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Running Title: IS THE NAIRU MORE USEFUL IN FORECASTING INFLATION THAN THE NATURAL RATE?

Abstract: Recent studies have indicated that the terms "NAIRU" (non-accelerating inflation rate of unemployment) and "natural rate of unemployment" are not interchangeable. While NAIRU is an empirical macroeconomic relationship estimated via a Phillips curve, the natural rate is an equilibrium condition in the labor market, reflecting the market's microeconomic features. This paper evaluates comparatively the inflation-forecasting power of alternative time-varying estimates of the natural rate of unemployment relative to the NAIRU. I estimate the natural rate of unemployment in the U.S. since World War II. Three alternative methods are utilized: the Kalman filter, a structural determinants approach, and the Hodrick-Prescott filter. In the section that follows, I assess how each estimator of the natural rate compares to the others—as well as to the NAIRU derived from a Phillips curve—in forecasting inflationary changes in the United States in the second half of the twentieth century. The analysis reveals that the overall inflation-forecasting utility of the natural rate of unemployment relative to the NAIRU is not very different. Moreover, the conclusion appears to be quite robust to various estimators of the natural rate.

I. INTRODUCTION

Recent studies correctly indicate that the terms "NAIRU" (non-accelerating inflation rate of unemployment) and "natural rate of unemployment" are not interchangeable. For example, Chang (1997) holds such a view and bases it upon the notion that unemployment-inflation tradeoffs may arise in more than one way. Espinosa-Vega and Russell (1997) go further than Chang and argue that the presence of two expressions for these similar concepts was born out of the interaction of the classical and Keynesian schools and the neoclassical synthesis.

Grant (2002) identifies NAIRU as an empirical macroeconomic relationship estimated via a Phillips curve, and the natural rate as an equilibrium condition in the labor market, reflecting the market's microeconomic features. Given this distinction, Grant employs Okun's Law to estimate a time-varying natural rate, and then examines the utility of the estimated natural rate series to forecast inflation relative to an estimated NAIRU series derived from a Phillips curve. Despite their theoretical and empirical differences, the two yield similar inflation-forecasting power.

While Okun's Law affords one avenue for estimating the natural rate of unemployment, it is not the only method for estimating the rate of unemployment consistent with equilibrium in the labor market. Hence, while Grant makes a key contribution toward assessing the relative utility of NAIRU and the natural rate in forecasting inflation, it is not clear whether Grant's conclusion is robust to alternative estimators of the natural rate of unemployment.

The purpose of this paper is to extend Grant's analysis to evaluate comparatively the inflation-forecasting power of alternative time-varying estimates of the natural rate of unemployment relative to the NAIRU. The analysis proceeds as follows. In the next section of the paper, I estimate three different time paths of the natural rate of unemployment in the U.S. since World War II. Three alternative methods are utilized: the Kalman filter, a structural determinants approach, and the Hodrick-Prescott filter. In the section that follows, I assess how each estimator of the natural rate compares to the others—as well as to the NAIRU derived from a Phillips curve—in forecasting inflationary changes in the United States in the second half of the twentieth century. The analysis indicates that Grant's result is robust to estimators of the natural rate of unemployment beyond Okun's Law. Following presentation and discussion of the results, I provide a few concluding comments.

II. ESTIMATION OF THE TIME PATH OF THE NATURAL RATE OF UNEMPLOYMENT

A. The Kalman Filter

1. *The Model*

The actual rate of unemployment, which is observed frequently and relatively easily, may be thought of as the sum of two distinct components. One component, the rate of cyclical unemployment, captures the unemployment associated with changes in business conditions. The other component, which I will refer to as the natural rate component, includes frictional as well as structural unemployment. Hence, at any given time *t*, this relationship may be expressed as

$$U_t = U_t^{NAT} + \beta_t, \tag{1}$$

where U_t is the observed actual unemployment rate, U_t^{NAT} is the natural rate of unemployment, and β_t is the rate of cyclical unemployment.

