1980s, the separation rate has partially offset this effect with a continuing secular decline. We also show that, unlike business-cycle frequency movements, most of the low-frequency variation in the unemployment rate could be accounted for by changes in the trend of separation rates rather than job-finding rates. The exception was the last decade, when clear trend changes in both flows imply opposing effects on the trend unemployment rate and slower worker reallocation for the US economy.

The next section discusses the related literature, especially that on the natural rate, and where our approach fits in. Section 3 presents our simple, reduced form model, which describes the comovement of real GDP with unemployment flows. This section also includes our description of the data, particularly how we construct unemployment flow rates and conduct our estimation. Section 4 presents our estimation results and two numerical exercises, in which we address whether the last recession changed the trend of the unemployment rate and which flow is the main driving force behind the low-frequency variation in the unemployment rate. Section

[1] For a survey of the labor market search literature, see Mortensen and Pissarides (1999). Pissarides (2000) provides a nice textbook treatment of the subject.

5 concludes.

2 Related Literature

Our estimate for the long-run trend of the unemployment rate, as we noted earlier, is reminiscent of the natural rate of unemployment. The concept dates back at least to Friedman (1968) and Phelps (1968)[2]. It is probably one of the most frequently used, yet most vaguely defined, concepts utilized by macroeconomists. Rogerson (1997) criticizes this in his review essay, concluding that "economics would benefit from being deprived of these concepts" and that "we have reached a point where our theories of unemployment are ahead of language" (Rogerson 1997, 74–75). We can trace the origin of the "natural rate of unemployment" concept to Milton Friedman. In his presidential address to the members of the American Economic Association (1968, p. 8), Friedman spelled out this concept. He did not provide a clear, well-defined characterization of this concept, but rather described some features that it should have:

> The "natural rate of unemployment"... is the level that would be ground out by the Walrasian system of general equilibrium equations, provided there is imbedded in them the actual structural characteristics of the labor and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and labor availabilities, the cost of mobility, and so on.

Although he further qualified this concept elsewhere, it turned out to be vague enough to make it hard for economists to agree on a clear way to map the concept into a quantitative measure (Rogerson, 1997). Some economists developed this concept into yet another vaguely defined concept, the NAIRU (non-accelerating inflation rate of unemployment). This concept assumes an inherent trade-off between inflation and the unemployment rate in the sense that when the unemployment rate is above the NAIRU because of slack in the labor market, there will be downward pressure on prices and wages, and inflation will go down. Similarly, a lower

[2] For a good discussion on the topic, one can look at papers in the Journal of Economic Perspectives (Winter 1997) and the American Economic Review, Papers and Proceedings (May 1988), as well as a survey by Johnson and Layard (1986).

measured unemployment rate relative to the NAIRU is assumed to put upward pressure on prices and wages. However, if anything, Friedman (1968, p. 9) made it clear that he used the term "... 'natural' for the same reason that Wicksell did—to try and separate real forces from monetary forces." Thus, from this perspective, we do not consider the NAIRU concept useful, and it will not be our focus here[3].

Another point Friedman emphasized in his address was that the natural rate itself might change over time due to market forces or economic policies. This is very intuitive. For instance, labor market policies such as high unemployment compensation, strict firing rules, and severance policies have been blamed for persistently high unemployment in Europe. It is conceivable that these policies resulted in a higher "natural" rate for Europe, thereby keeping the actual (measured) unemployment rate high during the past three decades as well (Blanchard, 2006).

In our attempt to measure this "natural" rate of unemployment, we follow this guidance and look for a rate that is not affected by nominal variables, is moving at a relatively low frequency, and could potentially change over time, albeit smoothly. For the purposes of this paper, we will call this the long-run trend of the unemployment rate or the natural rate, interchangeably. The unique aspect of our approach is that we estimate the natural rate by first isolating the underlying trends in the job-finding and job-separation rates. We then employ these rates to estimate the long-term trend in unemployment by using the fact that it can be expressed as the ratio of the separation rate to the overall reallocation rate. We think that this exercise gives us a useful empirical concept, which clearly maps into the theory of unemployment in many ways.

In principle, one can use a benchmark search model and estimate it structurally to back out this long-run trend from the model. However, we think that there are at least two reasons why we might do better by pursuing a useful empirical concept instead. First, this class of models is subject to well-known problems that manifest themselves as inability to match many key moments for the labor market variables, including those for unemployment itself. In particular, Hall (2005) and Shimer (2005) argue that standard models of labor market search

[3]Nevertheless, we should note that the NAIRU has been the focus of a large body of literature, where it is sometimes used synonymously with the natural rate concept we have discussed; see, for example, Ball and Mankiw (2002). A substantial body of literature focuses on estimating the NAIRU, and some of it uses unobserved components methods similar to those employed here or a variant of the Phillips curve; see, for example, Staiger, Stock, and Watson (1997 and 2001), and King and Watson (1994). The usefulness of this concept for policy is a whole different topic; see, for example, Rogerson (1997), David Gordon (1988), Robert Gordon (1997), and Orphanides and Williams (2002), among others.

require implausibly large shocks to generate substantial variation in key variables: unemployment, vacancies, and market tightness (the vacancy-to-unemployment ratio). This quantitative problem makes it harder to use this class of models for a measurement exercise like the one we have in mind here. Secondly, many of the low-frequency changes in the underlying flows represent low-frequency changes in the economic environment, such as labor market policies, demographic changes, and technological advances (in either production or matching technology); incorporating all of these potential driving forces into a parsimonious model would be fairly complicated. By imposing a low-frequency change in these flows, our simple, reduced form model allows for these potential channels to the extent that they affect unemployment flows. If inflow into unemployment turns out to be the main driving force that determines the long-run trend, that is, the "natural rate," as we find, then one can potentially focus on theoretical features in these models, which would manifest themselves as changes in inflows[4]. Hence, we believe that our approach here could also be useful for modelling unemployment in the long run.

Our reduced form empirical model and the estimation method we employ are closely related to the study of measuring the cyclical component of economic aggregates, as in Clark (1987, 1989) and Kim and Nelson (1999). Our approach—identifying the trend of the unemployment rate over time via long-term trends of the underlying flows into and out of unemployment—is perhaps most closely related to Darby, Haltiwanger, and Plant (1985) and Barro (1988). Darby, Haltiwanger, and Plant (1985) look into the importance of heterogeneity in worker flows for unemployment persistence. Barro (1988) focuses on the same long-run equilibrium condition for unemployment that we focus here, that is, the separation rate over the sum of the separation rate and the job-finding rate; he emphasizes how worker reallocation determines persistence in unemployment. In this paper, however, we try to tease out the cyclical variation in these flows from the trend changes, in order to estimate the unemployment rate trend. More recently, Dickens (2009) also proposes an empirical model that uses information from the Beveridge curve. Although he incorporates unemployment flows into the model, his main focus is to estimate a time-varying NAIRU.

