The Ins and Outs of Unemployment in the Long Run: Unemployment Flows and the Natural Rate*

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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 5.6 percent. Numerical exercises 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. The results appear to be robust to the exclusion of the end of sample (Great Recession period) and the inclusion of participation channel. However, there is some evidence suggesting a change in labor market dynamics vis a vis output fluctuations after 1985. Finally, I highlight several desirable features of the framework, including statistical precision, the significance of required revisions to past estimates with subsequent data additions, policy relevance and its tight link with the language of the modern theory of unemplyment.

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

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1 Introduction

The Great Recession pushed the unemployment rate to levels that have not been seen in the U.S. since mid 1980s and the recovery that ensued was not able to bring it down to more 'normal' rates in a short period of time. This issue motivated a whole debate addressing whether the resulting jump in the unemployment rate was mostly cyclical or to some extent structural, indicating a rise in the trend of the unemployment rate. This paper contributes to this debate by providing a novel approach 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 accomplish this goal, 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 unemployment rate *in the limit* 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, increasing by as much as 1/2 percent relative to late 1990s followed by a gradual decline to the current level of 5.6 percent. The Great Recession, however, did not cause a permanent rise in the underlying trend rate, suggesting that most of the increase in the observed unemployment rate could be perceived as cyclical. Underlying this relative stability 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 aftermath of the recessions. In particular, the model suggests that the exceptionally persistent unemployment rate after the Great Recession was partly because of the slower worker reallocation rate (the

[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.

sum of the separation and job-finding rates). I also provide a quantitative exercise highlighting the potential impact of "weaker" output growth during the current recovery on this adjustment process. Therefore, even if the rise in the observed rate was mostly cyclical, the prospect of a quick cyclical adjustment during the recovery was dim ex-ante, because of other forces that might be structural, such as a decline in the overall labor market dynamism. I argue that these experiments show the potential usefulness of the model.

I show that the baseline estimate of the unemployment rate trend is robust to the exclusion of the data from the Great Recession. The results for the past 25 years also does not change much at all, when transitions involving non-participation is incorporated into the model. We find some evidence, however, that the Great Moderation might have changed the dynamics of the comovement between unemployment flows and output. Job-finding rate became somewhat more persistent and the countercyclical jumps in the separation rate became less pronounced. As a result, when only post-1985 data is used to estimate the model, some of the decline in the job-finding rate trend in the recent past is attributed to a large but persistent cyclical drop, rather than a trend decline. This lowers the natural rate at the end of the sample by as much as 3/4 percentage points. Finally, I compare this estimate of the natural rate with more traditional estimates (including a NAIRU) and argue that the model with flows has several desirable statistical features including 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. 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.

The next section presents the model describing the comovement of real GDP and unemployment flows. Section 3 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 4 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 were on the dynamics of the unemployment rate. Section 5 presents the robustness issues followed by the literature review and a comparison to the alternative measures of the natural rate in section 6.

2 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 cyclical 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.

Unemployment rate evolves over time as result of the interaction between these flow rates. Following Elsby, Michaels and Solon (2009) and Shimer (2012), $\hat{u}_{t+1}$, unemployment rate next period, can be expressed as

$$\hat{u}_{t+1} = \left(1 - e^{-F_t - S_t}\right) u_t^* + e^{-F_t - S_t} \hat{u}_t, \tag{4}$$

where $u_t^* = \frac{S_t}{S_t + F_t}$. Therefore, the unemployment rate itself does not provide any additional information for us, and is absent from the model. Based on this equation of motion, I define the trend unemployment as the unemployment rate in the limit, given by the current trend estimates. I simply define it as the unemployment rate trend that is consistent with current flow rates is $\lim_{k\to\infty} \hat{u}_{t+k} = \bar{u}_t = \frac{\bar{s}_t}{\bar{s}_t+\bar{f}_t}$.

Note that, this definition yields a time-varying unemployment trend. The second equality follows from equation (4), the stationary of the cyclical components (f_t,s_t) and the random walk nature of the trends ($\bar{f}_t$,$\bar{s}_t$). This rate is in principle different from the expected unemployment rate, $\mathbf{E}[\hat{u}_{t+k}]$, or the steady state unemployment rate implied by (4), as the random walk trends will induce variations over time. Instead, I interpret $\bar{u}_t$ as the rate to which the unemployment will converge to given the current trends in flow rates, in the absence of further shocks.

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:

$$\begin{bmatrix} Y_t \\ F_t \\ S_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \rho_1 & \rho_2 & \rho_3 & 0 & 1 & 0 \\ 0 & \theta_1 & \theta_2 & \theta_3 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_t \\ y_t \\ y_{t-1} \\ y_{t-2} \\ g_t \\ \bar{f}_t \\ \bar{s}_t \end{bmatrix} + \begin{bmatrix} 0 \\ \varepsilon_t^{fc} \\ \varepsilon_t^{sc} \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} \bar{y}_t \\ y_t \\ y_{t-1} \\ y_{t-2} \\ g_t \\ \bar{f}_t \\ \bar{s}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_{t-1} \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ g_{t-1} \\ \bar{f}_{t-1} \\ \bar{s}_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{yn} \\ \varepsilon_t^{yc} \\ 0 \\ 0 \\ \varepsilon_t^{g} \\ \varepsilon_t^{fn} \\ \varepsilon_t^{sn} \end{bmatrix} \tag{6}$$

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 U.S. data, I can back out an estimate of a time-varying unemployment rate trend by using the estimates of the unobserved trend components.[2] In principle, this methodology can also provide an estimate of the trend output, $\bar{y}_t$, hence a measure of the output gap. The implied output gap from this parsimonious model quantitatively seems to be in-line with the ones produced by state of the art approaches, reassuring that the results I obtain is not driven by unreasonable measurement of the output gap (see Appendix A, for details).

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 (5)-(6), is subject to an identification

[2]Note that the model is estimated simultaneously for all the observables, even though output process seems to drive the other variables. Isolating the output at the first stage and then estimating the flow variables ignores the valuable feedback from the behavior of the flow rates (hence, unemployment) on the output fluctuations. In the estimation stage we use F and S as log transformations.

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.

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 it is better to use a reduced-form approach, 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) show 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 perceived 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 modeling unemployment in the future.

2.1 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 2014:Q2.[3] 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, 2012) 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 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 unemployed less than five weeks in month t and l_t the size of the labor force in month t. At

[3] It is seasonally adjusted at an annual rate and expressed in chained 2009 dollars.

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:

$$\frac{du_t}{dt} = S_t(l_t - u_t) - F_t u_t. \tag{7}$$

Given this simple accounting equation, I start with a typical unemployed worker's probability of leaving unemployment. As Shimer (2012) and Elsby, Michaels, and Solon (2009) show, job-finding probability will be given by the following relationship:

$$\hat{F}_t = 1 - \left[\left(u_{t+1} - u^s_{t+1}\right)/u_t\right] \tag{8}$$

which maps into an outflow hazard, job-finding rate, $F_t = -\log(1 - \hat{F}_t)$. This formulation in (8) 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.

$$u_{t+1} = \frac{\left(1 - e^{-F_t - S_t}\right) S_t}{F_t + S_t} l_t + e^{-F_t - S_t} u_t \tag{9}$$

Given the outflow hazard, F_t, measured through (8), and data on u_t and l_t, I can solve for S_t numerically for each month t. Note that, as long as the labor force does not change by a lot between t and $t+1$, i.e. $\frac{l_t}{l_{t+1}} \approx 1$, (9) implies (4).[4]

One potential problem that could bias the estimates is the redesign of the CPS in 1994. As discussed by Shimer (2012) 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[5]. 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 provides me with the final data I need for unemployment flow rates.

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

[4] Gross change in our data, l_t/l_{t+1}, is on average 0.999 at monthly frequency and 0.996 at quarterly frequency.

[5] See Polivka and Miller (1998) and Abraham and Shimer (2001) for more details.