To complete the model, assumptions must be made regarding the evolution of both the natural rate and the cyclical rate. In their widely cited work,[1] Blanchard and Quah (1989) interpret fluctuations in output and unemployment as the result of two types of shocks: one that has a permanent impact, and one that does not. In Blanchard and Quah's view, shocks which exhibit a more permanent impact are shocks in supply: changes in technology or capital, oil disruptions, and baby booms. Such disturbances can alter the location of the long-run aggregate supply curve, simultaneously changing the level of full-employment output. Alternatively, demand shocks tend to be more ephemeral: autonomous changes in consumption or investment (Keynes's "animal spirits"), changes in foreign income, and fiscal and monetary policy changes. Moreover, demand shocks do not influence the location of the long-run aggregate supply curve and, therefore, do not influence the full-employment level of output.

Similarly, I introduce two disturbances to unemployment: one that has a temporary effect and one that is permanent. Again, it is helpful to regard the permanent disturbances as supply shocks that change the full-employment level of output, and the temporary disturbances as demand shocks that cannot change the full-employment level of output.

Specifically, I follow King, Stock, and Watson (1995), Staiger, Stock, and Watson (1997a), Gordon (1997 and 1998), Wieland (1998), Laubach (2001), and Apel and Jansson (1999a, 1999b) and assume that the natural rate of unemployment U_t^{NAT} follows a random walk. Further, I let the cyclical rate of unemployment β_t exhibit serial correlation; Apel and Jansson (1999a, 1999b) make the same assumption. Again, as in the work of Blanchard and Quah, shocks to cyclical unemployment are thought to be from the demand side, and limited in persistence.

Thus I incorporate the assumption that shocks to cyclical unemployment are temporary and that shocks to the natural rate of unemployment are permanent. Therefore, a given policymaker's best approximation to her stochastic environment may be characterized as:

$$U_t = U_t^{NAT} + \beta_t, \tag{1}$$

$$U_t^{NAT} = U_{t-1}^{NAT} + \varepsilon_t, \tag{2}$$

$$\beta_t = \rho\beta_{t-1} + \eta_{t,} \tag{3}$$

where ρ is between zero and one and where ε_t and η_t are independently distributed error terms with

$$\varepsilon_t \sim N(0,\sigma_\varepsilon^2), \qquad \eta_t \sim N(0,\sigma_\eta^2).$$

Observe that the use of independently distributed shocks permits the isolation of shocks to the cyclical rate of unemployment from shocks to the natural rate of unemployment. I specify the model in this fashion for two reasons. First, as stated above, I wish to follow as closely as possible the spirit of Blanchard and Quah's analysis. Second, for the decomposition of the unemployment rate that follows, it is helpful to maintain a clear dichotomy between the two sources of shocks. Of course, such a specification precludes the possibility of hysteresis in unemployment. That is, shocks to cyclical unemployment can never have an impact upon the natural rate of unemployment, and *vice versa*.

2. *Empirical Model Estimation*

The series of data that I use in order to estimate the natural rate of unemployment via the Kalman filter is the civilian unemployment rate taken from the Bureau of Labor Statistics's Current Population Survey. The data are annual, ranging from 1947 to 1998.[2]

The Kalman filter is useful in providing an optimal updating scheme for the unobservable natural rate of unemployment, and may be used to produce smoothed estimates of an unobservable series. Figure 1 depicts the unemployment rate series together with the estimated series of its underlying components from 1949 to 1998. The estimated natural rate appears fairly stable over the period. The analysis indicates that the natural rate was near five percent at the beginning of the period, rose to about six percent during the early 1980s, and then fell to a 1998 level of approximately 5.73%. Complete results are given in Table 1. Inspection of the resulting series indicates that the natural rate ranged from as high as 6.03% in 1983 to as low as 4.94% in the years 1951-52. Further observe that the highest estimated natural rate of 6.03% in 1983 closely corresponds to the highest level of unemployment in the period, 9.7% in 1982. Also of note are the years during which the analysis indicates that the unemployment rate lay below the natural rate of unemployment. These periods occur in 1951-57, 1964-70, 1973-4, 1979, 1988-90, and 1995-98.

Having generated an estimate of the natural rate of unemployment, it is logical to ask whether these estimates outperform other estimates in any way. Such issues are taken up in the following sections.

B. A Structural Estimator of the Natural Rate

1. *The Model*

As the previous section produced estimates of the natural rate via the Kalman filter, this section of the analysis generates an alternative to those estimates for use in the comparative evaluation taken up later in the paper. Specifically, in this section I adapt the technique of Adams and Coe (1990) to estimate the natural rate of unemployment in the United States using structural determinants. My estimation differs from that of Adams and Coe in two ways, however. First, instead of quarterly data, I use annual data. Second, while Adams and Coe conduct their analysis for the period 1965 to 1988, my sample period is considerably longer: 1948-1996. The reason the sample period does not extend further forward is due to the fact that the data series representing the unemployment insurance replacement ratio are not yet available beyond 1996 at the time of this writing.