[4]See for instance, Shimer (2007), Elsby, and Michaels and Solon (2009) for the cyclical contributions of flows to unemployment fluctuations in the US.

3 A Simple Model

We are going to write down a simple, reduced form model that incorporates the comovement of flows into and out of unemployment into previous attempts at estimating the natural rate, such as Clark (1987, 1989) and Kim and Nelson (1999). The reduced form model assumes that real GDP has both a stochastic trend and a stationary cyclical component, where only real GDP is observed by the econometrician. We also assume that both flow rates, F_t and S_t, (job-finding and separation rate respectively) have a stochastic trend as well as a stationary component. Furthermore, the stochastic trend follows a random walk, but the cyclical component in the flow rates depends on the cyclical component of real GDP. More specifically, let Y_t be log real GDP, $\bar{y}_t$ a stochastic trend component and y_t the stationary cyclical component. Similarly, let F_t (S_t) be the quarterly job finding (separation) rate, $\bar{f}_t$ ($\bar{s}_t$) its stochastic trend component and f_t (s_t) the stationary cyclical component. Then we consider the following unobserved components model:

$$Y_t = \bar{y}_t + y_t; \quad \bar{y}_t = g_{t-1} + \bar{y}_{t-1} + \varepsilon_t^{yn}; \quad g_t = g_{t-1} + \varepsilon_t^{g}; \quad y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \varepsilon_t^{yc} \tag{1}$$

$$F_t = \bar{f}_t + f_t; \quad \bar{f}_t = \bar{f}_{t-1} + \varepsilon_t^{fn}; \quad f_t = \rho_1 y_t + \rho_2 y_{t-1} + \rho_3 y_{t-2} + \varepsilon_t^{fc} \tag{2}$$

$$S_t = \bar{s}_t + s_t; \quad \bar{s}_t = \bar{s}_{t-1} + \varepsilon_t^{sn}; \; s_t = \theta_1 y_t + \theta_2 y_{t-1} + \theta_3 y_{t-2} + \varepsilon_t^{sc} \tag{3}$$

where g_t is a drift term in the stochastic trend component of output which is also a random walk, following Clark (1987). All the error terms, ε_t^{yn}, ε_t^{g}, ε_t^{yc}, ε_t^{fn}, ε_t^{fc}, ε_t^{sn}, ε_t^{sc}, are independent white-noise processes. There is nothing very controversial about (1), which governs the movement in real output. We impose a stochastic trend, which might be subject to occasional drifts, and a persistent but stationary cyclical component. What is more unconventional is the comovement in the rates of job finding and separations in (2) and (3). We argue that the low-frequency movements in the trends, $\bar{f}_t$ and $\bar{s}_t$, will capture the effects of institutions, demographics, tax structure, labor market rigidities, and the long-run matching efficiency of the labor markets, which will be more important in determining the steady state of unemployment, consistent with our arguments in the preceding section. The cyclical components, f_t and s_t, on the other hand, are moving in response to purely cyclical changes in output. One can easily legitimize this in a simple extension of the textbook search model with endogenous job destruction and shocks to aggregate productivity, as in Mortensen and Pissarides (1994). In this class of models, market tightness—hence the job-finding rate—increases during expansions and declines during recessions. Similarly, when aggregate productivity is temporarily low, there will be a surge of separations, resulting in higher unemployment, because some existing matches cease to be productive enough in the recession. Hence, the assumed relationship of (2) and (3) is in line with the predictions of the search theory of unemployment.

Recall that the natural rate of unemployment, according to our definition, is pinned down by the stochastic trend components of the job-finding and separation rates. We can estimate our model and use a Kalman filter to back out the underlying trends in order to get an estimate of a time-varying natural rate. To start, we can write down the system of equations in (1)-(3), in the following state-space representation:

$$\begin{bmatrix} Y_t \\ F_t \\ S_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \rho_1 & \rho_2 & \rho_3 & 0 & 1 & 0 \\ 0 & \theta_1 & \theta_2 & \theta_3 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_t \\ y_t \\ y_{t-1} \\ y_{t-2} \\ g_t \\ \bar{f}_t \\ \bar{s}_t \end{bmatrix} + \begin{bmatrix} 0 \\ \varepsilon_t^{fc} \\ \varepsilon_t^{sc} \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} \bar{y}_t \\ y_t \\ y_{t-1} \\ y_{t-2} \\ g_t \\ \bar{f}_t \\ \bar{s}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_{t-1} \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ g_{t-1} \\ \bar{f}_{t-1} \\ \bar{s}_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{yn} \\ \varepsilon_t^{yc} \\ 0 \\ 0 \\ \varepsilon_t^{g} \\ \varepsilon_t^{fn} \\ \varepsilon_t^{sn} \end{bmatrix} \tag{5}$$

where all error terms come from an i.i.d. normal distribution, with zero mean and variance σ_i such that $i = \{yn, g, yc, fn, fc, sn, sc\}$. Once we estimate this model using US data, we can back out our estimates of the natural rate by using the estimates of the unobserved trend components. In particular, $\bar{u}_t = \frac{\bar{s}_t}{\bar{s}_t + \bar{f}_t}$ will give us the desired rate of unemployment trend, that the trend in the flows will predict in the long-run. In principle, this methodology can also provide an estimate of the trend output, $\bar{y}_t$. However, two principal problems need to be tackled in this estimation strategy. First, we need data on job-finding and separation rates for the aggregate economy, which are not readily available. Second, the model, as spelled out in equations (4)-(5),is subject to a stochastic singularity problem. That is, even though we have only three observables, we are attempting to estimate parameters for seven shocks. We explain in detail how we handle these problems in the following data and estimation subsections.

3.1 Data

Our measure of real output is calculated as quarterly gross domestic output in billions, from the Bureau of Economic Analysis (Department of Commerce) and spans the period 1948:Q1 through 2010:Q2[5]. Flow rates, on the other hand, are not readily available for the aggregate economy. However, recent research on the cyclical features of unemployment, led by Shimer (2005, 2007) and, more recently, by Elsby, Michaels, and Solon (2009) provides us with a simple method to measure these rates using Current Population Survey (CPS) data. The method infers continuous time hazard rates into and out of unemployment by using readily available short-term unemployment, aggregate unemployment, and labor force data. Here we briefly describe the method used to infer these rates, without getting too far into the tedious details. Our presentation will closely follow that of Elsby, Michaels, and Solon (2009).