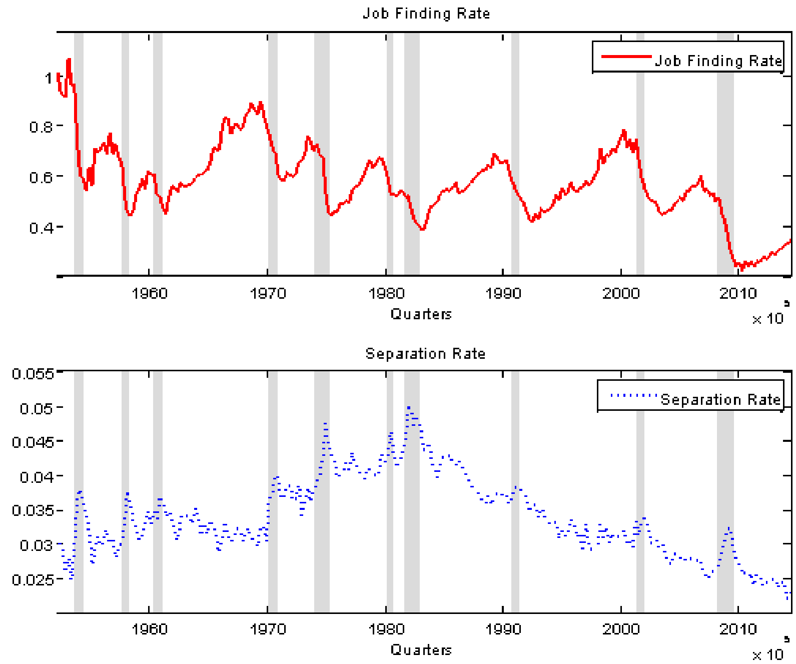

Figure 1: Job-finding and separation rates are constructed using equations (8) and (9) and corrected for CPS redesign. Shaded areas indicate NBER recession periods. Rates are the quarterly averages of the monthly data.

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. Subsequently, the unemployment rate falls. However, this highly stylized description of cyclical movements in the flow 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 (2012) 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[6]. 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 the next section.

For the robustness section, I also compare the results of the baseline model to the alternative where the flow rates are constructed directly from the micro CPS data. This allows me to address robustness of the unemployment trend estimate to different measurement approaches

[6] For the debate on which flow drives unemployment fluctuations over business cycles, see, for instance, Shimer (2012), Elsby, Michaels, and Solon (2009), and Fujita and Ramey (2009).

as well as the potential effects of the transitions involving non-participation. To construct the transition rates from the micro data, we follow Elsby, Hobjin and Sahin (2012) and Nekarda (2009), and correct for margin-error and time-aggregation bias. Unfortunately, constructing micro level transitions is only possible from 1976.[7] The constructed data, with the exception of the micro transitions from the CPS, cover all 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. The next task is to estimate the underlying trend in both flow rates, more specifically, $\bar{f}_t$ and $\bar{s}_t$.

2.2 Estimation

I estimate the reduced form model in (1)-(3) via maximum likelihood, and use the state-space representation in (5)-(6). Since the stochastic trend and cyclical components of the variables are not observable, I rely on a Kalman filter to infer them and construct the 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, $\gamma_y = \frac{\sigma_{yn}}{\sigma_{yc}}$, $\gamma_g = \frac{\sigma_g}{\sigma_{yc}}$. 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 the 8-quarter ahead forecast error for the actual unemployment rate. The idea here is to maximize the likelihood of the model while at the same time obtaining a sensible prediction for the unemployment rate in the medium term. As a result of this exercise, for the benchmark case I choose a parameterization where $\gamma_f = 1.25$, $\gamma_s = 1.625$. I report the robustness of my estimation to other values for γ_f, γ_s in Appendix B.

[7]The data from June 1967 and December 1975 were tabulated by Joe Ritter and made available by Hoyt Bleakley. I downloaded this data from Robert Shimer's website: https://sites.google.com/site/robertshimer/research/flows.

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

[9]They are 0.85 and 0.027, respectively.

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.

3 Results

Here, I present the results of the benchmark estimation, imposing the restrictions $\gamma_f = 1.25$, $\gamma_s = 1.625$, $\gamma_y = 0.85$, $\gamma_g = 0.027$. This implies that I only estimate 11 parameters. As Table 1 shows, most parameters of the reduced form model in (1)-(3) are quite tightly estimated. Given parameter estimates, 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 desired series, $\bar{u}_t = \frac{\bar{s}_t}{\bar{s}_t+\bar{f}_t}$. 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, $\bar{f}_t + \bar{s}_t$.

Table 1: Estimation Results: 1952:Q1-2014:Q2

	Estimate			Estimate	
ϕ_1	1.6336	(0.0566)	θ_2	1.9090	(1.3703)
ϕ_1	-0.6798	(0.0555)	θ_3	1.8206	(0.7756)
ρ_1	3.1406	(1.0869)	σ_{yn}	0.0058	(0.0002)
ρ_2	4.2148	(1.8164)	σ_{fn}	0.0257	(0.0014)
ρ_3	-0.1526	(1.1667)	σ_{sn}	0.0181	(0.0010)
θ_1	-5.2727	(0.8353)	L	1643.2	

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. 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

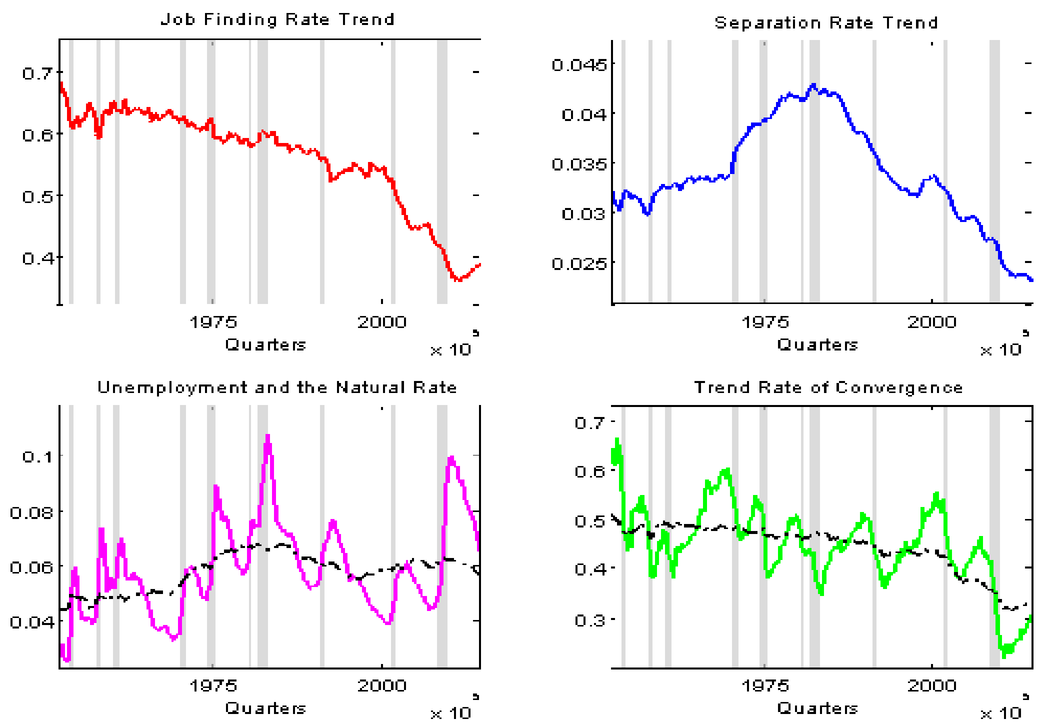

Figure 2: Unobserved trend in all variables are backed out and smoothed by Kalman filter. Shaded areas indicate NBER recession dates. In the lower-left panel, the dashed line indicates the natural rate as defined in the text. The observed and the trend rate of convergence are given as $1 - e^{-(f_t +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

estimates suggest that throughout our sample period, the unemployment rate trend has moved between 4.5 percent and 6.8 percent, and currently stands around 5.6 percent. If anything, the unemployment trend gradually increased to 6 1/4 percent neighborhood prior to the Great Recession from around 5.6 percent in mid 1990s. Since it reached its local peak of 6 1/4, it gradually came down, led by a significant decline in the separation trend.

