KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
WORKING PAPER SERIES

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Working Paper 1233
November 2012

KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
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The Ins and Outs of Unemployment in the Long Run: Unemployment Flows and the Natural Rate*

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This version: October 2012
First version: August 2010

Abstract

This paper proposes an empirical method for estimating a long-run trend for the unemployment rate that is grounded in the modern theory of unemployment. I write down an unobserved components model and identify the cyclical and trend components of the underlying unemployment flows, which in turn imply a time varying estimate of the unemployment trend, the natural rate. I identify a sharp decline in the outflow rate - job finding rate- since 2000, which was partly offset by the secular decline in the inflow rate – separation rate – since 1980s, implying a relatively stable natural rate, currently at 6 percent. Numerical examples show that slower labor reallocation along with the weak output growth explains most of the persistence in unemployment since the Great Recession. Contrary to the business-cycle movements of the unemployment rate, a significant fraction of the low-frequency variation can be accounted for by changes in the trend of the inflows, especially prior to 1985. Finally, I highlight several desirable features of this natural rate concept that makes it a better measure than traditional counterparts. These include statistical precision, the significance of required revisions to past estimates with subsequent data additions, policy relevance and its tight link with the theory.

Key words: Unemployment; Natural Rate; Unemployment Flows; Labor Market Search
JEL classification: E24; E32; J64

*An earlier, substantially different working paper version of this work circulated with the title: "The Ins and Outs of Unemployment in the Long Run: A New Estimate for the Natural Rate?" I would like to thank Ken Beauchemin, Charles Carlstrom, Todd Clark, Tim Dunne, Martin Fukac, Brent Meyer, Mark Schweitzer and seminar participants at the Federal Reserve Bank of Cleveland (2010) and Federal Reserve Bank of Boston (2010), EBES (Istanbul, 2011), Midwest Economic Association Meetings (Evanston, 2012), Midwest Macroeconomics Meetings (Notre Dame, 2012) and two anonymous referees. I am grateful to Saeed Zaman for his able research assistance. The views expressed herein are the author's and not necessarily those of the Federal Reserve Bank of Cleveland or the Federal Reserve System.

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1 Introduction

The main goal of this paper is to provide an empirical method for estimating a long-run trend for the unemployment rate that is grounded in the modern theory of unemployment. I argue that the large body of literature on the search theory of unemployment makes a compelling case for the key role unemployment flows play in the long-run behavior of the unemployment rate.[1] To implement this, I write down an unobserved components model and identify the cyclical and trend components of the underlying unemployment flows. These trend estimates for the flows serve as inputs for my estimate of the unemployment rate in the long-run. It is defined as the *steady state* unemployment rate that is implied by the current *trend* estimates of the flow rates. I interpret this rate as the rate of unemployment in the long run, to which the actual unemployment rate would converge. The method essentially provides us with a time-varying trend estimate for the unemployment rate. I argue that this trend rate has several key features that are reminiscent of a "natural rate"; hence, I use the terms "natural rate" and "unemployment trend" interchangeably from here onward.

I show that, measured this way, the natural rate has been hovering around 6 percent over the past decade, even after the most recent recession. Underlying this level are two offsetting trends in the flows; the first is the trend in the outflow rate -job-finding rate- which, after being relatively stable for decades, declined significantly since 2000, pushing trend unemployment up. The second is the trend in the inflow -separation rate-, which has partially offset the effect of the job-finding trend by showing a secular decline since the early 1980s. Unlike business-cycle frequency movements of the unemployment rate, a significant fraction of the low-frequency variation in the rate can be explained by changes in the trend of the separation rate rather than the trend of the job-finding rate, especially before 1985. The exception was during the last decade, when the changes in the flows that caused opposing effects on the trend unemployment rate also implied a slower rate of worker reallocation for the US economy.

Furthermore, I show -via a set of numerical exercises- that this slow worker reallocation has important implications for the adjustment process of the unemployment rate in the near term. In particular, the flow model suggests that because the worker reallocation rate (the sum of

[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.

the separation and job-finding rates) has slowed, unemployment will decline substantially less in the near term. I also provide a quantitative example of the potential impact of "weaker" output growth during the current recovery on this adjustment process. The experiments show the potential usefulness of the model I propose.

Moreover, I compare my estimate of the natural rate with more traditional estimates (including a NAIRU) and argue that the model with flows has several desirable statistical features such as precision of the estimates and minor retrospective revisions it requires with additional data. Moreover, this framework offers subtle implications for policy relevant objectives as well as a tighter link with the predominant theory of unemployment. Finally, I briefly discuss how allowing for flows into and out of inactivity or extending the exercise to different countries is straightforward. These empirical qualities, I argue, make the flow model a better and more useful framework for understanding the natural rate than the more traditional counterparts.

In principle, one can use a benchmark search model and estimate it structurally to back out this long-run trend from the model. However, there are at least two reasons why I think one 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 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 I 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. To the extent that these low-frequency changes affect the trend of the unemployment flows, my simple, reduced form model incorporates these potential channels with relative ease. Moreover, this empirical approach should be percieved as complementary to more theoretical modelling challenges. For instance, if the flow into unemployment (separation rate) turns out to be the main driving force that determines the long-run trend, as I find for early part of the sample, then one can potentially focus on theoretical features in these models, which would manifest themselves as changes in inflows. Hence, I believe that the approach advocated here could also be useful for modelling unemployment in the future.

The next section presents a discussion of the literature followed by section 3, which presents the simple, reduced-form model, describing the comovement of real GDP and unemployment flows. It also includes my description of the data, particularly how I construct unemployment flow rates and conduct the estimation. Section 4 presents estimation results and unemployment rate decompositions due to each flow rate, both at the business cycle frequency and over the long run and includes a discussion of the relation between identified trends in flows and the persistence of the unemployment rate. Section 5 includes a discussion on the Great Recession in light of the model where I address whether the last recession changed the trend of the unemployment rate, and how significant the effects of slow worker reallocation and weak output growth will be on the dynamics of the unemployment rate in the near term. Section 6 presents some of the desirable features of the flow model relative to more traditional estimates of natural rate and makes a case for the flow model. Section 7 provides a brief discussion of extending the model to include flows into and out of inactivity and implementing the same method for other countries. The last section concludes.

2 Related Literature: Looking for a 'natural' rate

The estimate I propose for the long-run trend of the unemployment rate 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 my theories of unemployment are ahead of language" (Rogerson 1997, 74–75). One 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),

[2] For a good discussion on the topic, one can look at a set of papers in two volumes: 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).

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.

I argue that the search theory of the labor markets provides a nice framework to think about the structural characteristics, frictions and imperfections of the labor market that Friedman addressed, however stylized it may be. 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 point 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 my attempt to measure this "natural" rate of unemployment, I follow this guidance and use an empirical approach to look for a rate that is moving at a relatively low frequency, and could potentially change over time, albeit smoothly. I implicitly assume that the trend components of the unemployment flows I estimate capture the structural characteristics of the labor and commodity markets, including market imperfections, and the cost of search for both sides of the market, i.e. gathering information about job vacancies and labor availabilities, the cost of mobility, and so on. Moreover, identifying cyclical components that are transient in these flows using the information on comovements with the aggregate economy, can be thought of as isolating the 'stochastic variability in demands and supplies.' I then use this information about the trend in unemployment flows to evaluate the equilibrium steady state condition for unemployment in the standard labor market search model to pin down my estimate of the natural rate.

Although Friedman 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). One obvious reason for this, of course, is the inherently unobservable *nature* of the *natural rate*. Some economists developed this concept into yet another one, the NAIRU (non-accelerating inflation rate of unemployment). It 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 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."

Nevertheless, NAIRU has been the focus of a large body of literature, where it is sometimes used synonymously with the natural rate concept I have discussed; 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 (Staiger, Stock, and Watson (1997 and 2001), and King and Watson (1994)). Several studies discuss the usefulness of this concept for policy and it is still very much debatable; Rogerson (1997), David Gordon (1988), Robert Gordon (1997), and Orphanides and Williams (2002), among others. One can argue that NAIRU might still be a useful measure for policy makers; either because it predicts inflation very well or gives a better idea about the labor market slack. I show that in section 6, that is not the case when I compare my measure with several traditional estimates, one of which is a NAIRU.

The reduced form model and the estimation method I 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)[3]. My 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 I focus on here, that is, the separation rate over the sum of the separation rate and the job-

[3] The idea is similar to the one employed by Laubach and Williams (2003), where they estimate the unobserved natural rate of interest.

finding rate. He emphasizes how worker reallocation determines persistence in unemployment. In this paper, however, I 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 proposed 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. Moreover, it is not clear how one should interpret the empirical Beverdige curve, especially for its implications about the matching efficiency of the labor markets, as cyclical movements could be misidentified as structural ones.[4]

This paper is also related to the recent work that focus on teasing out the particular flow that drives unemployment fluctuations over the business cycle; Shimer (2007), Elsby, Michaels, and Solon (2009), Fujita and Ramey (2009) and Barnichon and Figura (2010), as well as earlier work by Darby, Haltiwanger, and Plant (1986). Different from this body of work, I can meaningfully distinguish between the cylical and trend components of these flows by providing structure for their relationship with real output. This distinction between trend and cyclical components not only helps us to decompose unemployment fluctuations over lower frequencies, but also provides us with a mechanism to relate those flows to the persistence of unemployment over time. The results confirm that outflows from unemployment accounts for most the unemployment rate's fluctuations , both over the cycle and in the long-run. Inflows, on the other hand, accounts for a significant fraction of the long-term variation in the natural rate prior to 1985. Davis et. al. (2010) relate the secular decline in business volatility, and job destruction at the establishment level to unemployment and its inflows. They conclude that one third of the decline in the inflow rate can be explained by the decline in the job-destruction rate at the establishment level which in turn explains a portion of the long-term decline in the unemployment rate. This paper does not address job flows at the establishment level. However, by identifying the trends in unemployment flows, it relates the long-term declines in *both* unemployment flows to the level and persistence of the unemployment rate in a novel way.