In particular, let u_t be the number of unemployed in month t of the CPS, u_t^s, the number who are unemployed less than five weeks in month t and l_t the size of the labor force in month t. At the heart of the measurement is a simple equation determining the evolution of unemployment over time in terms of flows into and out of unemployment:

$$\frac{du_t}{dt} = S_t(l_t - u_t) - F_t u_t. \tag{6}$$

in terms of flows into and out of unemployment. Given this simple accounting equation, we

[5] It is seasonally adjusted at an annual rate and expressed in chained 2005 dollars

start with a typical unemployed worker's probability of leaving unemployment. As Shimer (2007) and Elsby, Michaels, and Solon (2009) show, job-finding probability will be given by the following relationship:

$$\hat{F}_t = 1 - \left[\left(u_{t+1} - u^s_{t+1}\right)/u_t\right] \tag{7}$$

which maps into an outflow hazard, job-finding rate, $F_t = -\log(1 - \hat{F}_t)$. This formulation in (7) computes the job-finding probability for the average unemployed person by implicitly assuming that contraction in the pool of unemployed, net of newcomers to the pool (u^s_{t+1}), results from people finding jobs. The next step is to estimate the separation rate S_t. This step involves solving the continuous-time equation of motion for unemployment forward to get the following equation, which uniquely identifies S_t.

$$u_{t+1} = \frac{\left(1 - e^{-F_t - S_t}\right) S_t}{F_t + S_t} l_t + e^{-F_t - S_t} u_t \tag{8}$$

Given the outflow hazard, F_t, measured through (7), and data on u_t and l_t, we can solve for S_t numerically for each month t. One potential problem that could bias our estimates is the redesign of the CPS in 1994. As discussed by Shimer (2007) and Elsby, Michaels, and Solon (2009), the CPS redesign deflated the actual number of short-term unemployed by changing the way it computes this for every rotation group except the first and the fifth[6]. To correct for this bias, we follow Elsby, Michaels, and Solon (2009) and use the average fraction of short-term unemployment among the unaffected first and fifth rotation groups to inflate the aggregate short-term unemployment number. This reduces to multiplying every month's u^s_{t+1} by 1.1549 from February 1994 through the end of the sample period. Following this correction finally provides us with the data we need for unemployment flow rates.

As figure (1) shows, these flows generally follow a pattern in a typical business cycle. As the economy enters a downturn, separations start rising, and job-finding rates start falling. These movements cause the overall unemployment rate to rise. But the separation rate usually stabilizes before the unemployment rate peaks. After the separation rate levels off, most of the subsequent increase in the unemployment rate is caused by a low job-finding rate. Note that this combination implies that the average duration of unemployment gets longer, although the

[6] See Polivka and Miller (1998) and Abraham and Shimer (2001) for more detail.

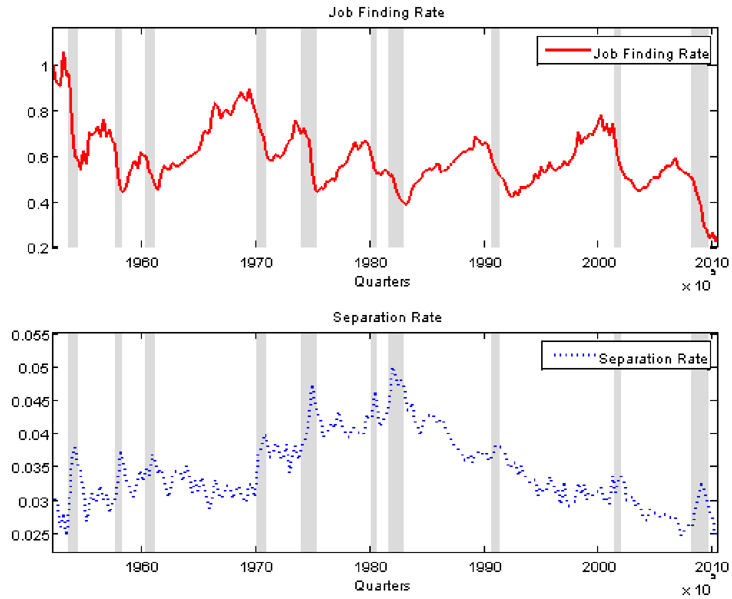

Figure 1: Job-finding and separation rates are constructed using equations (7) and (8) and corrected for CPS redesign. Shaded areas indicate NBER recession periods. Rates are the quarterly averages of the monthly data.

flow of people into the pool of unemployed workers does not increase. The low job-finding rate means that the flow of workers out of the pool slows enough to cause an increase in the average duration of unemployment. When the economy finally starts recovering, durations decrease as firms create new jobs and absorb some of the unemployed. The unemployment rate falls. However, this highly stylized description of cyclical movements in these rates ignores the varying degree of importance of one flow or another in accounting for unemployment fluctuations over a particular cycle. For instance, separations seem to have been less responsive to the most recent cycle than during the previous two cyclical downturns. This was, indeed, what led Shimer (2007) to conclude that the job-finding rate is the more important flow, at least not important for cyclical changes in unemployment; it also spurred a large body of literature that explicitly assumed that separations are not cyclical. But our focus in this paper is not to tease out which flow is driving the fluctuations in the unemployment rate over the business cycle. We leave this task to others. The final word in this debate is still not out[7].

Our constructed data cover most of the post–World War II recessions; however, we only

[7] See, for instance, Shimer (2007), Elsby, Michaels, and Solon (2009), and Fujita and Ramey (2009).

present the data since 1952 here, to be consistent with our estimation in the next section. More importantly, figure (1) shows that there are cyclical fluctuations in these flow rates and some general low-frequency movement, which is especially apparent for the separation rates. Hence, we believe that the reduced form model we laid out is a sensible one. Our next task is to estimate the underlying trend in both flow rates, more specifically, $\bar{f}_t$ and $\bar{s}_t$. This is what we discuss in the next section.