Perhaps the most interesting point about the results is that worker reallocation, as measured by the sum of the job-finding and separation rates, 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. 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

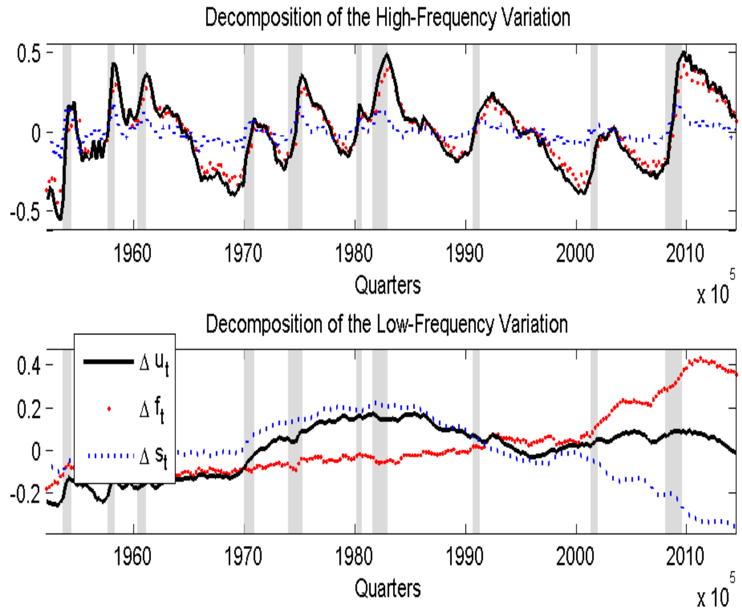

Figure 3: Upper panel plots Δu_t, in the data as well as the counterfactuals with only variations in Δs_t and Δf_t over time. Lower panel shows same objects for the trend component of the unemployment rate, $\Delta \bar{u}_t$.

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 high levels of unemployment in the wake of a recession towards its trend will take longer than it would in an economy with more churning. The next section presents some evidence that this was indeed the case in the current recovery.

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 as in the long-run. For instance, 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 over the cycle. Implementing such a decomposition confirms that at least 75 percent of the variation in the cyclical unemplyment is accounted for by the cyclical variation in the job-finding rate throughout the full sample period. Let Δx_t be defined as the log deviation from the variable's mean (or trend), then one can generate counterfactual unemployment rates, both at a high frequency with $\Delta u_t = \log\left(\frac{u_t}{\bar{u}_t}\right)$, and at a low frequency with $\Delta \bar{u}_t = \log\left(\frac{\bar{u}_t}{\bar{u}}\right)$ to analyze the role of each flow.[10]

[10] In $\Delta \bar{u}_t = \log\left(\frac{\bar{u}_t}{\bar{u}}\right)$, $\bar{u}$ will be the sample mean of the unemployment trend $\bar{u}_t$.

Figure (3) shows the respective variation in the cyclical and trend components of the unemployment rate. 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 recent sample period (figure 2). The picture for the last decade is starkly 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.

Figure (3) presents visually the contributions of the cyclical and trend components of the flow rates on the cyclical and trend components of the unemployment rate, respectively. In light of the substantial decline in both of the flow rate trends and its potential impact on the reallocation rate (hence, short-term adjustment), I also expect the trend movements to affect the cyclical adjustment to some extent. In order to understand this issue, I conduct a simple numerical exercise by generating counterfactual unemployment rate dynamics implied by the absence of (estimated) trend changes for one type of flow at a time. Since I have well-defined cyclical and trend components for the flow rates at any point in time, I can easily isolate one component at a time. In particular, I want to see how unemployment would have evolved in the absence of a trend change in one single flow.

Figure (4) presents the results of this exercise for every post-war recession after 1952. Every episode starts with the quarter prior to the NBER recession start date and ends 16 quarters later, unless another recession starts earlier.[11] Line denoted by 'fixed f' refers to the case when only the trend of F, $\bar{f}_t$, is assumed to stay constant at its pre-recession level throughout the horizon and everything else (f_t, $\bar{s}_t$, or s_t) is assumed to follow estimated historical realizations. Similarly, for the line indicated by 'fixed s', $\bar{s}_t$ is assumed to stay at its pre-recession level during the recession and the recovery.[12]

Even in a relatively short time period, the cumulative effect of the changes in flow trends could be substantial. Figure (4) shows that during the business cycle episodes when both flows registered secular declines - last three episodes-, unemployment rate observed during the recovery was the result of countervailing forces. For instance, the secular decline in the separation rate trend kept the unemployment rate trajectory lower after the last three recessions, by as much as 1 full percentage point. Similarly, the job finding rate trend decline kept the unemployment rate higher, as much as 1.4 percentage points. This exercise highlights the importance of understanding the flow trend movements, not only for their role in the unemployment trend

[11] This appears to be the case in 1957-58 and 1980 episodes, where the recovery period ends prior to 16 quarter horizon.

[12] Note that when all components, $\bar{f}_t$, f_t, $\bar{s}_t$, s_t follow the historical realizations implied by the estimation, we obtain the actual path of unemployment.

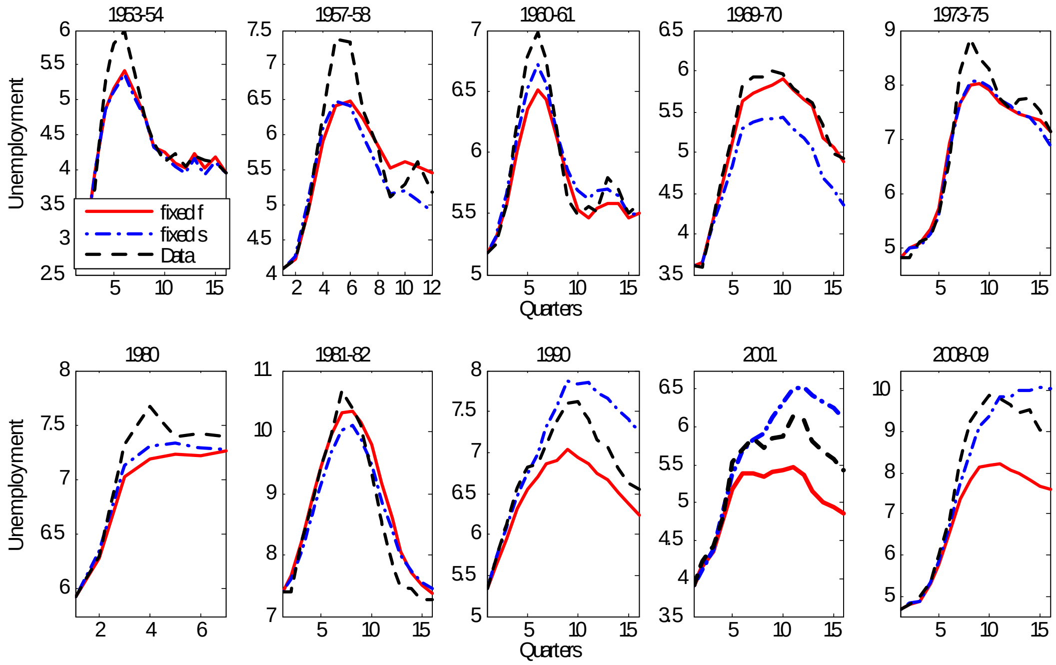

Figure 4: Unemployment dynamics after post-war recessions. Data and the counterfactuals with constant f trend or s trend cover the first16-quarters after the begining of each recession, unless it reaches another business cycle episode (i.e. 1957-58 and 1980).

but also for their potentially substantial influence on the evolution of the unemployment rate over the business cycle.

4 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 4.3 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 percent in late 2009. Currently, more than 11 million people are officially unemployed, and many are underemployed. The 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. Median unemployment duration reached 25 weeks in June 2010, about twice longer than at previous cyclical peaks. These large effects stemming from the aggregate shock on the labor market raise some obvious questions that can be addressed through the simple flow model presented in the preceding section: Has the recession changed the long-run trend for the unemployment rate? Why was the elevated unemployment rate so persistent?

4.1 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 6.1 percent. Even though the natural rate hit 6 1/4 percent in the midst of the recession, it gradually came back to 5.6 percent at the end of the sample. The majority of the slight increase in the trend over the recession can be attributed to 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, if anything.

Another issue that has been raised about the effects of the last recession is that the comovement of unemployment with output has changed substantially[13]. Hence, one might need to analyze the data from the perspective of this model, isolating the end of the sample. Even when I estimate the model with data through 2007:Q4, and use those parameter estimates to infer the unemployment trend over the last recession, I get almost identical results.[14] The difference at the end of the sample is less than 1/4 percentage points. Therefore, I conclude that the Great Recession did not substantially change the comovement between output and the unemployment flows.