Finally, this paper is related to the recent research aimed at understanding the sources of the high and persistent unemployment since the Great Recession. Surveys of the labor market evidence in the aftermath of the Great Recession seem to find that cyclical factors played a

[4] For a non-technical explanation of this problem, see Lindner and Tasci (2010).

major role behind the surge in the unemployment rate rather than an increase in the long-run trend (Elsby, Hobijn, Sahin, and Valetta (2011), and Rothstein (2012)). I arrive at the same conclusion and do not find a significant jump in the natural rate over the recent past, whereas Weidner and Williams (2011) and Daly, Hobijn, Sahin and Valetta (2012) identify a somewhat larger increase, from a relatively lower baseline (relative to my estimate) prior to the recession. I discuss the implications of the model and estimates of the flow rates in the context of the Great Recession in section 5. A novel contribution of this paper is its ability to relate the evolution of the unemployment rate over the last several years to the decline in the overall reallocation rate and the sub-par output growth by historical standards.

3 Modeling Output and Unemployment Flows

I 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, but these components are not observed by the econometrician. I 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 I 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. I 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). I 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 my 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 trend of the unemployment rate, according to my definition, is pinned down by the stochastic trend components of the job-finding and separation rates. I can estimate my model and use Kalman filter to back out the underlying trends in order to get an estimate of a time-varying trend. To start, I 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 I estimate this model using US data, I can back out an estimate of a time-varying unemployment rate trend 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, one needs 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 an identification problem. Even though I have only three observables, I am estimating parameters for seven shocks. I explain in detail how I handle these problems in the following data and estimation subsections.

3.1 Data

The measure of real output is the quarterly gross domestic output in billions, from the Bureau of Economic Analysis (Department of Commerce) and spans the period 1948:Q1 through 2012:Q2[5]. As mentioned in the previous section, 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 I briefly describe the method used to infer these rates, without getting too far into the tedious details. The presentation will closely follows that of Elsby, Michaels, and Solon (2009).

Let u_t be the number of unemployed in month t of the CPS, u_t^s, the number who are

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

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:

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

Given this simple accounting equation, I 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 unemployed workers 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, I can solve for S_t numerically for each month t. One potential problem that could bias the 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, I 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

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

provides us with the data I need for unemployment flow rates.

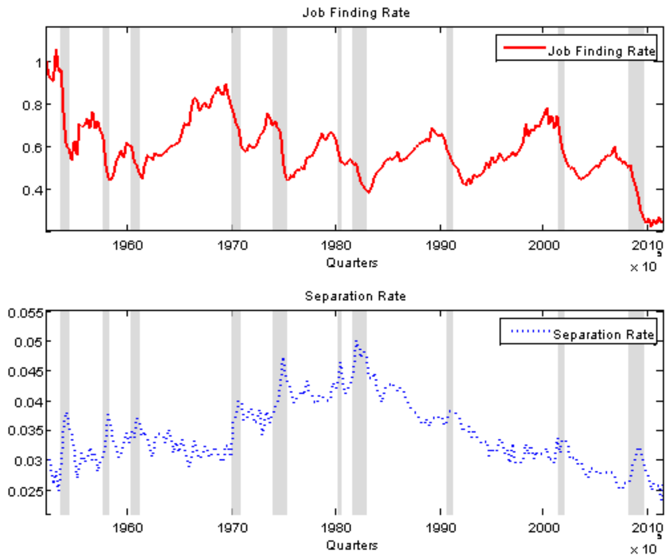

Figure 1: Job-finding and separation rates are constructed using equations (7) and (8) and corrected for CPS redesign. Shaded areas indicate NBER recession periods. Rates are the quarterly averages of the monthly data.

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 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 of unemployed 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 the 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 more responsive to the most recent cycle compared to the previous two cyclical downturns. In fact, this relative dominance of the job finding rate was what led Shimer (2007) to conclude that the job-finding rate is the more important flow, at least for cyclical changes in unemployment. Consequently, it also spurred a large body of literature that explicitly assumed that separations are not cyclical[7]. Since I have a model which distinguishes between cyclical and trend components of these flows, I can analyze the contributions of each flow to unemployment fluctuations more explicitly. Findings regarding this decomposition is presented in section 4.1.

The constructed data cover most of the post–World War II recessions; however, I only present the data since 1952 here, to be consistent with my 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, I believe that the reduced form model laid out here is a sensible one. The next task is to estimate the underlying trend in both flow rates, more specifically, $\bar{f}_t$ and $\bar{s}_t$.

3.2 Estimation

I 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 the variables are not observable, I rely on a Kalman filter to infer them and construct my log-likelihood. One important issue I need to address is the identification 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[8]. 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 my estimation and, in principle, my results might depend on the value of γ_f. Similarly, $\gamma_s = \frac{\sigma_{sn}}{\sigma_{sc}}$,would be a parameter of my estimation with regard to the behavior of the separation rate. The problem is also evident for the real output, since I have three error terms governing movements in the observable output. I 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, $\gamma_y = \frac{\sigma_{yn}}{\sigma_{yc}}$, $\gamma_g = \frac{\sigma_g}{\sigma_{yc}}$.

[7] For the debate on which flow drives unemployment fluctuations over business cycles, see, for instance, Shimer (2007), Elsby, Michaels, and Solon (2009), and Fujita and Ramey (2009).

[8] Laubach and Williams (2003) addresses a similar problem in the context of an unobserved components model for the natural rate of interest.

Hence, I pick the γ_y, $\gamma_g$that yields the highest log-likelihood[9]. Unfortunately, the case for γ_f, γ_s is less obvious. In that case, I estimate my model for various values of γ_f, γ_s and pin down my 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. As a result of this exercise, for the benchmark case I choose a parameterization where $\gamma_f = 1$, $\gamma_s = 1.5$. I report the robustness of my estimation to other values for γ_f, γ_s in Appendix A.

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

4 Results

Here, I present the results of the benchmark estimation, imposing the restrictions $\gamma_f = 1$, $\gamma_s = 1.5$, $\gamma_y = 0.85$, $\gamma_g = 0.027$. This implies that I 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 estimates of the parameters, one can use Kalman filter to back out the unobserved state variables, namely, $\bar{f}_t$, $\bar{s}_t$ and $\bar{y}_t$. Given these unobserved states, I 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 along with rate of convergence for unemployment implied by the the worker reallocation rate, $f_t + s_t$, and its trend, $\bar{f}_t + \bar{s}_t$.

[9] They are 0.85 and 0.027, respectively.

Table 1: Estimation Results: 1952:Q1-2012:Q2

	Estimate			Estimate	
ϕ_1	1.6273	(0.0595)	θ_2	0.1013	(0.0468)
ϕ_1	-0.6757	(0.0582)	θ_3	0.0399	(0.0251)
ρ_1	1.1490	(0.5728)	σ_{yn}	0.0060	(0.0003)
ρ_2	3.7341	(0.9403)	σ_{fn}	0.0187	(0.0012)
ρ_3	-1.1197	(0.6337)	σ_{sn}	0.0006	(0.00005)
θ_1	-0.2005	(0.0312)	L	2515.0	

Standard deviations 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, my definition of the time-varying unemployment trend would imply an increase in its level. According to the 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, the estimates suggest that over the last four decades, the unemployment rate trend has moved between 5 percent and 7 percent, and currently stands around 6.0 percent.

This simple empirical framework delivers more than an estimate of the natural rate. In what follows, I will use this framework and the estimation results to address two interesting issues; the contribution of different flows to both cyclical and trend variation in the unemployment, as well as the implications for persistence of unemployment. Enabling us to address these issues is a novelty of this framework which is absent from more traditional methods of determining the natural rate.

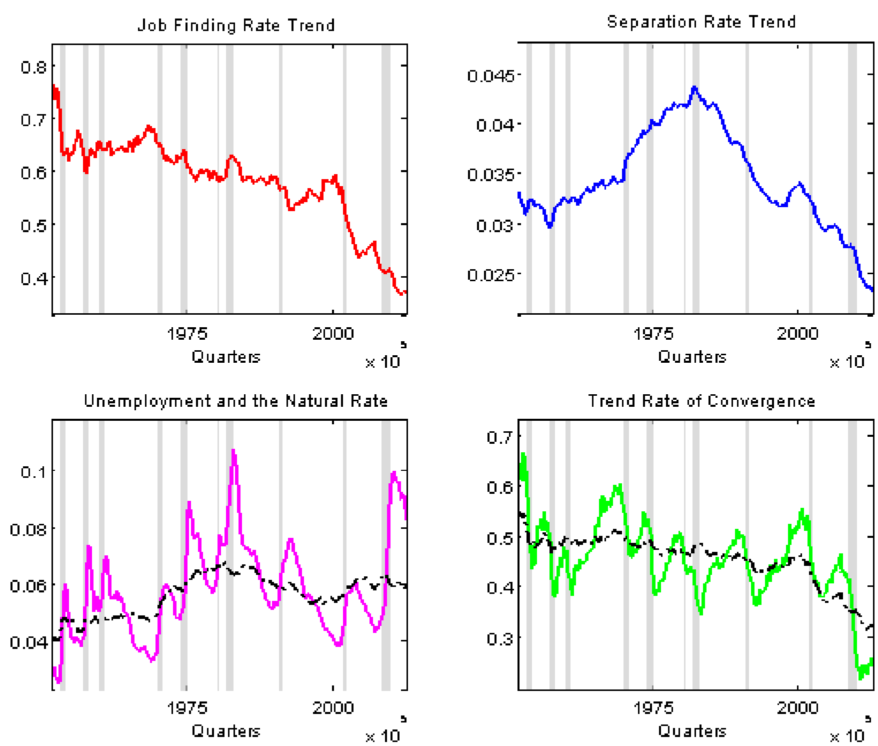

Figure 2: Unobserved trend in all variables are backed out and smoothed by Kalman filter. Shaded areas indicate NBER recession dates. In the lower panel, line (-.) indicates the natural rate as defined in the text. Observed and the trend rate of convergence are given as $1-e^{-(f_t+s_t)}$ and $1-e^{-(\bar{f}_t+\bar{s}_t)}$, respectively.