3.2 Estimation

We estimate the reduced form model in (1)-(3)via maximum likelihood, and use the state-space representation in (4)-(5). Since the stochastic trend and cyclical components of our variables are not observable, we rely on a Kalman filter to infer them and construct our log-likelihood. One important issue we need to address is the stochastic singularity problem. This arises from the fact that one observable variable in each equation, (1)-(3)is forced to identify movements in more than one error term. One way to get around this problem is to impose a relative ratio for the standard deviations of trend and cyclical components. For instance, let $\gamma_f = \frac{\sigma_{fn}}{\sigma_{fc}}$ be the relative variance of the error in the trend of the job-finding rate to that in its cycle. This will be a free parameter in our estimation and, in principle, our results might depend on the value of γ_f. Similarly, $\gamma_s = \frac{\sigma_{sn}}{\sigma_{sc}}$,would be a parameter of our estimation with regard to the behavior of the separation rate. The problem is also evident for the real output, since we have three error terms governing movements in the observable output. We start with relative ratios based on those reported in Kim and Nelson (1999) for output. One encouraging fact is that the likelihood function varies in a significant way with the relative ratios, $\gamma_y = \frac{\sigma_{yn}}{\sigma_{yc}}$, $\gamma_g = \frac{\sigma_g}{\sigma_{yc}}$, in a significant way. Hence, we pick the γ_y, $\gamma_g$that yields the highest log-likelihood[8]. Unfortunately, the case for γ_f, γ_s is less obvious. In that case, we estimate our model for various values of γ_f, γ_s and pin down our preferred values by looking at two statistics—the log-likelihood and correlation between the inferred natural rate and the trend of the actual unemployment rate—using a bandpass filter. The idea here is to preserve the likelihood of the model while at the same time inferring a natural rate that is not far from the low-frequency statistical trend of actual unemployment. We discuss our results from this robustness check below. As a result of this

[8] They are 0.85 and 0.027, respectively.

exercise, for the benchmark case we choose a parameterization where $\gamma_f = 1$, $\gamma_s = 1.5$. In the next section, we report how our estimation varies with other values for these parameters.

Another minor point in our estimation concerns the random-walk nature of our model. The stochastic trend components are modeled as random walks; hence, we need to initialize the variance–covariance matrix for the Kalman filter with something other than the unconditional mean. To get around this problem, we start with a diffuse prior, that is, a high initial variance for our unobserved state variables, and remove the first 16 quarters from our actual estimation in order to reduce the impact of this arbitrary initialization. Therefore, we report our estimates starting from 1952:Q1 instead of the beginning of our sample.

4 Results

Here, we present the results of our benchmark estimation, imposing the restrictions $\gamma_f = 1$, $\gamma_s = 1.5$, $\gamma_y = 0.85$, $\gamma_g = 0.027$. This implies that we only estimate 11 parameters. As Table 1 shows, all parameters of the reduced form model in (1) - (3)are quite tightly estimated, with the possible exception of θ_3 Given our estimates of the parameters, we can use a Kalman filter to back out the unobserved state variables, namely, $\bar{f}_t$, $\bar{s}_t$ and $\bar{y}_t$. Given these unobserved states, we can compute the implied long-run steady state of the unemployment rate for every quarter with the identity $\bar{u}_t = \frac{\bar{s}_t}{\bar{s}_t + \bar{f}_t}$. Figure (2) shows the trends in the job-finding rate, the job-separation rate, and the unemployment rate using these estimates.

Table 1: Estimation Results: 1952:Q1-2010:Q2

	Estimate			Estimate	
ϕ_1	1.6299	(0.0596)	θ_2	0.1074	(0.0474)
ϕ_1	-0.6827	(0.0588)	θ_3	0.0366	(0.0255)
ρ_1	1.1177	(0.5792)	σ_{yn}	0.0060	(0.0003)
ρ_2	3.8061	(0.9482)	σ_{fn}	0.0189	(0.0012)
ρ_3	-1.1398	(0.6393)	σ_{sn}	0.0006	(0.00005)
θ_1	-0.2040	(0.0315)	L	2425.6	

Standard errors of the parameter estimates are in ().

Looking into the underlying trends in unemployment flows gives us considerable insight into the nature of time variation in the trend of the unemployment rate, that is, the natural rate. Both the job-finding and separation rates have trended down over time—the separation rate for almost three decades, the job-finding rate mostly in the last decade. If there were not any significant decline in the trend of the job-finding rate, but only an increase in the trend of the separation rate, our definition of the time-varying unemployment trend would imply an increase in its level. According to our estimates, this was indeed the case throughout the 1970s. The opposite has been happening since then for the separation rate trend; it has shown a secular decline since the early 1980s. Over the course of three decades, the separation rate trended down by almost 50 percent. Over the same period, however, the job-finding rate trend declined by a smaller magnitude. Hence, the implied "natural rate" started to decline from its peak levels in the early 1980s. These general patterns seem to be consistent with findings in the literature on the natural rate. Overall, our estimates suggest that over the last four decades, the unemployment rate trend has moved between 5 percent and 7 percent.

Perhaps the more interesting point about our estimates of these trends is that worker reallocation, as measured by the sum of the job-finding and separation rates, is declining in the US. This is a crucial result with important implications for the natural rate as well as how the adjustment in the observed unemployment rate might evolve over time. These results give us considerable insight into the nature of recent changes in unemployment rates. We see that the declining job-finding rate is not temporary, but part of a long-run trend. Along with the more obviously declining trend in separation rates, the declining trend in job-finding rates essentially implies that US labor markets are exhibiting increasingly less worker reallocation. Not only are workers finding jobs at a slower rate on average; independent of the state of the economy, they are also losing (or leaving) their jobs at a slower average rate. This picture of less reallocation also appears to apply to jobs. Several studies show that job reallocation in the US has shown signs of decline over the course of the last two decades; see Faberman (2008) and Davis et al. (2010). Slower worker reallocation affects the rate of convergence of observed unemployment towards its long-run trend. The sum of these two rates, in essence, determines how fast the economy is able to gravitate to its imputed trend. Hence, one clear implication is that the adjustment from current levels of unemployment towards the level of 5.7 percent will take longer