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 arguments 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 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

[13] See, for instance, Daly and Hobjin (2010) and Gordon (2010a and 2010b).
[14] See the figure (17) in Appendix B.

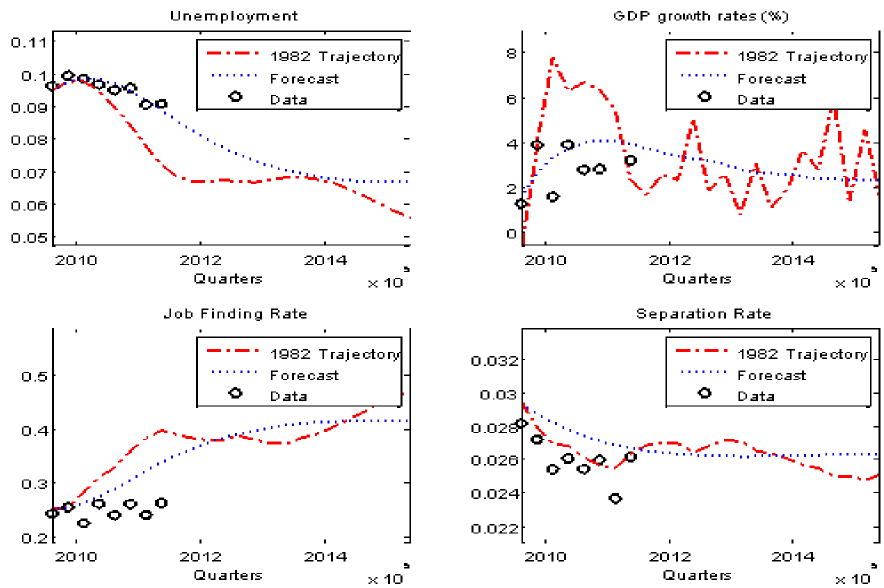

Figure 5: The line, '1982 Trajectory (-.)' plots model simualtions with $\varepsilon_t^g, \varepsilon_t^{yn}, \varepsilon_t^{yc}$ set to their realizations during the 24 quarters after 1982:Q3. 'Forecast (...)' presents the unconditional forecast from the model. GDP growth rates are annualized. Data refers to the first 8 quarters of the recovery.

natural rate.

4.2 Why was the decline in the unemployment rate so slow?

Even though I contend that there was NOT a significant increase in the natural rate over the last recession, I can safely argue that the convergence to the estimated natural rate from its cyclical peak was slow for two reasons. The first is the sheer extent of the gap between the cyclical unemployment rate peak and its estimated trend level. This gap reflected the size of the aggregate shock that hit the economy at the time. When the U.S. economy experienced a similarly sized shock after the 1981–82 recession, it took several years for the observed unemployment rate to drop to levels closer to the trend, 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 (5) provides some evidence that this may indeed be the case. According to the model, the growth rate of real GDP, at that 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 (5) 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 first 8 quarters of the recovery. Overall, the results of this exercise suggest that some of the persistence in 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. 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 0.41 and 0.026, respectively. Using the equation of motion for unemployment, eq. (7), 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 (6). 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

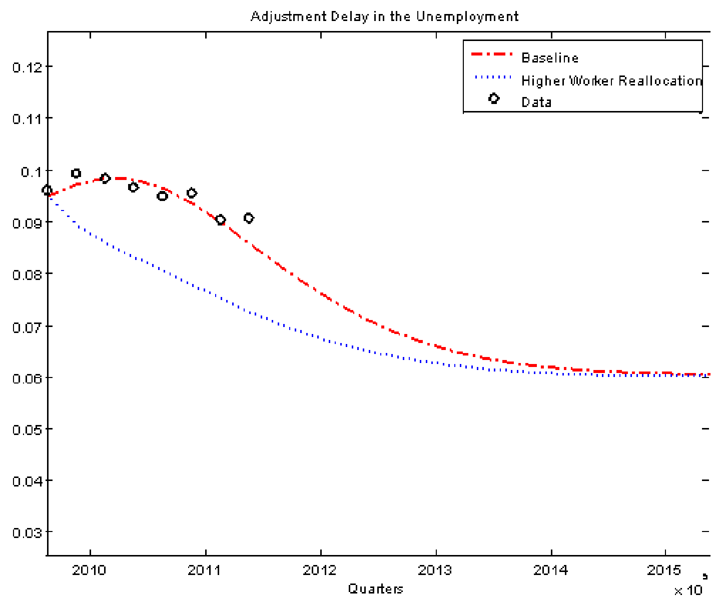

Figure 6: Unemployment is imputed based on the simple equation of motion for unemployment, (7), and predicted values of flow rates. Baseline refers to the benchmark case where worker reallocation rates are consistent with current estimates. Data refers to the first 8 quarters of the recovery.

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 (6) 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 exercises suggest, having a relatively unchanged unemployment rate trend even after the last recession does not necessarily imply a quick transition for the unemployment rate in the aftermath. The strength of the growth in real output and the effects of slower worker reallocation in the US labor market are 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.

5 Robustness

I address the robustness of my estimates for the unemployment trend over time in this section. Two important measurement issues stand out in this respect. First, the construction of the data for job finding and separation rates in the previous section relied on the duration based approach pioneered by Shimer (2005) as opposed to directly observed transitions from the matched sub-sample of the CPS. Moreover, so far the discussion ignored potential transitions including non-participation. Finally, I address whether the comovement dynamics between unemployment flows and output changed during the Great moderation period.

5.1 Transitions from matched CPS data

I relied on the measurement of the transition rates between unemployment and employment following Shimer (2005, 2012). One big adventage of this approach is that it is easily constructed with publicly available unemployment duration data since 1948, whereas it is only possible to match individuals between two consecutive CPS surveys since 1976. One potential problem with this measurement is that, it could provide a biased estimate of the flow, F. This is due to the potential inflows into the unemployment pool, as they appear in the CPS, by those who have been unemployed more than 5 weeks. Even though the bias has been minimal in the past, Elsby, Hobjin, Sahin and Valetta (2011) identified a significant bias during the last recession, which manifests itself as a disproportionately larger decline in the duration based job-finding rate. Therefore, one might be concerned whether the large drop in the estimated $\bar{f}_t$ will be robust to this alternative measurement.

Figure (7) presents the flow measures computed with these two alternatives for comparison. Cyclical variation seems to follow each other very closely. There is clearly a level difference, however. Estimates from the CPS micro data rely on the matched samples, which only consists of the 75 percent of the sample in a given month, at most. In addition, duration-based approach is silent about the transitions into and out of unemployment that involve non-participation, which is explicitly controlled for in the micro approach. This difference in nature could lead to a quantitatively different trend estimate in the underlaying flow rates. For instance, separation rates do not present as large of a decline by the micro approach. Elsby, Hobjin, Sahin and Valetta (2011)'s concern about the potential bias is also evident in the upper panel of figure (7), where the duration-based approach registers a much larger drop in the job-finding rate. In principle, these differences in levels do not necessarily imply a different unemployment trend, based on our definition, presenting an empirical question.

To answer this empirical question, I estimate the model using data on flow rates, based on each approach separately, for the feasible sample period, 1976-2014. Note however, one needs to exercise caution in interpreting the results, given the differences in what they exactly measure, as described above. Nevertheless, the resulting comparison presented in figure (8) is informative. The general contours of the estimated unemployment trend over time are similar.