4.1 The Ins and Outs of the Natural Rate

Unemployment flows provide us with more information about the unemployment rate than unemployment itself could provide. One 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 magnitude of one flow relative to the other. The flow model laid out in the previous section gives us the estimates of cyclical and trend components in the underlying flow rates, thereby enabling us to tease out the particular flow that drives unemployment fluctuations over the business cycle, as well in the long-run. Hence, in principle, one can use a similar decomposition used in Fujita and Ramey (2009) to analyze the contribution of each flow rate to variations in the unemployment rate, both at the high frequency and the low frequency. In particular, let $\Delta u_t = \log\left(\frac{u_t}{\bar{u}_t}\right) = \log\left(\frac{S_t}{S_t+F_t}/\frac{\bar{s}_t}{\bar{s}_t+\bar{f}_t}\right)$ denote the variation in the unemployment rate in period t from its time-varying trend implied by the model. Similarly, define the variation in the separation and job finding rate from their time-varying trends respectively as $\Delta s_t = \log\left(\frac{S_t}{\bar{s}_t}\right)$ and $\Delta f_t = \log\left(\frac{F_t}{\bar{f}_t}\right)$. Fujita and Ramey (2009) shows that the contributions of each worker flow to high-frequency variation in the unemployment rate are given by factors, $\beta^s = \frac{cov((1-\bar{u}_{t-1})\Delta s_t, \Delta u_t)}{var(\Delta u_t)}$ and $\beta^f = \frac{cov((1-\bar{u}_{t-1})\Delta f_t, \Delta u_t)}{var(\Delta u_t)}$. One can write down a similar decomposition for the low-frequency variation in the unemployment rate's trend, i.e. variations in the estimate of the natural rate, $\bar{u}_t$, relative to its historical mean, $\bar{u}$, by redefining the objects, $\Delta \bar{u}_t = \log\left(\frac{\bar{u}_t}{\bar{u}}\right)$, $\Delta \bar{s}_t = \log\left(\frac{\bar{s}_t}{\bar{s}}\right)$ and $\Delta \bar{f}_t = \log\left(\frac{\bar{f}_t}{\bar{f}}\right)$, where $\bar{u}$, $\bar{s}$ and $\bar{f}$ denote average trend values for the relevant variable. Corresponding factors for the trends are then defined as $\bar{\beta}^s = \frac{cov((1-\bar{u})\Delta \bar{s}_t, \Delta \bar{u}_t)}{var(\Delta \bar{u}_t)}$ and $\bar{\beta}^f = \frac{cov((1-\bar{u})\Delta \bar{f}_t, \Delta \bar{u}_t)}{var(\Delta \bar{u}_t)}$.

Figure (3) shows the respective variation in the cyclical and trend components of both flows. It is clear that most of the variation in cyclical components is driven by the variation in the job finding rate's cyclical component. However, as the lower panel of figure (3) shows, for most of the sample period, separation rates alone can explain much of the variation in the trend component of 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

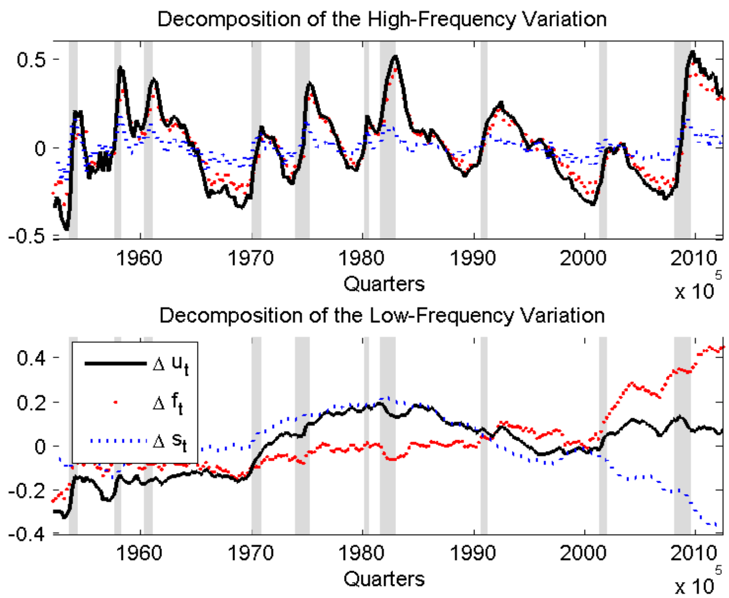

Figure 3: Upper panel plots Δu_t, Δs_t and Δf_t over time. Lower panel shows $\Delta \bar{u}_t$, $\Delta \bar{s}_t$ and $\Delta \bar{f}_t$.

different. It is clear that neither of the flow rate trends by themselves can generate the observed variation in the estimated natural rate in figure (3). Effects of the trend changes in two flows seems to offset each other.

Table 2 summarizes the information in figure (3) in a different way by providing the variance decomposition factors at different frequencies and sample-periods. It seems like, throughout the whole sample period, job finding rate consistently explain more than 70 percent of the variation in the cyclical component of the unemployment rate. The dominant role for the job finding rate, however, is mostly present for the variation in the unemployment rate trend after 1985. For the period before 1985, the separation rate trend explains more than 60 percent of the variation in the natural rate. This changes in the rest of the sample by the job finding rate explaining 90 percent of the variation in the trend unemployment. Hence, this paper not only confirms the dominant role of the job-finding rate for unemployment fluctuations at the business cycle frequency, but also for the variation in the natural rate, especially over the last three decades. Moreover, this decomposition underscores the importance of the separation rate for the long-run trend in unemployment, especially for the first half of the sample period.

Table 2: Variance Decomposition for the Unemployment Rate

	Cyclical Component				Trend Component		
	pre - 1985	post - 1985	1952- 2012		pre - 1985	post - 1985	1952- 2012
β^f	0.7264	0.8016	0.7576	$\bar{\beta}^f$	0.3554	0.9090	0.6828
β^s	0.2767	0.2049	0.2471	$\bar{\beta}^s$	0.6457	0.0906	0.3145

4.2 Reallocation and the Persistence in Unemployment

Perhaps the most interesting point about the results is that worker reallocation, as measured by the sum of the job-finding and separation rate, is declining in the U.S. 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. The declining job-finding rate is not temporary, but part of a long-run trend. Along with the more apparent trend in separation rates, the declining trend in job-finding rates essentially imply that U.S. 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, for instance Faberman (2008) and Davis et al. (2010). This paper is the first paper to my knowledge, that identifies the trend decline in the outflow rate. 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 towards its imputed trend. Hence, one clear implication is that the adjustment from current levels of unemployment towards the level of 6.0 percent will take longer than it would in an economy with more churning.

The rate at which unemployment rate adjusts in is given by the rate of convergence, $1 - e^{-(f_t+s_t)}$.[10] In the long-run, this rate will converge to $1 - e^{-(\bar{f}_t+\bar{s}_t)}$. Both of these measures are presented in the lower panel of figure (2). Even though we see a lot of procyclical variation in this rate, the trend has declined by about 40 percent from around 0.46 in mid 1980s to 0.32

[10] See Elsby, Hobjin and Sahin (2011) for the same interpretation.

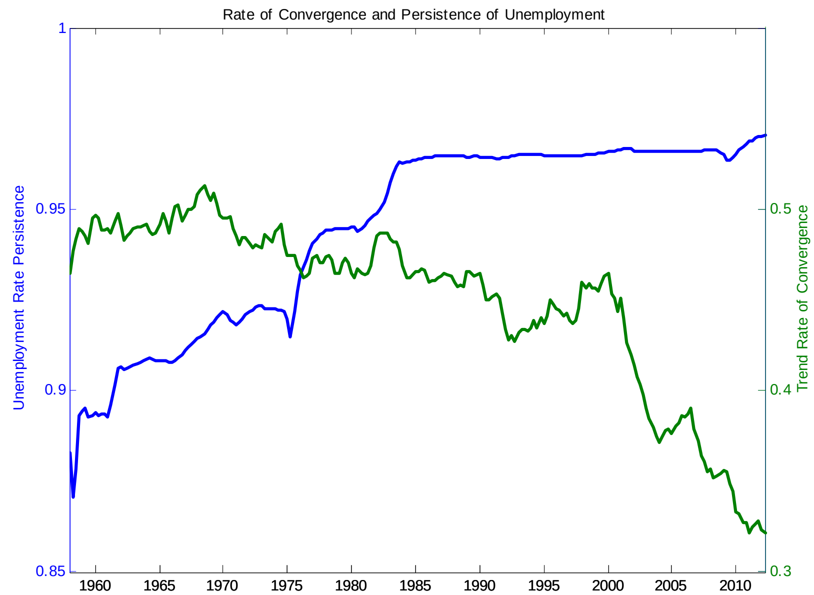

Figure 4: Trend rate of convergence is $1 - e^{-(\bar{f}_t + \bar{s}_t)}$. The persistence in unemployment rate is measured by the first order auto-corrlation of the data over time.

today. This will unambiguously increase the persistence of the unemployment rate in the U.S. In fact, figure (4) shows that the first order auto-correlation for the observed unemployment rate has increased over time. In the post-1985 period, which coincides with the slowdown in the reallocation rates, first order autocorrelation of unemployment is 0.98, up significantly from pre-1985 level of 0.91. This slowing adjustment channel might be important for specific episodes, where the cyclical lows in the rate of adjustment falls well below the trend shown in figure (4). Next section provides a numerical exercise that aims to quantify the impact of this channel on the behavior of unemployment in the aftermath of the Great Recession.