Following directly Adams and Coe, the regression equation for the demographically adjusted unemployment rate at time t, U_t, has the following form:

$$U_t = k + \phi_1(y_t - y_t^{tr}) + \phi_2 NWLC_t + \phi_3 UIRR_t + \phi_4 SL_t RMW_t + \phi_5 UNN_t + \tau_t, \qquad (4)$$

where y_t is real GDP at time t; y_t^{tr} is trend real GDP at time t; RMW_t is the relative minimum wage, calculated as the ratio of the minimum wage to the average hourly wage; SL_t is the share of the labor force aged 16-24; UNN_t represents union membership as a percentage of nonagricultural unemployment; $NWLC_t$ is employers' contributions for Social Security and pension funds as a percentage of total wages and salaries; and $UIRR_t$ is the unemployment insurance replacement ratio, calculated as the ratio of the average weekly unemployment insurance benefit to the average weekly wage in covered employment.

The expected signs of the estimated coefficients on all of the structural variable terms are positive. As the GDP gap term represents actual GDP less trend GDP, the predicted sign of the estimated coefficient is negative. Adams and Coe (1990) and Coe (1990) both obtain the predicted signs in all cases. However, significance of the regression coefficients varied widely across the studies and alternative specifications.

2. *Data and Estimation*

Unemployment rate and labor force data are taken from the Bureau of Labor Statistics's Current Population Survey. Real GDP data are from the Survey of Current Business. RMW_t is the ratio of the minimum wage to the average hourly earnings of production workers; average earnings data are from the Bureau of Labor Statistics. SL_t is calculated directly from Bureau of Labor Statistics labor force data.

Unfortunately, unionization data have not been collected consistently by the same collector throughout the period. Hence, the series is constructed from several sources. Ashenfelter and Card (1986) supply data for the following years that had been missing prior to their study: 1971, 1973, 1975, 1977, and 1982. The data point for 1979 and data for 1990 and 1996 are from the Bureau of Labor Statistics and from the *Statistical Abstract of the United States*, respectively. The data point for 1981 is linearly interpolated from surrounding data; all other UNN_t data are from Kurian (1994).[3] $NWLC_t$ is calculated as total employee compensation less wage and salary accruals as a percentage of wage and salary accruals, the same calculation used by Adams and Coe; data are from the Survey of Current Business. $UIRR_t$ is the ratio of the average weekly unemployment benefit amount to the average weekly total wage in taxable and reimbursable unemployment; data are from the Department of Labor's Employment and Training Financial Data Handbook 394.

Defining y^{tr} as a linear trend,[4] initial estimation of equation (4) suggests, according to the Durbin-Watson statistic, the presence of first-order serially correlated errors. As Adams and Coe test alternative specifications of the model in order to purge any impure serial correlation, testing alternative specifications here appears redundant and, further, beyond the scope of the present analysis. Hence, I use Beach and MacKinnon's (1978) estimation method to correct for the serial correlation. Estimation of the model incorporating the AR(1) correction, and then assuming that the cyclically neutral output gap is zero, yields the following structural equation for the natural rate of unemployment:

$$\hat{U}_t^{NAT} = -10.712 + 0.130 NWLC_t + 40.654 UIRR_t - 5.262 SL_t RMW_t + 0.053 UNN_t. \qquad (5)$$

Equation (5) may then be employed to generate an estimated time series for the natural rate of unemployment over the sample period. The resulting estimated series of the natural rate appears in Figure 2. In the figure I also include the actual unemployment rate series, unadjusted for labor market shares.

The maximum estimated natural rate of unemployment under the structural approach occurs in 1982, when the estimate rises to 8.0%. The lowest estimated natural rate is 4.4% in 1951.

C. The Hodrick-Prescott Filter

In a well-known 1981 working paper—more recently published in the *Journal of Money, Credit, and Banking*—Hodrick and Prescott (1997) present a method of decomposing a time series into two components: a smooth trend component and a cyclical component. Such a decomposition procedure is especially amenable to the problem of estimating the natural rate due to the cyclical and noncyclical composition of the actual rate of unemployment mentioned earlier. If the Hodrick-Prescott filter can provide a decomposition of the actual unemployment rate into its cyclical and noncyclical components, then the noncyclical series that results is an estimate of the natural rate of unemployment.