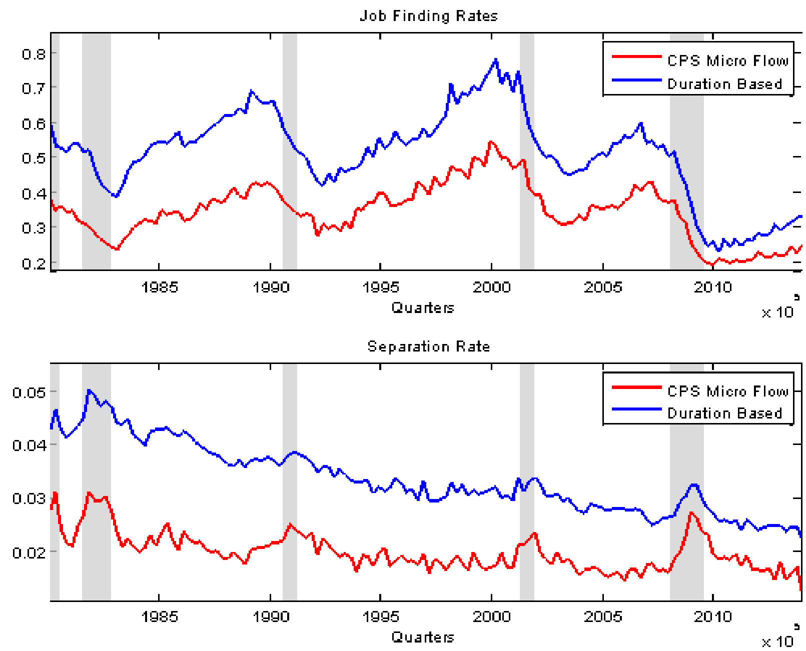

Figure 7: Measured flows from CPS micro transitions versus the duration based approach.

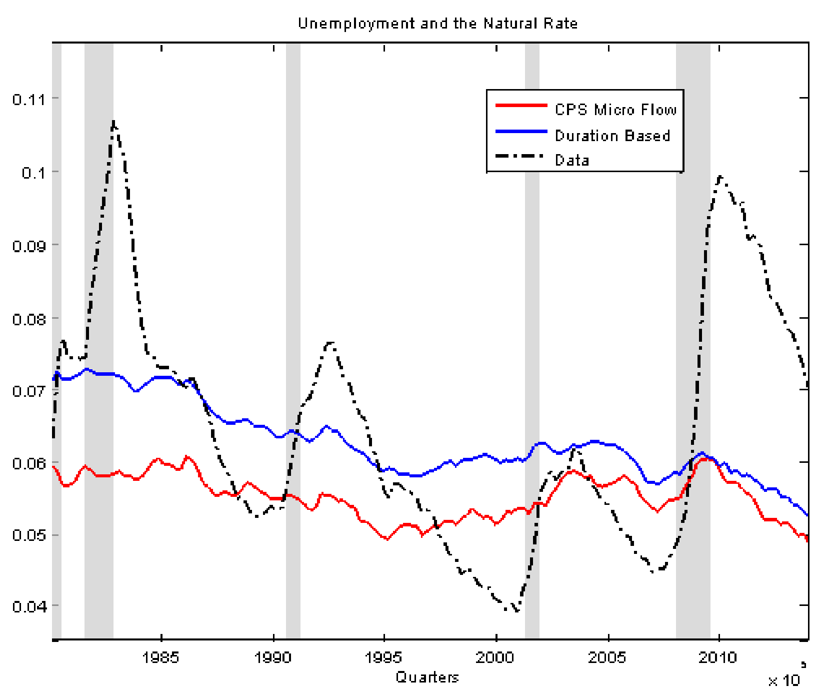

Figure 8: Estimated unemployment trends from CPS micro transitions versus the duration based approach.

5.2 Non-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 matched micro data from the CPS, as we did above.

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. Note that, this redefinition provides us with the correct comparison, unlike the preceding subsection.

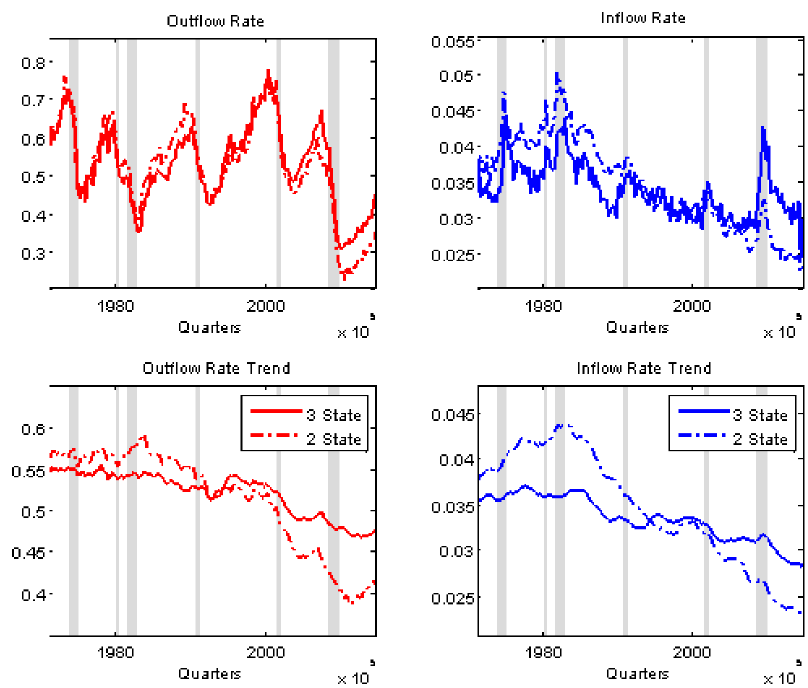

Figure 9: Inflow and outflow rates and their estimated trends when we allow for transitions through inactivity.

Figure (9) plots the flow rates with and without this explicit accounting of the indirect transitions through non-participation. Measurement with three states to some extent mitigates the drop in the outflow trend identified in the baseline model. The effect of transitions into

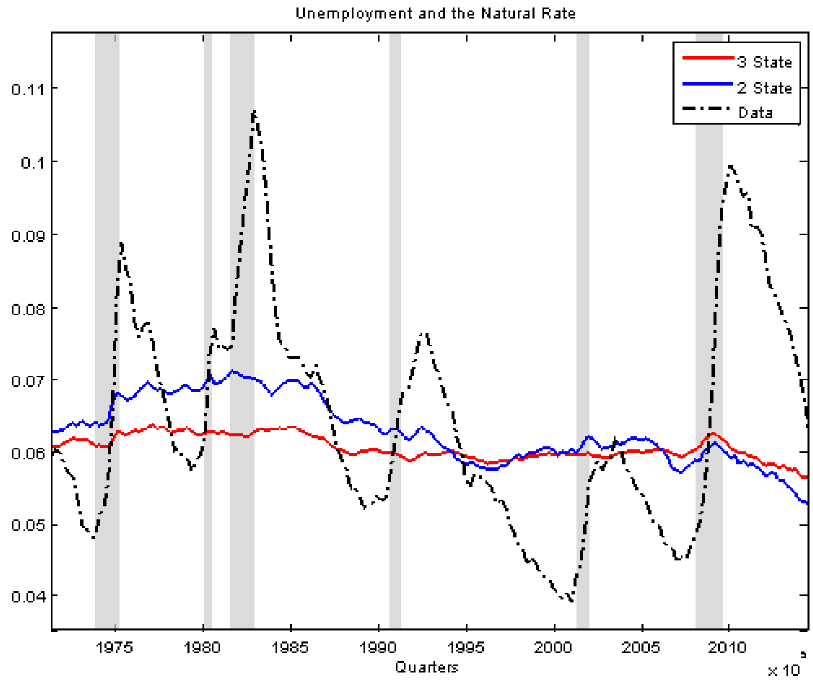

Figure 10: Unemployment and the estimated trends, baseline model and the extended model with inactivity.

non-participation from unemployment (instead of into employment) is especially evident at the end of the sample. A similar situation is true for the inflow hazard as well. As a larger fraction of the transitions from employment involved non-participation, the two-state measurement underestimated the inflows. The overestimation of the flow rates early in the sample, especially for the inflows, is most likely due to the general secular rise in the labor force participation behavior at the time. As a result, estimated trends for the flow rates have less pronounced declines relative to the baseline, which ignored the inactivity channel.

Even though the estimation of the model with different flow rates produce slightly different trajectories for the unobserved trend components for the flows, the effect on the unemployment trend is in principle ambiguous, depending on the relative magnitudes. In fact, figure (10) shows that sizeable differences in the underlying trends does not necessarily lead to a substantially different path for the unemployment rate for the past 25 years. The largest discrepancy between the alternative trends hovered around 3/4 percentage points in the midst of 1981-82 recession. Since 1990s, implied unemployment trend seems to be quite robust to the explicit handling of the non-participation behavior. Currently, the 3-state version stands less than 1/4 percentage point above the baseline model estimate.