5 The Great Recession

Between December 2007 and June 2009, the US economy experienced one of the worst recessions since the Great Depression. Over the course of that recession, the US economy shrank by 4.7 percent. This large aggregate shock had correspondingly large effects on the labor market. A total of 8.7 million jobs were lost from December 2007 to February 2010, and the unemployment rate rose from 4.7 percent to a peak of 10.1 percent in late 2009. Currently, more than 12 million people are officially unemployed, and many are underemployed. Unemployment rate has stayed above 8 percent for 43 months in a row, until September 2012, the longest such stretch in the post-war period. More striking is the length of time people remain unemployed. Unemployed workers stay jobless for 39 weeks on average now, about twice longer than at previous cyclical peaks. These large effects stemming from the aggregate shock on the labor market raise some obvious questions: Has the recession changed the long-run trend for the unemployment rate? Why is the unemployment rate so persistent?

5.1 Has the Great Recession changed the long-run trend?

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 deepest recession since World War II. It is conceivable that sectoral reallocation, lower matching efficiency, and longer durations of eligibility for unemployment insurance might lead to changes in the natural rate. To the extent that these changes are reflected in the measured flow rates, our framework can capture this change in the trend. One obvious way to answer this question is to look at the estimates of the natural rate before and after the recession. In 2007:Q4, just before the recession started, it was approximately 6.3 percent. Even though the natural rate hit 6.4 percent in the midst of the recession, it is back to 6.0 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 of the separation rate. The Kalman filter seems to have identified the surge in separations partly as a trend slowdown. Thus, the natural rate measured within this framework seem to suggest only a modest increase in the natural rate during the recession.

The conclusion is slightly different from Weidner and Williams (2011), where they argue that natural rate might have increased as much as 1.7 percentage points to 6.7 percent. Their conclusion about the prospect of short term adjustment, however, is similar to arguements here. A more descriptive analysis of the recent episode, which is framed within the language of the labor market search theory, has been provided by Daly, Hobijn, Sahin and Valetta (2012). By tracing out two theoretically founded and empirically observable curves that capture the labor supply and labor demand factors, they conclude that the natural rate must have risen over the recession and the recovery by about one percentage point to around 6 percent. Surveys

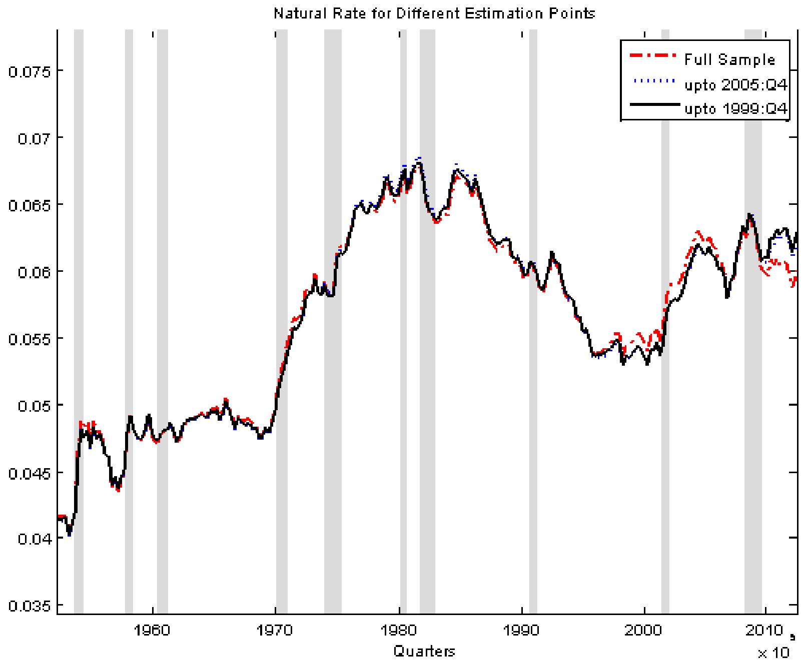

Figure 5: Shaded areas indicate NBER recession dates.

of the labor market evidence related to the Great Recession seem to find that cyclical factors played a major role behind the surge in the unemployment rate rather than more 'structural' or 'permanent' factors such as an increase in the long-run trend (Elsby, Hobijn, Sahin, and Valetta (2011), and Rothstein (2012)). Taken together with these recent studies, I argue that most of the rise in the unemployment rate over the last several years was not due to an increase in the natural rate.

Another issue that has been raised about the effects of the last recession is that the comovement of unemployment with output has changed substantially[11]. One can argue that recessions that delivered jobless recoveries might have led to a different relationship between the unemployment flows and the real output. The framework provided in this paper can be used as a nice testing ground for this. Obviously, since this is not a structural model, it is impossible for me to distinguish between potential reasons. However, in a reduced form sense, I can see whether the last recession in fact changed the underlying nature of the comovement between output and flows into and out of unemployment. I conduct this test by estimating the model for different

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

sample periods during which I 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.

I re-estimate the flow 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 includes most of the recovery after the previous recession. The second subsample, which includes data until 1999:Q4, excludes data on the previous recession, that is, the previous jobless recovery episode. I present my results in figure (5) for both subsamples and the full sample. Note that, regardless of where I end my estimation, the implied natural rate is very close to the estimated one from the full sample, except the last two-three years. The differences between the three reported estimates at the end of the sample are very small, around 1/4 percentage points. This discrepancy between the full sample result and the other two stem from the fact that job finding rate did not recover much since the Great Recession ended. I think that this simple test shows that the last recesssion episode did not significantly change the natural rate through its effects on the parameters of the model. In Appendix B, I explore whether this extends to the entire Great Moderation period, i.e. post 1985. Results indicate that, comovement between unemployment flows and GDP changed in such a way that it actually might have had a sizeable impact on the natural rate, especially over the last 15 years. This is mostly due to the increasing cyclicality of the job finding rate over time, which is consistent with my discussion in section 4.1 and the results reported in Table 2.

5.2 Why is the decline in the unemployment rate so slow?

Even though I contend there has not been a significant increase in the natural rate over the last several years, I 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 U.S. economy experienced a similarly sized shock after the 1981–82

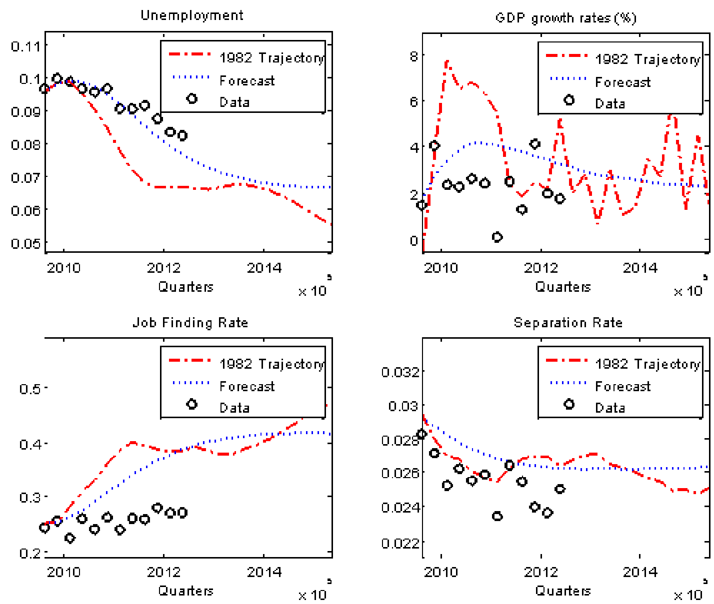

Figure 6: The line labeled '1982 Trajectory (-.)' plots the results from model simualtions with $\varepsilon_t^g, \varepsilon_t^{yn}, \varepsilon_t^{yc}$ set to their realizations during the 24 quarters after 1982:Q3, when the recovery started according to the NBER. 'Forecast (...)' presents the unconditional forecast from the model. They are both expressed as averages of 10,000 simulations of 24 quarters starting from 2009:Q3, when the current recovery started. GDP growth rates are annualized.

recession, it took several years for the observed unemployment rate to drop to levels closer to the trend, even though the rebound in output growth was exceptionally strong relative to the current episode. Second, as I 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.

I present two numerical exercises in this section to show the quantitative significance of these implications. The first exercise compares the behavior of labor market aggregates since 2009:Q3 with a hypothetical scenario in which output growth rate experiences the same shocks as it did after the 1982 recession. The second exercise, on the other hand, compares simulations which use current reallocation rates with the counterfactual, in which labor markets have much more churning.

Clearly, this simple empirical model implies that strong output growth will lead to a faster recovery in the labor market, as the cyclical components of the job finding and separation rates disappear sooner. There is some concern among economists that the current pace of the economic recovery is relatively weak compared to historical norms, especially before the mid 1980s. The upper right panel of figure (6) provides some evidence that this may indeed be the case. According to my model, the growth rate of real GDP, at this point in the recovery, is predicted to be well above the rate observed in the data. These predictions are based on the average of 10,000 simulations of the model, each one for 24 quarters, starting from the third quarter of 2009. Based on the parameter estimates reported in Table 1, average GDP growth rates at this point in the cycle would have been somewhat above 3 percent, gradually declining to slightly more than 2 percent.