I apply the filter to the 1947-1998 annual unemployment rate series; the resulting natural rate series appears in Figure 3. The highest estimated natural rate using the Hodrick-Prescott filter is 7.6%, which occurs in 1983. The lowest estimated natural rate is in 1947, when the natural rate is estimated to be 4.1%.

III. COMPARATIVE EVALUATION OF NATURAL RATE ESTIMATORS

As Grant (2002) indicates, estimates of the NAIRU are derived from estimation of a Phillips curve. The purpose of this section is to evaluate such Phillips curve estimates of the NAIRU relative to the aforementioned time-varying estimates of the natural rate of unemployment in terms of their inflation-forecasting utility. To make this possible, the one-step-ahead inflation forecasting power of the NAIRU will be assessed and compared to that of natural rate estimates derived from the Kalman filter, the Hodrick-Prescott filter, and the structural determinants method. In all cases, the Phillips curve is used as the forecasting equation.

The importance of such testing lies in the fact that monetary policy does not consist of evaluating the overall fit of an equation during some past sample period. Instead, policymakers must make forecasts upon which policy actions will be founded.

A. Phillips-Curve Estimation of the NAIRU

I employ a variant of the Phillips curve estimated by Roberts (1995). The general form is

$$\pi_t - \pi_t^e = c_0 - \lambda(U_t - U^{NAT}) + c_1 \Delta rpoil_t + c_2 \Delta rpoil_{t-1} + \mu_t, \tag{6}$$

where π_t is the rate of inflation, π_t^e is the expected rate of inflation, U_t is the unemployment rate, U^{NAT} here is the NAIRU, and λ is a parameter greater than zero. Like Roberts, I include a role for oil price shocks. Since the oil price shocks of the 1970s and early 1980s, economists have realized that the Phillips curve should include supply shocks (Mankiw 2000, p. 365). Hence, again following Roberts, $rpoil_t$ represents the real price of crude petroleum. Two measures of expected inflation are considered: one-period lagged inflation and the 12-month-ahead Livingston survey prediction of the inflation rate.[5]

While the preceding specification can work quite nicely in conducting in-sample estimation, a problem arises if one wishes to conduct out-of-sample forecasting of inflation. Observe that the preceding specification contains as explanatory variables the unemployment rate at time *t* and the real change in oil prices at time *t*, while the dependent variable is measured at time *t* as well. Hence, forecasting inflation changes via the expression above becomes problematic as next period's inflation rate cannot be predicted if the value of a key independent variable—the unemployment rate—is not known for next period either. To address this problem, I employ standard univariate time series forecasting techniques to generate forecasts of both oil prices and the unemployment rate.

Using a recursive least-squares procedure similar to that of Staiger, Stock, and Watson (1997b), I estimate equation (6) beginning with the first third of the entire sample period of 1947-1998. The estimated coefficients are saved and used in conjunction with the forecasts of the unemployment rate and the change in oil prices in order to forecast inflation for the following year. This is done for each year, with increasing sample size. In each year, the forecast of inflation is compared to the actual inflation rate, and the resulting forecast error is saved. As there are no lagged values of the dependent variable appearing on the right-hand side of the regression equation, calculation of the inflation forecasts is relatively straightforward.

Note that any possible multicollinearity between the two differenced oil price terms is not perfect since the coefficients on those terms change with each new regression. Also, the variation in those coefficients is not nearly as important here as the combined impact of those two terms.

I generate one-step-ahead forecasts of inflation twice, once using the Livingston data in place of the expected inflation term, and once using the lagged inflation rate. Their inclusion here amounts to a policymaker's incorporating such information in generating her forecast of inflation. I consider only the period ending in 1997 in order to match the latest possible forecast date using the data series from the structural method. After generating the forecasts, I calculate the root mean square forecast error.