5.3 The Great Moderation

The flow model estimation heavily relies on the cyclical response of the outflow and inflow rates for identification of the cyclical components. To the extent that the outflow and inflow rates respond differently to the output dynamics during the Great Moderation, estimated trends might change. There are reasons to think this might be the case. A closer look at the flow measures pictured in figure (1) reveals that the job-finding rate (outflow rate) might have become somewhat untethered from the output fluctuations post-1985, featuring more persistence even after the recessions are over. Similarly, the separation rate started to present much less pronounced bursts at the onset of a recession. Therefore, it is conceivable to question the robustness of the results for the Great Moderation period.

Figure (11) 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 after 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.

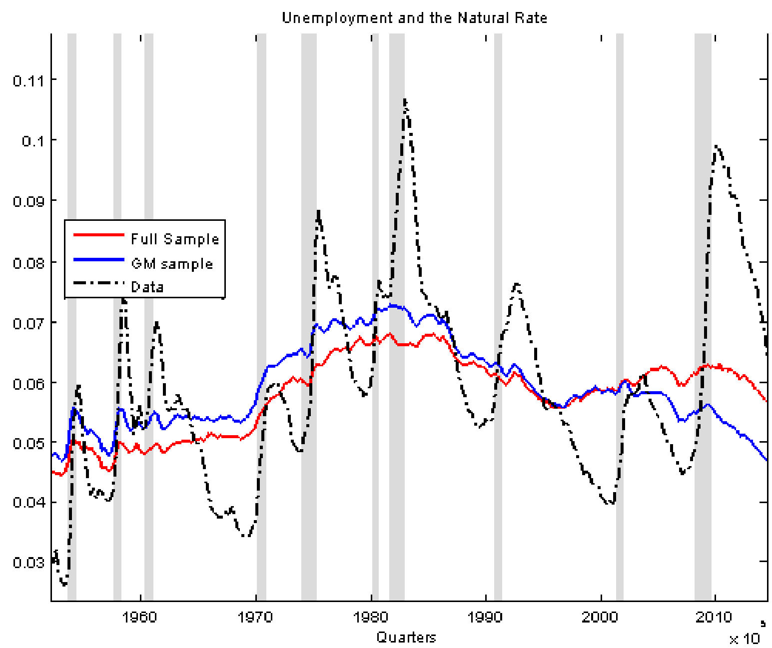

Figure 11: Unemployment rate and the estimated trend in the baseline model compared to the estimate based on the Great Moderation sample.

Table 2: Estimation Results: 1985:Q1-2014:Q2					
	Estimate			Estimate	
ϕ_1	1.6962	(0.0816)	θ_2	-7.0266	(1.8554)
ϕ_1	-0.7173	(0.0815)	θ_3	8.0199	(1.1560)
ρ_1	7.7564	(1.4201)	σ_{yn}	0.0040	(0.0003)
ρ_2	-7.3544	(2.1423)	σ_{fn}	0.0183	(0.0018)
ρ_3	9.5998	(1.5484)	σ_{sn}	0.0130	(0.0012)
θ_1	-1.2957	(1.1154)	L	1477.6	
Standard deviations are in ().					

The results suggest that the comovement between unemployment flows and real output might have changed the unemployment rate trend somewhat, especially in the last decade. As the parameter estimates in Table 2 show, the reason is not the muted response of the separation rates, but the more persistent nature of the job-finding rate.[15] As a result, the persistently low levels of job-finding rate after the Great Recession is now attributed to a smaller trend decline with a larger and persistent cyclical change. The difference at the end of the sample is about 3/4 percentage point, implying a natural rate of 4.7 percent as opposed to 5.6 percent in the baseline model.

6 Related Literature and the Case for the Flow Model

This section discusses the literature on the natural rate and makes a case for the flow model as a way to obtain it in an empirically useful and theoretically meaningful way.

6.1 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)[16]. 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 many 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), 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:

[15] Admitting lags for the outflow rates might be a more direct solution, but it is not feasible given the short sample size post-1985 and the challenge of trying to disentangle permanent changes from very-persistent but cyclical responses.

[16] 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).

> 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, 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 in the following subsection that, it 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)[17]. 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-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.[18]

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, including Shimer (2012), 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

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

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

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 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. 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.

6.2 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 D, 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, and will be susceptible to end of sample bias.

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).[19] The NAIRU estimation takes a simple form, relating the current inflation to lagged inflation and the 'unemployment gap' (Gordon (1997)).[20] For my measure of inflation I use

[19]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.

[20]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; $u_t^c = \theta_1 u_{t-1}^c + \theta_2 u_{t-2}^c + \varepsilon_u$.

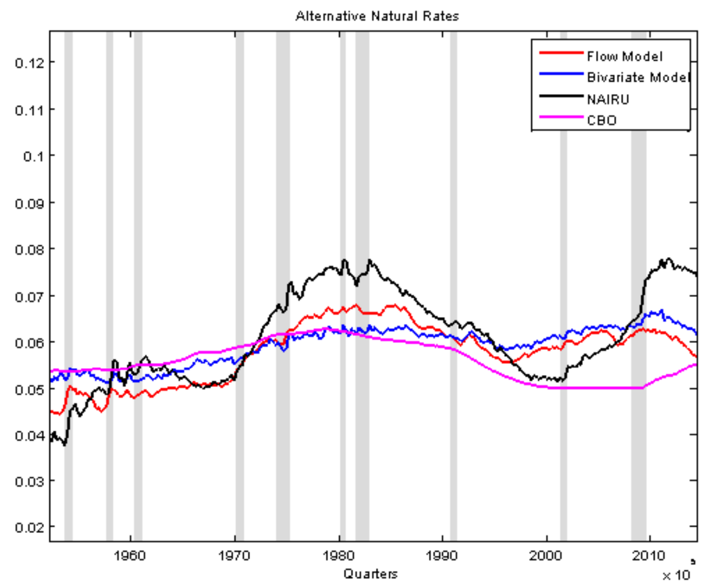

Figure 12: Three different estimates of the natural rate along with CBO's estimate.

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 for the unobserved trends in the flow rates. My comparison relies on these unobserved trends, which are interpreted as alternative natural rates.[21]

Figure (12) 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 (12) 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 5.5 percent (CBO measure) to 7.4 percent (NAIRU). The bivariate model puts the level of the natural rate at 6.1 percent relative to my preferred estimate from the flow model, 5.6 percent. All three empirical models predict an increase in the underlying rate prior to 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 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

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

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.

6.2.1 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 earlier, the difficulty of incorporating low-frequency changes in a structural labor search model and its well-known tendency to underpredict 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 modeling 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.

6.2.2 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

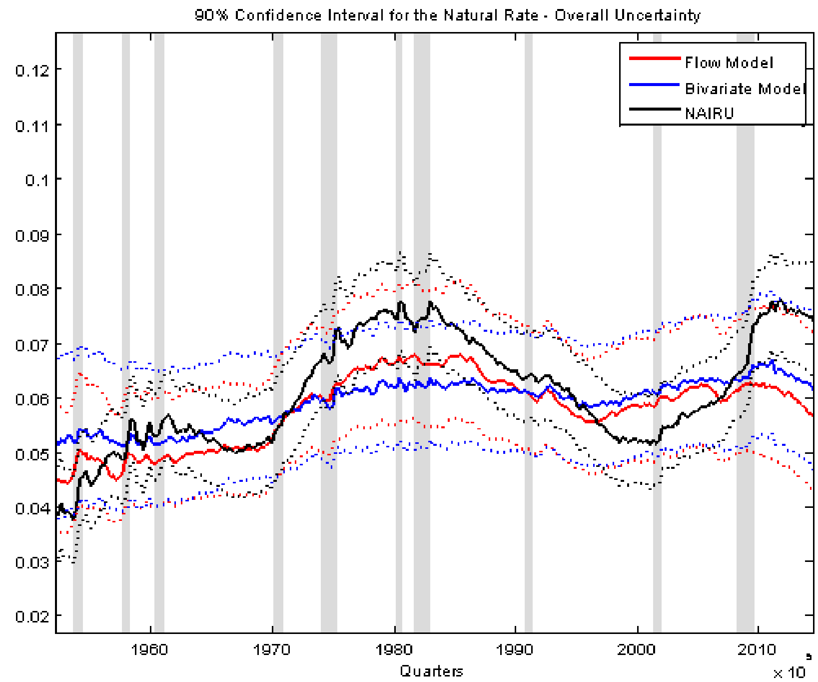

Figure 13: Flow model refers to the model expressed in equations (1)-(3). Lines indicated as Bivariate Model and NAIRU refer to the estimates from the models outlined above. Dashed lines correspond to the 90 percent confidence bands.

the unobserved state (unemployment's trend) in my model[22]. I compare the precision of my estimates with those estimated from a benchmark bivariate model, and a simple model of the NAIRU as outlined above.