One can compare the path of unemployment under this scenario with a particular realization of shocks, $\varepsilon_t^g, \varepsilon_t^{yn}, \varepsilon_t^{yc}$, in a specific episode. My benchmark here is the recovery after the 1982 recession. To do this comparison, I back out the realization of the shocks, $\varepsilon_t^g, \varepsilon_t^{yn}, \varepsilon_t^{yc}$, from 1982:Q3 onwards and feed them into the model simulations, generating a forecast for four variables conditional on a particular output growth path. Comparing this conditional forecast, which follows a post-1982 trajectory in terms of output growth, with the unconditional forecast from the model shows that, along the transition path, the decline in the observed unemployment rate could be significantly lower with a weaker recovery, by as large as 1.75 percentage points. Figure (6) also shows that the model overestimates the job finding and the separation rate in the near term, providing us with a relatively accurate forecast of unemployment for the past twelve quarters. Overall, the results of this exercise suggest that some of the persistence in the current level of the unemployment rate could be explained by the weakness of output growth, both relative to historical averages predicted by the model, and the particular recovery episode following the 1982 recession.

Next I try to quantify the effect of slower worker reallocation on the unemployment rate's convergence towards a long-run trend. I already showed the relationship between the slower worker reallocation and the persistence in unemployment rate in section 4.2. In this section, instead, the numerical experiment highlights the effect of slower worker reallocation on the pace of the adjustment process during the recent episode, which I find to be as strong as that of the weak output growth. This experiment involves comparing the path of unemployment under two different assumptions about worker reallocation. First, I generate a set of simulations using the levels of job finding and separation rate trends at the end of 2009:Q2, which turn out to be

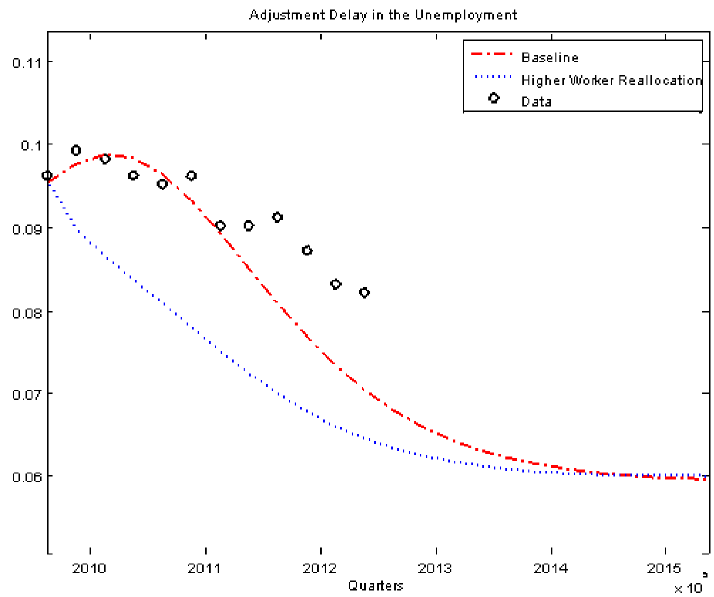

Figure 7: Unemployment is imputed based on the simple equation of motion for unemployment, (6), and predicted values of flow rates. Baseline refers to the benchmark case where worker reallocation rates are consistent with current estimates.

0.41 and 0.026, respectively. Using the equation of motion for unemployment, eq. (6), and an initial rate of unemployment, one can generate a forecast path for unemployment from 2009:Q3 onward. I label this path as the baseline in figure (7). The counterfactual is from a period where trend worker reallocation was very high, as measured by the sum of job finding and separation rate trends. More specifically, I set the job finding rate trend, $\bar{f}_t$, by 2009:Q2 to the level it was in 1982:Q4. This amounts to a counterfactually higher rate, $\bar{f}_t = 0.62$. Note that this is very close to the sample average of this rate, which is 0.59. Since trend flow rates follow a random walk, this amounts to assuming a large shock which will have permanent effects. In order to be consistent, I also set $\bar{s}_t$ to a higher level at the end of the sample so that the unemployment rate converges to the same level in the long-run under both scenarios. This requires setting $\bar{s}_t = 0.039$, which is very close to the separation rate trend in 1982:Q4. As figure (7) shows, higher worker reallocation clearly implies a faster decline in the observed unemployment rate. The difference could be as large as 1.6 percentage points along the transition path, even though both economies ultimately converge to the same long-run level.

As both of these experiments suggest, having a relatively unchanged unemployment rate trend even after the last recession does not necessarily imply an optimistic picture for the unemployment rate in the near term. The strength of the growth in real output and the effects of slower worker reallocation in the US labor market will be among the crucial factors determining this adjustment process. The significance of the latter factor is a novel feature of the framework I use in this paper, and it suggests that structural reasons behind slow worker reallocation might have important implications for unemployment dynamics over business cycles. Understanding these structural factors requires going beyond my reduced-form framework, and it is clearly beyond the scope of this paper.

6 The Case for the Flow Model

My attempt at defining and measuring the natural rate is in some ways different from the more traditional methods. In this section, I provide a discussion of several features of the natural rate concept from this flow model that makes it a better and more useful measure than the more traditional counterparts. In particular, I compare my estimate of the natural rate from the model with unemployment flows to those from a simple bivariate model and a simple NAIRU. A comparison to purely statistical filters, such as Hodrick-Prescott or Bandpass filter is presented in Appendix C, and shows that using purely statistical filters to infer the natural rate would only be appropriate if one uses data on the unemployment flows, as the model in this paper does. On the other hand, ignoring flow rates but focusing on the observed unemployment rate is bound to produce huge variation across estimates depending on the filter.

The bivariate model I have in mind is related to the flow model, but only uses data on the actual unemployment rate and real output as in Clark (1987, 1989) and Kim and Nelson (1999).[12] The NAIRU estimation takes a simple form, relating the current inflation to lagged inflation and the 'unemployment gap' (Gordon (1997)).[13] For my measure of inflation I use quarterly changes in headline CPI at an annualized rate since 1957. In both frameworks one can use Kalman filter to infer the unobserved trends in the unemployment rate much like I do

[12] Output is modeled as in equation (1). On the other hand, the observed unemployment has cyclical and trend components such that the trend component follows a random walk and the cyclical component depends on the cyclical component of the real output, much like the flow rates.

[13] More specifically, I assume that, $\pi_t = \beta_\pi \pi_{t-1} + \beta_u [u_t - \bar{u}_t] + \varepsilon_\pi$, where π_t, and u_t denote actual inflation and unemployment rate respectively. The natural rate, $\bar{u}_t$, follows a random walk, whereas the "unemployment gap", $u_t^c = u_t - \bar{u}_t$, is assumed to follow an AR (2) process; $u_t^c = \theta_1 u_{t-1}^c + \theta_2 u_{t-2}^c + \varepsilon_u$.

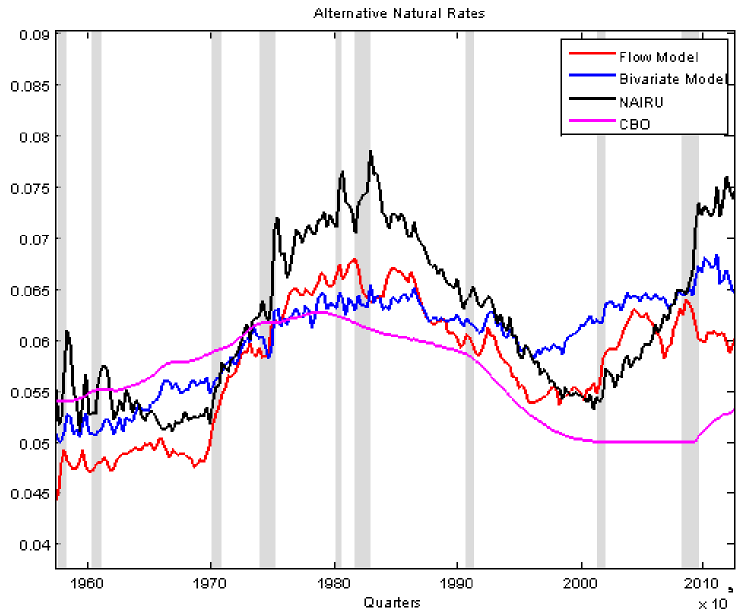

Figure 8: Three different estimates of the natural rate along with CBO's estimate.

for the unobserved trends in the flow rates. My comparison relies on these unobserved trends, which are interpreted as alternative natural rates.[14]

Figure (8) plots estimates from all three models over time along with the estimate of the natural rate from the Congressional Budget Office (CBO). CBO's estimate relies more on a micro approach based on a production function estimation and is conceptually different from the other three, but provides a good example of the wide-variety of interpretations of the natural rate. Figure (8) shows that there is a significant variation across different estimates of the natural rate over time and over the last several years, in particular. For instance, at the end of the sample, they range between 5.3 percent (CBO measure) to 7.5 percent (NAIRU). The bivariate model puts the level of the natural rate at 6.5 percent relative to my preferred estimate from the flow model, 6.0 percent. All three empirical models predict an increase in the underlying rate over the Great Recession which later subsides for all but the NAIRU. Both NAIRU and the bivariate model yield natural rate estimates that are very close to their respective peaks over time. What stands out about the CBO measure is that it does not show any variation over the past fifteen years with the exception of a small increase at the end of the

[14]Both alternative models are estimated using maximum likelihood estimation and results are available upon request.

sample (by a 1/4 percentage point). This large amount of variation across different approaches highlights the challenge of choosing one measure. Depending on what one thinks is the true value, policy implications might be drastically different, since they all imply different levels of labor market slack (Orphanides and Williams, (2002)). In what follows, I will argue that my preferred measure has certain desirable statistical and empirical features and is much closer to the language of the theory of unemployment. This makes the flow model a useful framework to think about the long-run trend in the unemployment rate.