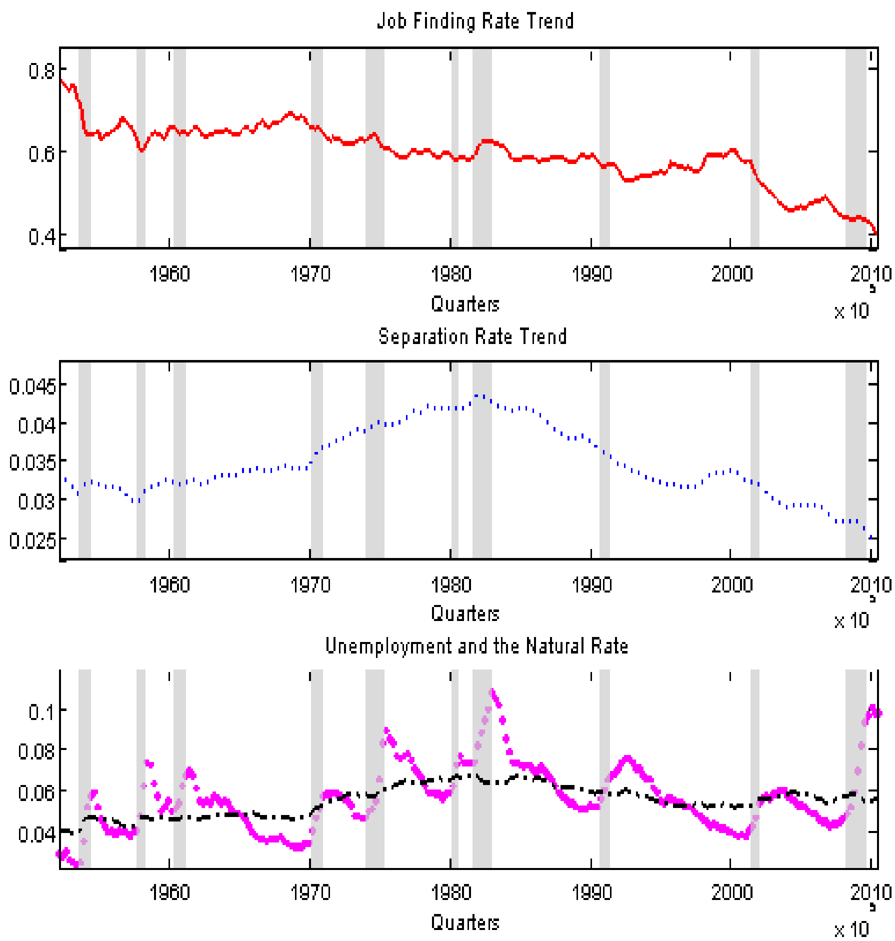

Figure 2: Unobserved trend in all three variables are backed out and smoothed by Kalman filter. Shaded areas indicate NBER recession dates. In the third panel, line (-.) indicates the natural rate as the ratio of separation trend ($\bar{s}_t$) over total worker reallocation ($\bar{s}_t + \bar{f}_t$).

than it would in an economy with more churning but the same implied natural rate.

These results, in principle, could be sensitive to the exact values of γ_f, and γ_s that we use. In our benchmark estimation, we stick to values of 1, and 1.5, respectively. As figure (1) shows, the separation rate has a much clearer low-frequency trend than the job-finding rate. Hence, it is reasonable to have a relatively smoother trend in the separation rate, as our benchmark values of γ_f, and γ_s imply. To pin down the exact numbers, we re-estimate our model over a fine grid for both γ_f, and γ_s; $\gamma_f = \{0.25, 0.375, 0.5...., 3.375, 3.5\}$ and $\gamma_s = \{0.5, 0.625, 0.75...., 3.875, 4\}$. We look at two moments to match: One is the maximum log-likelihood over this combination of points; the other is the correlation between the implied natural rate from our estimation and the trend of the observed unemployment rate, calculated using a bandpass filter. Since we do not use actual unemployment measures, we are trying to impose some discipline on our estimation by bringing in these data.[9]. The objective here is to maximize the likelihood of the model without getting an implied unemployment trend that is far from a statistical trend. Figure (3) shows how these two moments change across γ_f, and γ_s.

Our preferred benchmark values maximize the objective of high log-likelihood and high correlation, as is also clear in figure (3). For instance, we do not improve the likelihood of the model for higher values of γ_f, whereas smaller values result in substantial declines. The likelihood value seems more concave in γ_s, and our preferred value of 1.5 is close to its maximum. As we decrease γ_s, the trend of the separation converges to a straight line; hence, the natural rate will be determined more by the trend of the job-finding rate. The opposite is true when γ_f is small and its trend is close to a straight line. Hence, when one flow has a constant trend imposed (low γ_i), and the other flow has a very small cyclical variation (high $\gamma_j, j \neq i$), we miss the low-frequency movements in the observed unemployment rate by a significant margin. Our objective function determines the optimal trade-off between these two dimensions by putting more weight on the more informative moment, that is, by using the inverse of the covariance matrix as the weighting matrix. Finally, for almost all of the values of γ_f, and γ_s, the natural rate implied by the model varies between 5 percent and 6 percent at the end of the sample.

[9] Note that, with the flow rates themselves, the unemployment rate does not give any more information for our reduced form model; hence, it is not part of it.