Figure (13) 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 performs on par with other estimates. For instance, the width of the 90 percent confidence band implies, on average, a range of 2.40 percentage points around the mean estimate over time in the flow model (-0.98 and 1.43). The benchmark bivariate model performs virtually same, with a range of 2.39 percentage points around the mean estimate over time (-1.16 and 1.23). The NAIRU estimate I find produces a much smaller width of the confidence interval over time, on average 1.65 percentage point (-0.82 and 0.83). The standard deviation of the error band is also slightly smaller for the flow model relative to the bivariate model, 0.75 vs. 0.80 and is relatively larger to that of the NAIRU, 0.52. This better statistical precision for the NAIRU relative to the other two virtually disappears, if one ignores Great Recession episode. 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

[22] Details are available upon request.

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 similar to the one I presented above in section 4.1 and figure (17) in Appendix C. 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.	0.0631	0.0471	*0.0416*	*0.0297*	0.2023	0.2038
Std.	0.0705	0.0532	*0.0502*	*0.0368*	0.2432	0.2447

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 0.042 percentage points in the flow model when I include additional data covering the period after 2005:Q4, as opposed to 0.063 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 50 percent larger in the benchmark bivariate model and an order of magnitude larger for the NAIRU. Hence, I conclude that the framework based on unemployment flows is superior to alternative approaches used in the literature.

6.2.3 Policy Relevance

In practice, the natural rate attracts significant attention by 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 in understanding inflationary pressures. One might want to distinguish between an unemployment rate that is related to short-run fluctuations due to nominal rigidities and an underlying unemployment rate that would be converged to in the absence of these frictions. This is implicit in the concept of NAIRU. To the extent that those nominal rigidities are correlated with the aggregate cycle, the concept of the natural rate described in this paper can be quite helpful. Even though, I do not advocate this paper's framework and the natural rate estimate it implies as a substitute for NAIRU[23], I argue that it will be useful for policy makers to gauge what that underlying unemployment rate is. In fact, in a recent paper, Sengul and Tasci (2014) show that when inflation has a secular trend and some structural reasons leading its behavior (i.e. monetary policy independence or switching to inflation targeting), the presumed link between inflation and unemployment breaks down and is no longer informative about the labor market.

In general however, one might think that policy makers' interest stem from the motivation to pin down an inflation rate that is consistent with the prevailing labor market slack in the economy. Then one can argue that the ability to predict future inflation can be a good measure of the usefulness of the natural rate concept in question. Though the natural rate from the flow model 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 over-time with rolling windows.[24] 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 (14) 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.

There is at least one other reason why some policy makers are interested in a natural rate concept; to know where unemployment will stand once the cyclical fluctuations have disappeared. This issue gained new urgency as monetary policy makers are trying to formulate a better forward guidance in the midst of extraordinary policy challenges that led to the emergence of unconventional monetary policy tools. For instance, in September 2012, FOMC decided to tie its asset purchases to a "substantial improvement" in labor market conditions and in December 2012 made the tightening of the policy rate conditional on the level of the unemployment rate. In particular the statement read:

> ... In particular, the Committee decided to keep the target range for the federal funds rate at 0 to 1/4 percent and currently anticipates that this exceptionally low range for the federal funds rate will be appropriate at least as long as the unemploy-

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

[24]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.

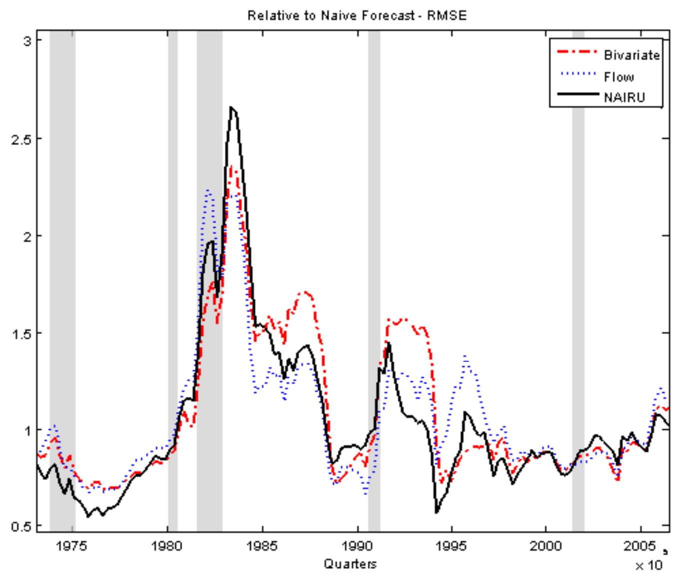

Figure 14: Root mean-squared errors for various forecasting models. Estimates from rolling regressions with 60 quarters of data and 20 quarters of forecast horizon.

> ment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored. - FOMC Statement, December 12, 2012.

Hence, the progression of the unemployment rate in the wake of a cyclical downturn became a central issue in the policy debate. I believe the flow model can be very useful for this objective too. In a recent paper, Barnichon and Nakerda (2012) shows that using worker 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. Following the same idea, in a recent study, Meyer and Tasci (2013) use the same flow model presented here to forecast the unemployment rate. They show that it is exceptionally better at the turning points, in particular after the recessions. In fact, the analysis in section 4.2, especially figures (5) and (6) exemplify this. Meyer and Tasci (2013) show that this good performance holds in every recovery episode since 1975, even with real time data.

Finally, 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 and over the last several years 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 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.[25] 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.

7 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. Using this framework, I show that this rate, at 5.6 percent by 2014:Q2, has been sligtly declining after the most recent recession, suggesting that the observed sharp increase in the unemployment rate does not reflect trend changes. The highly persistent nature of the unemployment early during the recovery, however, seems to be the result of countervailing effects of the flow rate trends. I also presented a simple decomposition of the unemployment rate dynamics both at low and high frequencies with my model, finding a non-trivial role for the separation rate at low-frequencies, especially prior to 1985.

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 much slower decline in the aftermath of rcessions than would have been possible with high churning, which was previously a distinguishing feature of US labor markets. Taken together, these two results suggest that even if the unemployment rate rised sharply due to *cyclical* factors, reducing it will take significantly longer due to the *structural* changes in the labor market that manifest itself as long-term declines in the unemployment flow rates. The results appear to be robust to the exclusion of the end of sample (Great Recession period) and the inclusion of participation channel. On the other hand, there is some evidence suggesting a changing labor

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

market dynamics vis a vis output fluctuations after 1985.

Understanding the actual structural changes that might have led to the observed changes in the trend 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[26]. Implementing the proposed natural rate estimation for different countries is also a potentially fruitful avenue for future research, as more quarterly data on inflow and outflow rates for unemployment come to light for different countries.[27]

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

[27] Several recent studies presented 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. Sengul and Tasci (2014), on the other hand, extended the model for Turkey.

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Appendix (Not intended for publication)

A Output Gap

The output gap in the model, $y_t = Y_t - \bar{y}_t$, is instrumental in identifying the cyclical components of the flow rates. Even though, the model in section 2 is rather a parsimonious and simple univariate approach, it produces a historical series for the output gap that is quite comparable to the more state-of-the art approaches. Fernald (2014) provides a very through discussion of the evolution of the output gap and compares various different approaches proposed in the literature. In figure (15), I present two of the measures from Fernald (2014); the one with TFP adjusted for model based utilization rates, and the one implied by the FRB/US model of the Federal Reserve Board. The CBO measure is based on the CBO's Potential GDP estimate. CBO and flow model estimates are adjusted to reflect the similar vintage for the measures from Fernald (2014). By the end of the sample in 2013, all measures, except the CBO indicate an output gap less than 3 percent. CBO stands out at 4.4 percent. Flow model generally follows the other measures, however, implies a smaller decline after the 2001 recession and a sharper recovery prior to the 2007 peak, with essentially no negative output gap until the Great Recession.