6.1 Language and Empirics Closer to the Theory

The model I propose relies on explicit use of unemployment flows and an implied long-run unemployment rate trend that is consistent with labor market search models. It enables us to analyze the relative contributions of inflows or outflows at different frequencies and over different time-periods. It relies on readily available aggregate data. The underlying assumption that both these flows have cyclical components that respond to the aggregate cycle is not very controversial. A simple extension of the search model with endogenous separations will be qualitatively consistent with my model.

Clearly, this model is still an empirical one with no explicit structure on the economic environment that delivers high-frequency and low-frequency changes in these underlying unemployment flows. However, as I have argued in the Introduction, the difficulty of incorporating low-frequency changes in a structural labor search model and its well-known tendency to under-predict business cycle frequency variation in unemployment (and vacancies) led to an empirical approach. I think of this as an important step towards bringing the language on the natural rate closer to the most widely-used theory of unemployment (Rogerson (1997)).

Note, however, the interpretation of the empirical model can be more general. In practice, any serious modelling of unemployment that tries to be consistent with fluctuations in the unemployment rate over time will produce inflows and outflows. Hence, this empirical model will still be a valid approach, potentially with a different mapping from the environment to the measured flows, which will be model-specific.

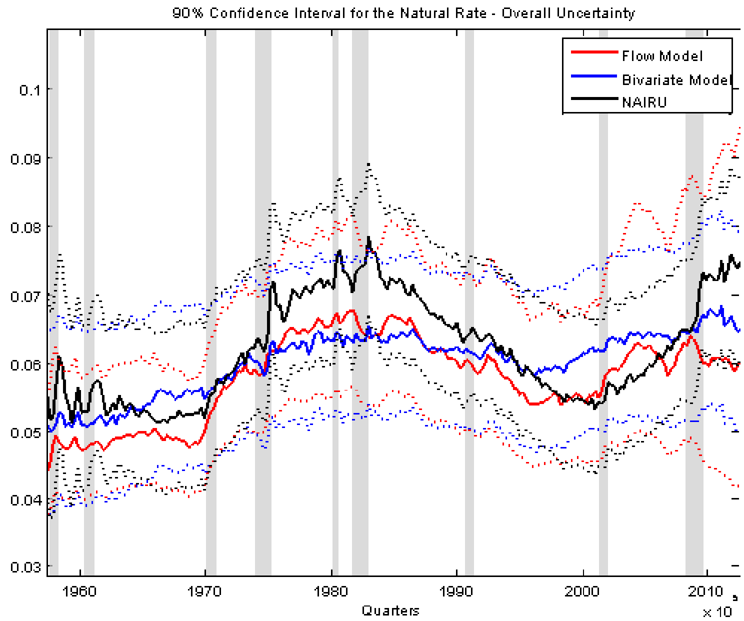

Figure 9: Flow model refers to the model expressed in equations (1)-(3). Lines indicated as Bivariate Model and NAIRU refer to the estimates from the models outlined above. Dashed lines correspond to the 90 percent confidence bands.

6.2 Precision of the Estimates and Revisions

An important issue in the empirical literature that tries to estimate the natural rate (of either unemployment or interest) is the precision of the estimates and the significant revisions observed with the inclusion of subsequent data. Here, I briefly discuss how the empirical model I proposed in this paper performs on these two fronts. I find that, in terms of precision of estimates, the model with unemployment flows performs as good as the bivariate model and the NAIRU described above. Moreover, the model with unemployment flows implies significantly less revisions to previous estimates of the unobserved trend, thereby making it a useful method to estimate a natural rate more consistently over time.

It is well-known that the estimated state vector of an unobserved components model such as the one here, is subject to both parameter and filtering uncertainty. Using a standard Monte Carlo procedure, I compute the 90 percent confidence bands around the estimates of the unobserved state (unemployment's trend) in my model[15]. I compare the precision of my estimates with those estimated from a benchmark bivariate model, and a simple model of the

[15] Details are available upon request.

NAIRU as outlined above.

Figure (9) plots the overall uncertainty around the estimate of the unemployment rate trend in all three cases. Even though it looks like the bivariate model has a narrower confidence band towards the end of the sample, on average the flow model does not perform exceptionally bad. For instance, the width of the 90 percent confidence band implies, on average, a range of 2.43 percentage points around the mean estimate over time in the flow model (-1.0 and 1.43). The benchmark bivariate model performs slightly better, with a range of 2.39 percentage points around the mean estimate over time (-1.16 and 1.23). The NAIRU estimate I find produce a smaller width of the confidence interval over time, on average 2.23 percentage point (-1.05 and 1.18). The standard deviation of the error band is also slightly smaller for the flow model relative to the bivariate model, 0.76 vs. 0.84 and is virtually identical to that of the NAIRU, 0.73. Hence, my empirical model does as well as the reasonably comparable alternatives that use a similar methodology but ignore the additional information in unemployment flows. If anything, the lack of precision extends to all models, which is consistent with Staiger, Stock, and Watson (1997).

Another desirable feature of my framework is its robustness to additional data. Since I use Kalman smoothing to back out the unobserved states, as additional information becomes available estimates of the unobserved state might change, in principle, all the way back to the beginning of the sample. In this respect, the model with unemployment flows performs remarkably well relative to the benchmark bivariate model or the model for NAIRU. The particular numerical exercise I conduct is the one I presented above in section 4.1: I re-estimate all three models with two more subsamples, before 2006 and before 2000 and compare the estimates of the unemployment rate trend for each case until 1999:Q4. Ideally, if I have a robust approach, the addition of a small set of new data should not change the estimates of the unobserved state, i.e. the natural rate, prior to 1999:Q4.

Table 3: Revisions to the Natural Rate (% points) before 1999:Q4

	Bivariate Model		Flow Model		NAIRU	
Excluded Data	post-2005	post-1999	post-2005	post-1999	post-2005	post-1999
Avg.	0.0820	0.0722	0.0394	0.0306	0.1381	0.1223
Std.	0.0909	0.0809	0.0475	0.0372	0.1662	0.1467

Table 3 presents some interesting moments from this numerical exercise. On average, the flow model revises its estimate of the natural rate by a much smaller margin than the benchmark bivariate model or the NAIRU. For instance, the natural rate estimate is revised on average by 0.034 percentage points in the flow model when I include additional data covering the period after 2005:Q4, as opposed to 0.078 percentage points in the benchmark bivariate model. As columns three, five and seven in Table 3 show, this result is robust to the inclusion/exclusion of the entire last decade. The variation in the required magnitude of revisions is almost twice as large in the benchmark bivariate model and more than three times for the NAIRU. Hence, I conclude that the framework based on unemployment flows is superior to alternative approaches used in the literature.

6.3 Policy Relevance

In practice, the natural rate attracts significant attention by the policy makers as it helps, presumably, to gauge how much slack there is in the labor market. This issue more recently took the form of a debate about the nature of the high unemployment rate after the Great Recession and whether it is purely cyclical or somewhat structural (Bernanke (2012), Kocherlakota (2010)). Measuring the extent of the labor market slack is especially a concern for monetary policy makers, as it is perceived to be potentially important to understand inflationary pressures. This is implicit in the concept of NAIRU. Even though I do not advocate this paper's framework and the natural rate estimate it implies as a substitute for NAIRU[16], I argue that it will be useful for policy makers too in a different manner.

The fact that this model helps to distinguish between the channels that affect the incidence versus the duration of the unemployment has significant implications for policy. The discussion about the persistence of the unemployment rate, both during the last two decades (section 4.2) and over the last several years (section 5.2) show that this particular concept of natural rate could be very useful. In some sense, the model can provide a richer understanding about the nature of the high unemployment and can deliver subtle implications for policy makers. To put it simply, our analysis show that even if the unemployment rate might be high due to *cyclical* factors, reducing it will take significantly longer due to the *structural* changes in the

[16] For that matter anything else that relates to nominal variables in general or inflation in particular.

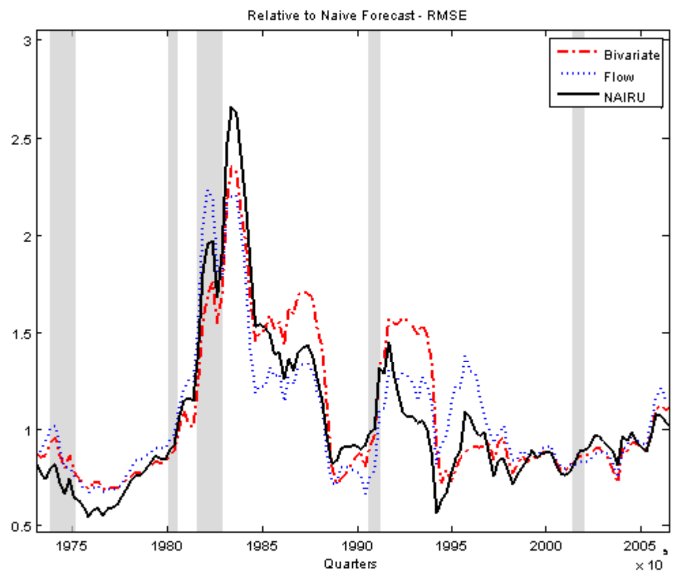

Figure 10: Root mean-squared errors for various forecasting models. Estimates from rolling regressions with 60 quarters of data and 20 quarters of forecast horizon.

labor market that manifest itself as long-term declines in the unemployment flow rates.