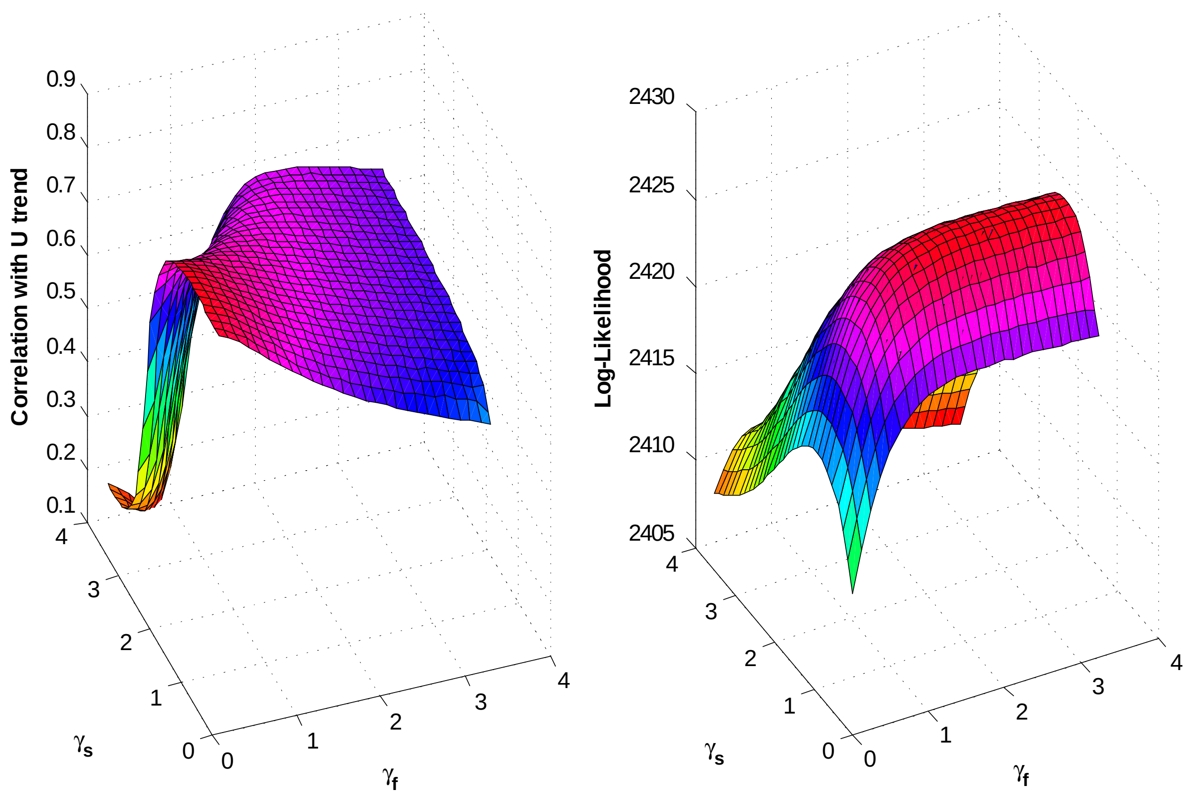

Figure 3: Left panel shows the correlation between the implied natural rate and the statistical trend of the observed unemployment rate computed by bandpass filter, for different values of γ_f, and γ_s. Right panel shows the value of log-likelihood for different γ_f, and γ_s.

4.1 The Great Recession and the Natural Rate

Between December 2007 and June 2009, the US economy experienced one of the worst recessions since the Great Depression, according to the most recent report of the NBER Business Cycle Dating Committee. Over the course of that recession, the US economy shrank by 4.15 percent. This large aggregate shock had correspondingly large effects on the labor market. A total of 8.3 million jobs were lost, and the unemployment rate rose from 4.7 percent to a peak of 10.1 percent in late 2009. Currently, more than 14.5 million people are officially unemployed, and many are underemployed. More striking is the length of time people remain unemployed. Unemployed workers stay jobless for 34 weeks on average now, about 50 percent longer than at previous cyclical peaks. These large effects of the aggregate shock on the labor market raise the obvious question: Has the recession changed the long-run trend for the unemployment rate? Given the accompanying substantial decline in employment in some sectors (construction, finance, manufacturing), it might be natural to expect a change in the trend after the longest recession since World War II. It is conceivable that sectoral reallocation, lower matching efficiency, and longer durations of unemployment insurance compensation might lead to changes in the natural rate. One obvious way to answer this question is to look at our estimates of the natural rate before and after the recession. Our estimate in 2007:Q3, just before the recession started, is approximately 5.7 percent. Even though the natural rate, estimated using our method, hit around 6 percent in the midst of the recession, it was back around 5.7 percent at the end of the sample. Most of the intervening slight increase over the recession resulted from a sharp increase in the separation rate, which represented a temporary slowdown in the declining secular trend in the separation rate. The Kalman filter seems to have identified the surge in separations partly as a trend slowdown. Given the high degree of uncertainty around these estimates, it is safe to say that, measured this way, there was no substantial increase in the natural rate.

Another issue that has been raised about the effects of the last recession is that the co-movement of unemployment with output has changed substantially[10]. Our framework provides a nice testing ground for this. Obviously, since we do not have a structural model, it is impossible for us to distinguish between potential reasons. However, in a reduced form sense we

[10] See, for instance, Daly and Hobjin (2010) and Gordon (2010a and 2010b).

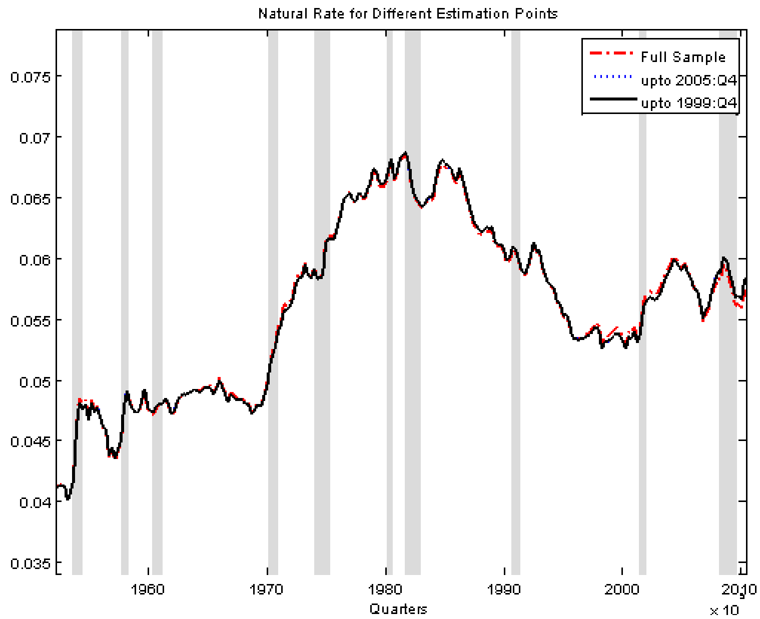

Figure 4: Shaded areas indicate NBER recession dates.

can see whether the last recession in fact changed the underlying nature of the comovement between output and flows into and out of unemployment. We conduct this test by estimating our model for different sample periods during which we think that these "structural" changes may have happened, and then letting the Kalman filter back out the unobserved states with the full-sample data. If there is any substantial difference between the implied natural rates, that difference will be due to the changing structure of the relationship between unemployment flows and output. This is obviously not a test for a regime change in the usual sense; however, it is a relatively simple way to address the question within the scope of this paper.

We re-estimate our model with two more subsamples, before 2006 and before 2000. The first subsample, which includes data through 2005:Q4, excludes data for the last business cycle and most of the recovery after the previous recession. However, the second subsample, which includes data until 1999:Q4, excludes data on the previous recession, that is, the last, jobless recovery episode. We present our results in figure (4) for both subsamples and the full sample. Note that, regardless of where we end our estimation, the implied natural rate is very close to the estimated one from the full sample. The differences between the three reported estimates range between 0.06 and 0.1 percentage point (approximately 1 percent to 2 percent of the level).

Hence, this simple test shows that the last recessionary episode did not significantly change the natural rate through its effects on the parameters of the model.