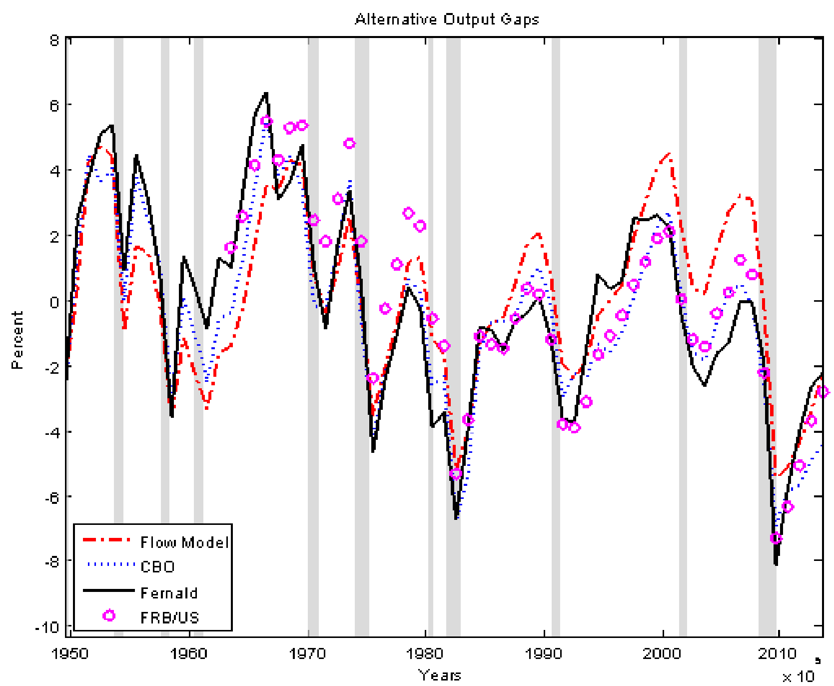

Figure 15: FRB/US output gap is from Fernald (2014).

B 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 8-quarter ahead root mean squared forecast error. 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.[28]. The objective here is to maximize the likelihood of the model while also getting a sensible prediction for the unemployment rate 2-yeasr forward. Figure (16) shows how these two moments change across γ_f, and γ_s.

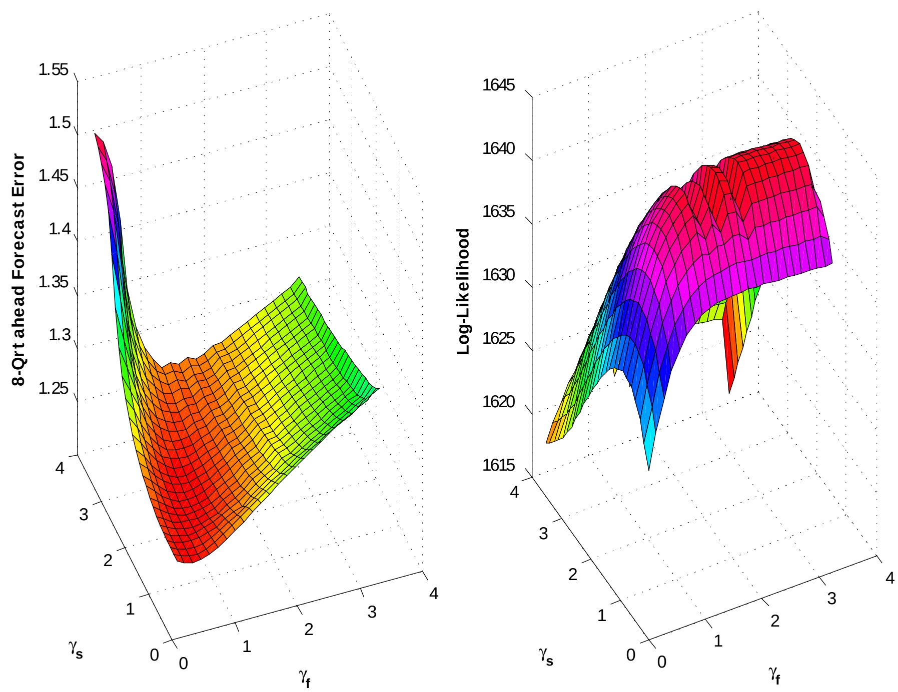

Figure 16: Left panel shows the 8-quarter ahead root mean squared forecast error, for different values of γ_f, and γ_s. Right panel shows the value of log-likelihood for different γ_f, and γ_s.

The preferred benchmark values maximize the objective of high log-likelihood and low forecast error, as is also clear in figure (16). For instance, I do not improve the likelihood of the model for higher values of γ_f, whereas smaller values result in substantial declines. The likelihood value seems more concave in γ_s, and the preferred value of 1.625 is very 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

[28]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.

covariance matrix as the weighting matrix.

C Great Recession and the Natural Rate

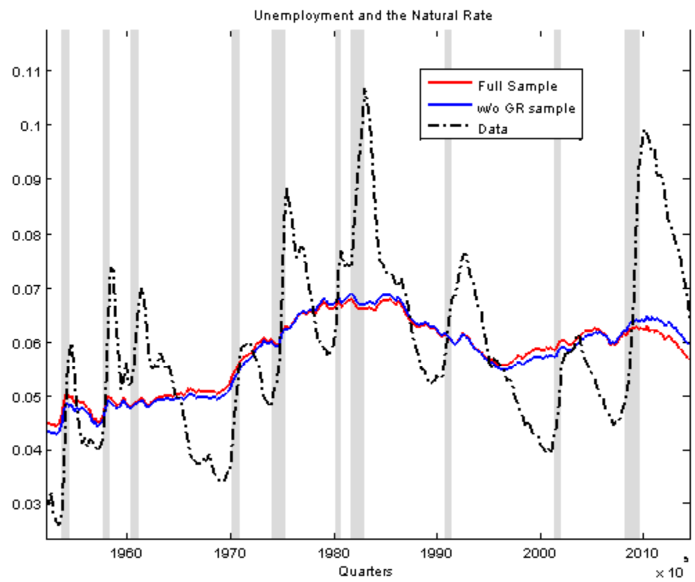

Figure 17: Unemployment and the natural rate in the baseline model relative to the model estimated without the Great Reecession.

D 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 (18) 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 underlying flows. As the upper panel of figure (18) shows, unemployment trends imputed this way

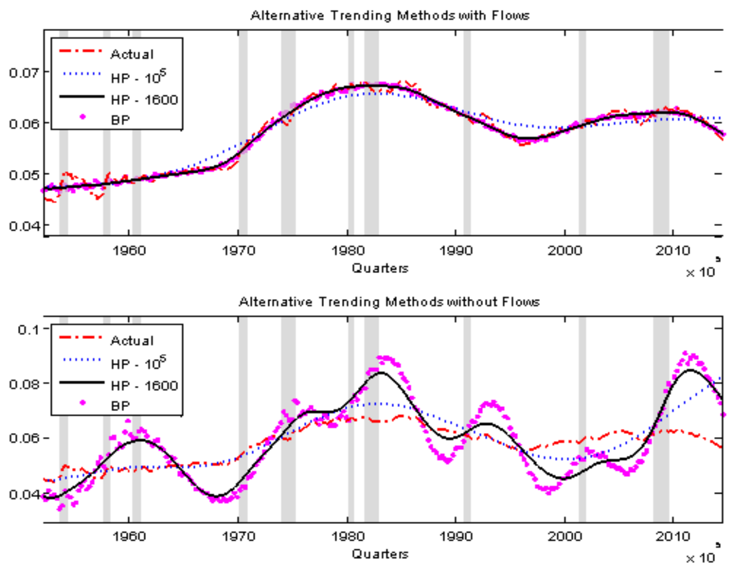

Figure 18: The upper panel presents unemployment rate trends imputed by different statistical filters on worker flow rates. The lower panel presents pure statistical trends based solely on unemployment rate data. The line labeled actual - displays our preferred version that is based on our model. We also use an HP-filter (with smoothing parameters 1600, and 10^5) as well as a bandpass filter (with parameters $(6, 32)$).

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.