This point has been recently emphasized as a theoretical concern in Blanchard and Gali (2010). In a New Keynesian model with nominal rigidities and labor market frictions, Blanchard and Gali (2010) show that the trade-off between inflation and unemployment stabilization now depends on the labor market characteristics. In particular, they conclude that "sclerotic" labor markets, i.e. countries with low turnover rates, will have intrinsically more unemployment persistence under inflation targeting. As part of a numerical exercise, they compare the optimal monetary policy response to productivity shocks between a sclerotic and a flexible labor market, which are calibrated to match observations for EU and U.S. respectively. One implication is that the cost of inflation stabilization will be higher in a sclerotic labor market due to persistent increases in the unemployment rate.[17] My discussion about the persistence of unemployment and the experience since the beginning of the Great Recession fits reasonably well in this context, not as a comparison across countries with different labor market characteristics, but as a comparison over time with changing labor market dynamics.

On a pure practical level, one might question the usefulness of natural rate from the flow

[17] Blanchard and Gali (2010), pp. 20-23.

model in predicting future inflation.[18] Though my measure is not intended for this purpose, in contrast to NAIRU, I argue that it is as good a variable for predicting future inflation. To address this question, I run a simple forecasting regression for inflation four quarters ahead overtime with rolling windows.[19] Each regression uses 60 quarters of data starting from 1958:Q2 onward and estimates are used to predict 20 quarters of inflation ahead. The root mean-squared error (RMSE) from these forecasts are compared across different specifications. The exercise is very close to Atkeson and Ohanian (2001) and compares the forecasting power of different 'gap' measures constructed with different estimates of the natural rate. Figure (10) plots RMSE for each specification over time, relative to the RMSE from a naive forecast, which is essentially a random walk forecast for inflation. It supports the claim that, the natural rate from the flow model is as good a predictor for inflation as the alternatives, including NAIRU. More importantly, none of the natural rate estimates stand out as exceptionally good predictors for inflation.

7 Extensions

As the preceding discussion shows, the method of estimating the natural rate using unemployment flows not only has several desirable empirical and statistical features, but it also nicely maps into theory and is very relevant for policy makers. In this section, I argue that it is fairly easy to extend the methodology to include fluctuations in and out of non-participation and implement the exercise for a variety of countries other than the US. Even though a more comprehensive execution of these extensions is left for future research, I want to highlight the potential uses and generalizations of the framework in this paper.

[18] In a recent paper, Barnichon and Nakerda (2012) shows that using labor force flows to predict unemployment in real-time dramatically outperforms Survey of Professional Forecasters, The Federal Reserve Board's Greenbook Forecast and basic time-series models.

[19] The regression I run takes the form: $\pi_{t+4} - \pi_t = \pi_t + \Delta\pi_t + \Delta\pi_{t-1} + \Delta\pi_{t-2} + \Delta\pi_{t-3} + u^g_t + \Delta u^g_t + \Delta u^g_{t-1} + \Delta u^g_{t-2} + \Delta u^g_{t-3} + \xi_t$ where π and u^g denote inflation and unemployment gap, respectively. Variables with Δ refer to first differences. Unemployment gap measure is $u^g_t = u_t - u^*_t$, where u_t is the actual unemployment rate and u^*_t refers to the time-varying 'natural rate' estimate from the respective model.

7.1 Labor Force Participation

The entire methodology I use for measuring worker flows has been standard since Shimer (2005). However, it does not allow for any separations into inactivity and flows into employment from out of the labor force. When these flows are taken into consideration, measures of job finding and separation rates will change. To the extent that these flows have non-negligible effects on the labor force participation rate, or more precisely flows into and out of the labor force, it potentially could affect the estimation. To extend this methodology in this direction requires incorporating additional flows using the large micro data from the CPS and will be more cumbersome. An advantage of the current methodology is that it only requires macro data that is publicly available at quarterly frequency as far back as 1948[20]. Moreover, it is not clear whether one would learn more about the driving forces behind the unemployment rate from such an experiment (Shimer (2007)).

In principle, extending the model to incorporate a third state, inactivity, is very straightforward. Let λ^{xy} denote the flow rate between labor market state x to state y, where both x and y can take one of the three values, $\{E, U, I\}$. Redefining $S_t = \lambda_t^{EU} + \lambda_t^{EI}[1 - \Psi_t]$, $F_t = \lambda_t^{UE} + \lambda_t^{UI}\Psi_t$,where $\Psi_t = \lambda_t^{IE} / \left[\lambda_t^{IE} + \lambda_t^{IU}\right]$, and interpreting S_t and F_t more generally as flows into and out of unemployment regardless where the destination or origin is, extends my methodology in a simple way. These expressions now take into account the possibility of making the transition between U and E indirectly through inactivity, I. Shimer (2007) presents evidence that the aggregate job finding rate is almost entirely driven by flows from unemployment to employment (at least in the aggregate)[21]. Similarly, separation rates closely follow the flow rate from employment to unemployment. Figure (11) presents employment and unemployment exit hazards calculated by Shimer (2007) using CPS. Unemployment exit hazard without inactivity corresponds to the estimate of the job finding rate I used in the model. Similarly, employment exit rate without inactivity is conceptually same as the separation rate I use. Figure (11) confirms the conjecture that, allowing for transitions in and out of inactivity will not change the main results, as the implied worker flow hazard rates I need will match the

[20] Using CPS micro files to redo this exercise is not possible for pre-1967, at least to our knowledge.

[21] More recently Elsby, Sahin and Hobjin (2012) claim that ignoring this third state might have a non-trivial impact, especially in certain episodes such as the last recession.

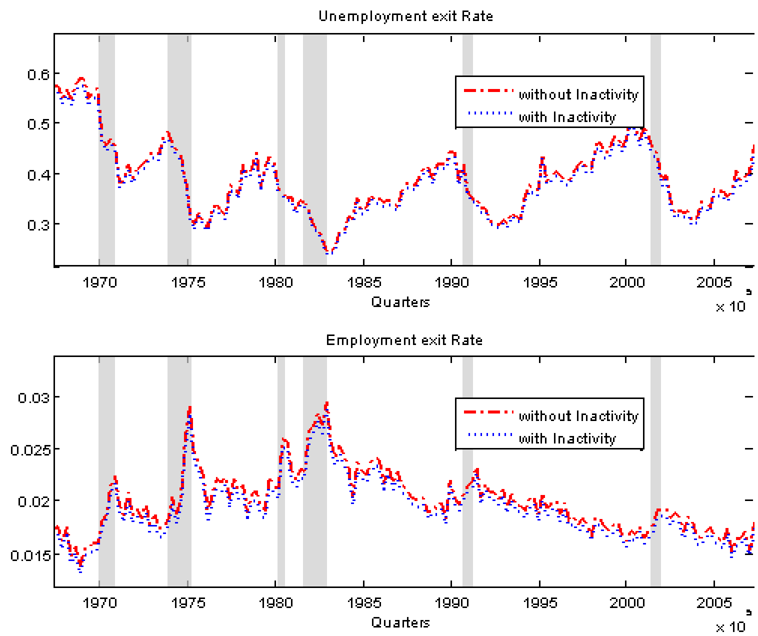

Figure 11: Data is available at http://sites.google.com/site/robertshimer/research/flows. Flows without inactivity refers to λ_t^{EU} and λ_t^{UE} and with inactivity refers to S_t and F_t.

longer time-series I used in my estimation.

On balance, I think the availability of a longer-time series that is more readily available and that does not require a lot of treatment on the data makes the two-state version of the model more desirable and practical.[22] Understanding the role of movements in and out of inactivity is still an important issue that I leave for future work.

7.2 Cross Country Implementation

Implementing this method for different countries is fairly straightforward, barring data limitations. Since Shimer (2005), we have seen a surge in research focusing on the underlying labor market flows in the US. More recently, this literature started to include new set of countries. Understanding the role of unemployment flows for different countries is an important objective in its own right, but also could be informative about the role of labor market institutions and policies that vary across countries. A very nice addition to this strand of the literature is Elsby, Hobijn and Sahin (2011) that looks into the role of inflows and outflows across OECD countries.

[22] The adjustments we have in mind include correcting for measurement, time aggregation and classification errors, see Abowd and Zellner (1985), Shimer (2007) and Elsby, Michaels and Hobjin (2012), among others.

They find that inflows and outflows play equally important roles over the cycle among Continental European countries relative to Anglo-Saxon economies. The former group of countries include countries with lower overall flow rates, and are generally considered to have more 'rigid' labor markets.

In order to implement the proposed natural rate estimation for different countries, one needs quarterly data on inflow and outflow rates for unemployment as well as real output. Unfortunately, obtaining flow rates for long enough sample periods is a challenge for many countries, if not impossible. For instance, Elsby Hobijn and Sahin (2011) can only estimate annual levels of the flow rates for a large set of OECD countries. More recently, though, several studies presented us with the estimates of the unemployment flow rates using country-specific household surveys: Petrongolo and Pissarides (2008) for UK, France and Spain, Smith (2011) for UK, and Hertweck and Sigrist (2011) for Germany. Estimating natural rate with the flow model for an expanded set of countries, including the aforementioned set, will provide a useful comparison and is left for future work.

8 Conclusion

I presented a simple model of comovement in real activity and unemployment flows in this paper and used it to uncover the trend changes in these flows, which determine the trend in the unemployment rate, i.e. the natural rate. I argued that this approach provides us with an empirically useful measure of the natural rate. I used the framework to show that this rate, currently at 6 percent, has been relatively stable in the last decade, even after the most recent recession. I also presented a simple decomposition of the unemployment rate dynamics both at low and high frequencies with my model.

The results also suggest that worker reallocation, measured by sum of the job-finding rate and the separation rate, has experienced a steady trend decline since 2000. This slow worker reallocation has important implications about the dynamics of the unemployment rate, predicting a much slower decline in the near term than would have been possible with high churning, which was previously a distinguishing feature of US labor markets.