Even though we contend that we most probably have not seen a significant increase in the natural rate over the last several years, we can safely predict that convergence to the estimated natural rate will be slow for two reasons: The first is the sheer extent of the gap between the current unemployment rate and its estimated trend level. This gap reflects the size of the aggregate shock that hit the economy. When the US economy experienced a similarly sized shock after the 1981–82 recession, it took several years for the observed unemployment rate to drop to levels closer to the trend. Second, as we argued earlier, slower worker reallocation will itself imply slower adjustment because the adjustment rate depends on how fast workers are reallocated between unemployment and employment.

4.2 The Ins and Outs of the Natural Rate

Throughout this paper, we have argued that flows provide us with more information about the unemployment rate than unemployment itself could provide. We can distinguish between the forces that affect the duration of unemployment versus those that affect its incidence. Unemployment at any point in time is determined by the importance of one flow relative to the other. As we discussed earlier in this paper, much of the high-frequency movement in the unemployment rate follows high-frequency variation in the job-finding rate, as shown in figure (1). There is a body of literature focused on teasing out the particular flow that drives unemployment fluctuations over the business cycle[11]. Since this paper focuses more on the long-term behavior of the unemployment rate, one can ask a similar question: Which flow drives the long-term trend in the unemployment rate?

In order to address this issue, we conduct the following numerical exercise: We construct two artificial "natural" rates, where only one flow is allowed to exhibit the estimated trend change over time and the other flow is set to its sample average. Hence, we can compute two different counterfactual series, each representing the role of a single flow in determining the trend of the unemployment rate over time. These two series, as well as the actual (estimated) natural

[11] See for instance, Shimer (2007), Elsby, Michaels, and Solon (2009), and Fujita and Ramey (2009), as well as earlier work by Darby, Haltiwanger, and Plant (1986).

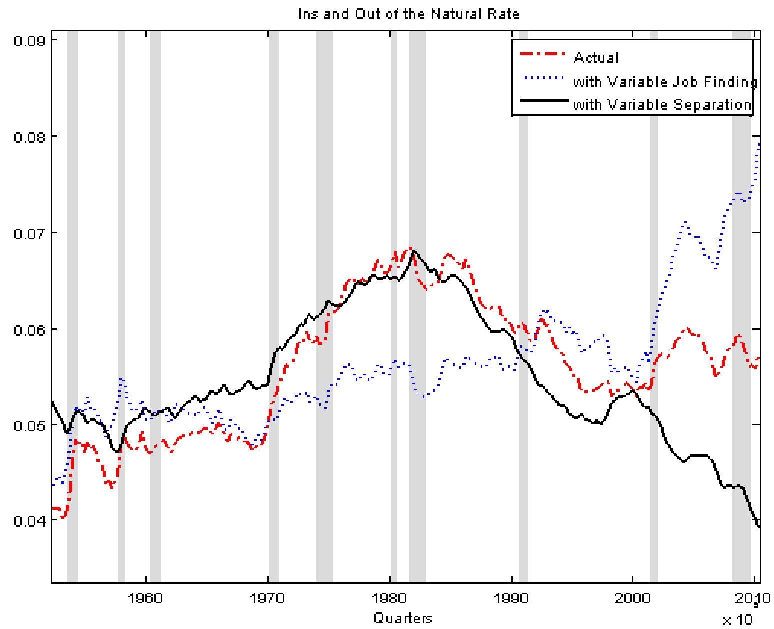

Figure 5: The actual natural rate, represented by the dashed line, is the one estimated from our model over time. The dotted line represents a counterfactual "natural" rate, where the separation rate trend is set at its sample average and only the job-finding rate trend is allowed to move over time, as the benchmark estimation predicts. The solid line shows the opposite condition, where the job-finding rate is fixed and the separation rate moves over time, following the estimated values for its trend.

rate are plotted in figure (5). What is quite striking is that, for most of the sample period, separation rates alone can explain much of the low-frequency variation in the unemployment rate. Until about the beginning of the 2001 recession, the separation rate trend can account for most of the behavior of the natural rate. In a sense, this is not very surprising, given the small variation in the job-finding rate trend over this period relative to the last 10 years in the sample (figure 2). The picture for the last decade is starkly different. It is clear that none of the flow rate trend by itself can generate the estimated natural rate in 5. We have to think about the offsetting effects of the trend changes in both flows. The divergence between the two counterfactual natural rates is striking: from 4 percent to almost 8 percent at the end of the sample. Hence, although the separation rate was dominant in determining the low-frequency variation in the unemployment rate for most of the post-war period, trend changes in the job-finding rate might prove to be crucial in offsetting the effects of the secular decline in the separation rate. This result contrasts with most of the evidence in the recent literature on the cyclical dynamics of the unemployment rate, which finds job finding more significant as a driving flow. Our analysis underscores the importance of the separation rates for the long-run trend in unemployment for most of our sample period and points to a more recent, troubling change in the job-finding trend.

5 Conclusion

We present a simple, reduced form model of comovements in real activity and unemployment flows in this paper and use it to uncover the trend changes in these flows that determine the trend in the unemployment rate. We argue that this trend rate has several key features that are reminiscent of a "natural rate." We show that the natural rate, measured this way, has been relatively stable in the last decade, even after the last recession hit the US economy. This relatively muted change was due to two opposing trend changes. On one hand, job-finding rate trend, after being relatively stable for decades, declined by a significant margin in the last decade, pushing trend unemployment up. On the other hand, the separation rate somewhat offset this by a continued secular decline since the early 1980s. We also show that, contrary to business-cycle-frequency movements, most of the low-frequency variation in the unemployment rate can be accounted for by changes in the trend of separation rates rather than job-finding rates. The last decade stands out as an exception: In those years, the clear trend changes in both flows imply opposing effects on the trend unemployment rate and slower worker reallocation in the US economy. Understanding the actual structural changes that might have led to the observed changes in the trends of unemployment flows, which would be the logical next step for future research, and is beyond the scope of this paper. Also potentially important is the effect of flows into and out of the labor force on our estimaion results[12]. Without an understanding of these structural forces, any policy conclusions based on the estimates from our reduced form model would be misleading and premature[13].

[12] In order to extend our methodology this way will require incorporating additional flows using the large micro data from the CPS and will be more cumbersome. Moreover, it is not clear whether we learn more about driving forces behind the unemployment rate, from such an experiment (see, for instance Shimer (2007)).

[13] See, for example, Lucas (1978).

References

[1] Abraham, Katharine and Robert Shimer. 2001. "Changes in Unemployment Duration and Labor-Force Attachment," in *The Roaring '90s: Can Full Employment be Sustained?* ed. Alan B. Krueger and Robert Solow, 3–60. New York: Russell Sage Foundation and Century Foundation.