I highlighted several desirable features of the natural rate from the model with unemployment flows that makes it a better measure than traditional counterparts. These include statistical precision, the significance of required revisions to past estimates with subsequent data additions, policy relevance and theoretical linkages. Potentially easy extensions of this approach to include flows into and out of inactivity or data for other countries are appealing features, but are left for future work.

Understanding the actual structural changes that might have led to the observed changes in the trends of unemployment flows, thereby the implied unemployment rate trend, should be the logical next step for future research. Without an understanding of these structural forces, any policy conclusions based on the estimates from this reduced form model would be misleading and premature[23].

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

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Appendix (Not intended for publication)

A Choosing γ_f and γ_s

In principle, the results in the paper could be sensitive to the exact values of γ_f, and γ_s that I use. In the benchmark estimation, I use 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 the benchmark values of γ_f, and γ_s imply. To pin down the exact numbers, I re-estimate the 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 $\gamma_s = \{0.5, 0.625, 0.75...., 3.875, 4\}$. I 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 the estimation and the trend of the observed unemployment rate, calculated using a bandpass filter. Since I do not use actual unemployment rate in the estimation, I am trying to impose some discipline on the estimation by bringing in these data.[24]. 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 (12) shows how these two moments change across γ_f, and γ_s.

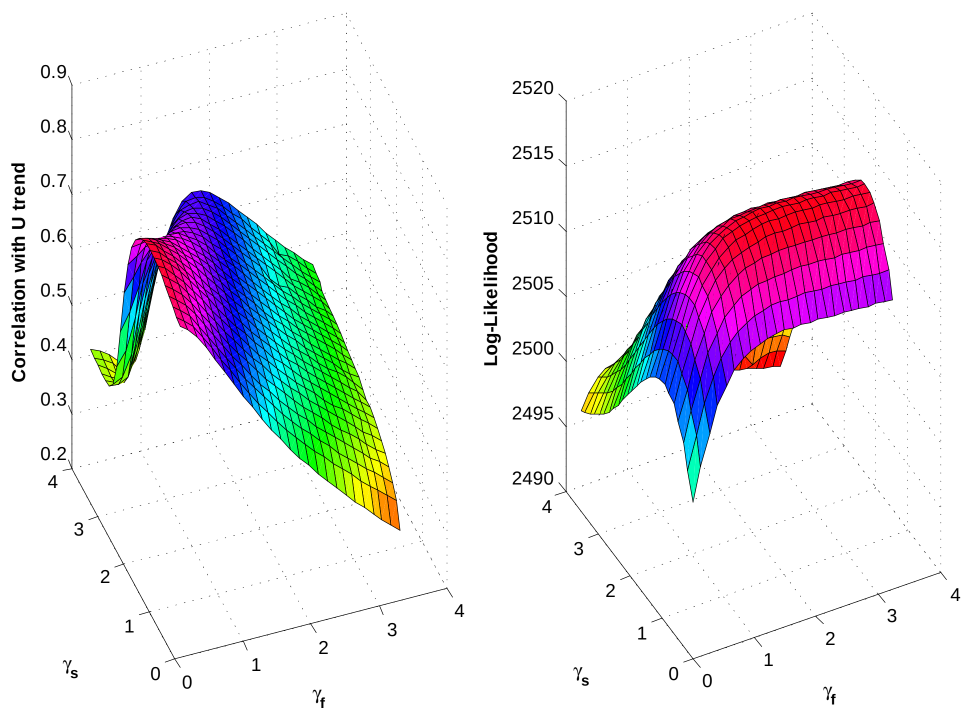

Figure 12: Left panel shows the correlation between the implied natural rate and the statistical trend of the observed unemployment rate computed by bandpass filter, for different values of γ_f, and γ_s. Right panel shows the value of log-likelihood for different γ_f, and γ_s.

The preferred benchmark values maximize the objective of high log-likelihood and high correlation, as is also clear in figure (12). For instance, I do not improve the likelihood of

[24]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.

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 the preferred value of 1.5 is close to its maximum. As γ_s declines, 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. The 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 5.5 percent and 6.4 percent at the end of the sample.

B Great Moderation and the Natural Rate

Figure (13) shows the impact of the great moderation on the estimates of the natural rate over time. The exercise I conduct is the following: I estimate the model only using data through 1984:Q4 and use these parameter estimates to back out a natural rate over time and compare it with the full sample results. Note that I use a sub-sample to estimate these alternative parameters, but use the full-sample to use Kalman smoother to back out the implied unobserved state variables. The results suggest that the comovement between unemployment flows and real output might have changed the natural rate somewhat during the Great Moderation. What changes in terms of parameter estimates is the cyclical response of the job-finding rate. In particular, if the cyclical response stayed similar to what it was prior to the Great Moderation, my model would have predicted a slightly lower natural rate by the end of the last century and a sharper rise since than. In fact, with those parameter estimates, current level of the natural rate would have been about 3/4 percentage points higher at the end of the sample.

C Statistical Filters and the Use of Unemployment Flows

One might argue that if the objective is to derive an empirically useful unemployment rate trend, a pure statistical trend of the unemployment rate might be more practical, if worker flow information does not seem to provide us with any additional information. Thus, in this section of the Appendix I focus on different statistical filtering methods with and without worker flows to distinguish the role they play.

Taking an HP-filter of the unemployment rate itself has been one approach used in the literature to identify a trend for the unemployment rate in the context of the natural rate debate (see Rogerson (1997)). I compare my estimate of the long-run trend for the unemployment rate with those that could be obtained using an HP or a bandpass filter. Figure (14) presents the results of this exercise. When I omit the information on unemployment flows and filter the quarterly unemployment rate, I find a lot of variation in the trend and significant diversion across different filters. For instance, applying an HP-filter with a high smoothing parameter gives a relatively smooth trend that moves closely with the preferred trend from the flow model. However, a bandpass filter or an HP-filter with a smaller smoothing parameter produces much more variation in the trend. The lower panel also shows the well-known problem of overemphasizing the end points of the sample.

A strikingly different picture emerges if I include information on unemployment flows and impute an unemployment rate trend, as I did in the paper, based on the trends of these under-

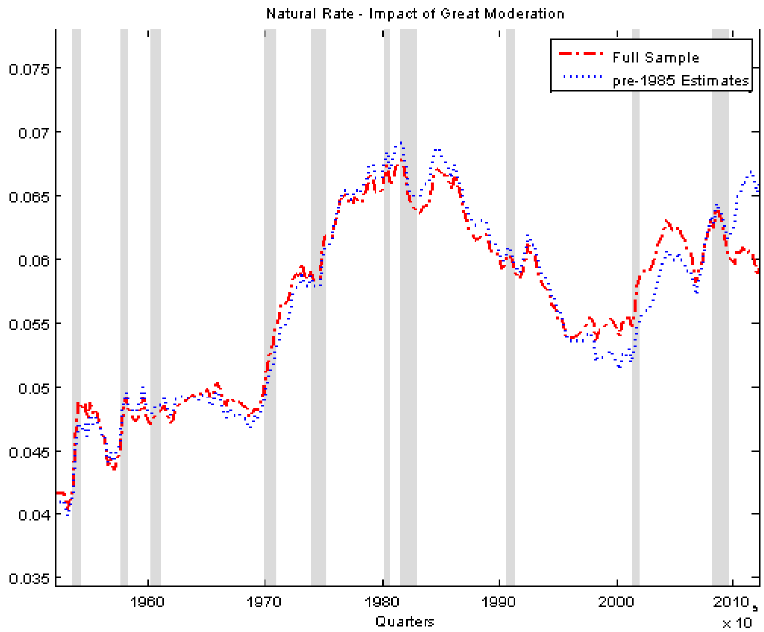

Figure 13: Shaded areas indicate NBER recessions. The natural rate estimate in (...) uses parameter estimates based on results from the data prior to 1985.

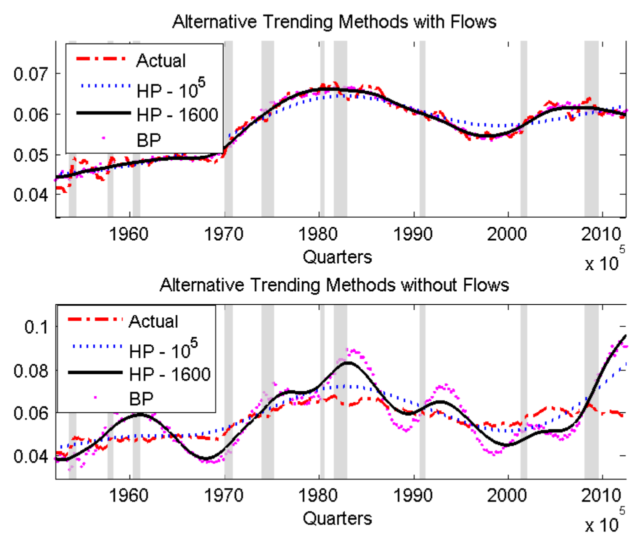

Figure 14: The upper panel presents unemployment rate trends imputed by different statistical filters on worker flow rates. The lower panel presents pure statistical trends based solely on unemployment rate data. The line labeled actual - displays our preferred version that is based on our model. We also use an HP-filter (with smoothing parameters 1600, and 10^5) as well as a bandpass filter (with parameters $(6, 32)$).

lying flows. As the upper panel of figure (14) shows, unemployment trends imputed this way do not vary much across different filters and are much smoother than the trend estimates based solely on unemployment rate information. Moreover, the flow model, which puts a lot more structure on the comovement of flows and real output, produces a trend that moves closely with these other filters. I interpret this result as evidence of the importance of unemployment flows in understanding the unemployment rate trend over the long run. The obvious discrepancy between various estimates of the trend with different filters when flows data are ignored makes it harder to get an empirically consistent, and otherwise useful measure.