[2] Ball, Laurence and N. Gregory Mankiw. 2002. "The NAIRU in Theory and Practice." *Journal of Economic Perspectives*, 16(4): 115–136.

[3] Barro, Robert J. 1988. "The Persistence of Unemployment." *American Economic Review: Papers and Proceedings*, 78 (2): 32–37.

[4] Blanchard, Olivier. 2006. "European Unemployment: The Evolution of Facts and Ideas." *Economic Policy*, Centre for Economic Policy Research, 21(45): 5–69.

[5] Clark, Peter K. 1987. "The Cyclical Component of U.S. Economic Activity." *Quarterly Journal of Economics*, 102(4): 797–814.

[6] Clark, Peter K. 1989. "Trend Reversal in Real Output and Unemployment." *Journal of Econometrics*, 40: 15–32.

[7] Daly, Mary and Bart Hobjin. "Okun's Law and the Unemployment Surprise of 2009." *Economic Letter*, Federal Reserve Bank of San Francisco, No. 2010–07.

[8] Darby, Michael R., John C. Haltiwanger, and Mark W. Plant. 1985. "Unemployment Rate Dynamics and Persistent Unemployment under Rational Expectations." *American Economic Review*, 75(4):614–637.

[9] Darby, Michael R., John C. Haltiwanger, and Mark W. Plant. 1986. "The Ins and Outs of Unemployment: The Ins Win." Working Paper 1997, National Bureau of Economic Research.

[10] Davis, Steven, Jason Faberman, John Haltiwanger, Ron Jarmin, and Javier Miranda. 2010. "Business Volatility, Job Destruction, and Unemployment." *American Economic Journal: Macroeconomics*, forthcoming.

[11] Dickens, William T. 2009. "A New Method for Estimating Time-Variation in the NAIRU," in *Understanding Inflation and the Implications for Monetary Policy: A Phillips Curve Retrospective*, ed. Jeff Fuhrer, Jane Sneddon Little, Yolanda K. Kodrzycki, and Giovanni P. Olivei, 207–230. Cambridge, MA: MIT Press.

[12] Elsby, Michael, Ryan Michaels, and Gary Solon. 2009. "The Ins and Outs of Cyclical Unemployment." *American Economic Journal: Macroeconomics*, 1(1): 84–110.

[13] Faberman, Jason. 2008. "Job Flows, Jobless Recoveries, and the Great Moderation." Working Paper 08-11, Federal Reserve Bank of Philadelphia.

[14] Friedman, Milton. 1968. "The Role of Monetary Policy." *American Economic Review*, 58(1): 1–17.

[15] Fujita, Shigeru and Gary Ramey. 2009. "The Cyclicality of Separation and Job Finding Rates." *International Economic Review*, 50(2): 415–430.

[16] Gordon, David M. 1988. "The Un-Natural Rate of Unemployment: An Econometric Critique of the NAIRU Hypothesis." *American Economic Review: Papers and Proceedings*, 78 (2): 117–123.

[17] Gordon, Robert. 1997. "The Time-Varying NAIRU and its Implications for Economic Policy." *Journal of Economic Perspectives*, Winter, 11(1): 11–32.

[18] Gordon, Robert. 2010a. "Okun's Law, Productivity Innovations, and Conundrums in Business-cycle Dating." *American Economic Review: Papers and Proceedings*, 100 (2): 1–9.

[19] Gordon, Robert. 2010b. "The Demise of Okun's Law and of Procyclical Fluctuations in Conventional and Unconventional Measures of Productivity." Working Paper, Northwestern University.

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

[21] Johnson, G.E., and P. R. G. Layard. 1986. "The Natural Rate of Unemployment: Explanation and Policy," in *Handbook of Labor Economics*, vol. 2, ed. Orley Ashenfelter and Richard Layard, 92–1000. Amsterdam: North-Holland.

[22] Kim, Chang-Jin and Charles R. Nelson. 1999. *State-Space Models with Regime Switching.* Cambridge, MA: MIT Press.

[23] King, Robert G. and Mark W. Watson. 1994. "The Post-War U.S. Phillips Curve: A Revisionist Econometric History." *Carnegie-Rochester Conference Series on Public Policy*, 41: 157–219.

[24] Lucas, Robert E. 1978. "Unemployment Policy." *American Economic Review: Papers and Proceedings*, 68(2): 353–357.

[25] Mortensen, Dale and Christopher A. Pissarides. 1994. "Job Creation and Job Destruction in the Theory of Unemployment." *Review of Economic Studies*, 61(3): 397–415.

[26] Mortensen, Dale and Christopher A. Pissarides. 1999. "New Developments in Models of Search in the Labor Market," in *Handbook of Labor Economics*, vol. 3B, ed. Orley Ashenfelter and David Card, 256–2627. Amsterdam: North-Holland.

[27] Orphanides, Athanasios and John C. Williams. 2002. "Robust Monetary Policy Rules with Unknown Natural Rates," *Brookings Papers on Economic Activity*, 2: 63–118.

[28] Phelps, Edmund. 1968. "Money-Wage Dynamics and Labor Market Equilibrium." *Journal of Political Economy*, 76(2): 678–711.

[29] Pissarides, Christopher A. 2000. *Equilibrium Unemployment Theory.* Cambridge, MA: MIT Press.

[30] Polivka, Anne E. and Stephen M. Miller. 1998. "The CPS after the Redesign: Refocusing the Economic Lens," in *Labor Statistics Measurement Issues*, ed. John Haltiwanger, Marilyn E. Manser, and Robert Topel, 249–286. Chicago, IL: University of Chicago Press.

[31] Rogerson, Richard. 1997. "Theory Ahead of Language in the Economics of Unemployment." *Journal of Economic Perspectives*, Winter 11(1): 73–92.

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

[33] Shimer, Robert. 2007. "Reassessing the Ins and Outs of Unemployment." Working Paper, University of Chicago.

[34] Staiger, Douglas, James H. Stock, and Mark W. Watson. 1997. "The NAIRU, Unemployment, and Monetary Policy." *Journal of Economic Perspectives*, Winter 11(1): 33–49.

[35] Staiger, Douglas, James H. Stock, and Mark W. Watson. 2001. "Prices, Wages and the U.S. NAIRU in the 1990s," in *The Roaring '90s: Can Full Employment be Sustained?* ed. Alan B. Krueger and Robert Solow, 3–60. New York: Russell Sage Foundation and Century Foundation.