Note that, for the purpose here of forecasting inflation, it is not necessary to know an explicit estimate of the NAIRU for each subperiod. To see this, simply rearrange equation (6) to form the regression equation

$$\pi_t - \pi_t^e = k - \lambda U_t + c_1 \Delta rpoil_t + c_2 \Delta rpoil_{t-1} + \mu_t, \tag{6a}$$

where

$$k = c_0 + \lambda U^{NAT}.$$

B. Kalman-Filter Estimation of the Natural Rate

Using estimates of the natural rate of unemployment via the Kalman filter to forecast inflation has several advantages over the recursive least squares technique given in the preceding section. First, even under a recursive least squares process such as that described above, least squares—by definition—yields only an estimate of the NAIRU that may be thought of as an average of the NAIRU over the period or subperiod being considered. Hence, while the estimate of the NAIRU is being updated with each new observation, least squares estimates give equal weight to data from 1957 and from 1997.

In contrast, the Kalman filter gives greater weight to more recent observations than to those made long ago in the dynamic framework, producing a time-varying estimate of the natural rate of unemployment. Thus the Kalman filter arguably uses information in a superior fashion than does the recursive least squares setting.

A second advantage of Kalman filter estimates of the natural rate in a forecasting context lies in the ability of the Kalman technique to provide forecasts of next period's actual and natural unemployment rates. Recall that the Kalman filter process generates one-step-ahead forecasts of the unobserved components prior to next period's observation. In fact, it is by comparing these forecasts to the eventual observation that the Kalman filter evaluates and updates itself. Since the Kalman filter does indeed give a prediction of next period's actual and natural unemployment rates, forecasting in a Phillips curve context becomes considerably more straightforward. Whereas the recursive technique used in the preceding section employed univariate time series techniques to forecast U and $\Delta rpoil$, Kalman forecast values of both the actual and natural rates of unemployment may now be included in the forecasting equation, although time series forecasts of the real change in petroleum prices must continue to be used.

Forecasting one-period-ahead inflation hence consists of first estimating

$$\pi_t - \pi_t^e = c_0 - \lambda(U_t - \hat{U}_t^{NAT}) + c_1 \Delta rpoil_t + c_2 \Delta rpoil_{t-1} + \mu_t, \tag{6b}$$

where $\hat{U}_t^{NAT}$ represents the estimate of the natural rate at time t yielded by the Kalman filter, beginning with the first one-third of the sample. The subsequent step requires generating a forecast of inflation for the following period using the estimated parameters, actual values of the independent variables, and the *forecast* values of the actual and natural rates of unemployment, as well as the univariate forecast of $\Delta rpoil$. The resulting inflation forecast is compared to actual inflation, the forecast error is calculated and saved, and this technique is repeated on a rolling basis with increasing sample sizes. Note that the coefficients in the regression equation are re-estimated each time. As before, the root mean squared error is calculated. Again both lagged inflation and Livingston expectations are used in place of the π_t^e term.

C. Hodrick-Prescott Filter and Structural Estimation of the Natural Rate

In addition to the Kalman filter estimates of the natural rate and NAIRU estimates gleaned from a Phillips curve, I also consider whether the estimates of the natural rate that follow from the Hodrick-Prescott filter and those arrived at via the structural method of Adams and Coe may prove superior to either of the others in forecasting one-period-ahead inflation. As in the Kalman filter case described in the preceding section, forecasts of the one-step-ahead unemployment rate, the one-step-ahead natural rate, and the one-step-ahead real oil price growth rate are needed in order to produce one-step ahead forecasts of the dependent variable.

In the Hodrick-Prescott filter case, and again beginning with the first third of the sample, the Phillips curve in (6b) is estimated with the Hodrick-Prescott estimated natural rate time series—rather than the Kalman estimates—included as a regressor. Once the Phillips curve coefficients have been estimated, one-step-ahead forecasts of the unemployment rate, the natural rate, and the growth rate of real oil prices are again required in order to predict the future value of the dependent variable. In the cases of oil prices and the unemployment rate, I again use the univariate time series forecasts described earlier. To predict the natural rate estimate that the Hodrick-Prescott filter would produce one period into the future, I simply run the Hodrick-Prescott filter over the series consisting of the observed unemployment rates up to the current period, with the one-step-ahead univariate time-series forecast of the unemployment rate tacked onto the end of that series. Once the filter has been run, I utilize the final point in the filtered series as the one-step-ahead forecast of the natural rate estimate that the HP filter might produce. After making the appropriate substitutions into the estimated Phillips curve equation, the resulting inflation forecast is compared to actual inflation, the forecast error is calculated and saved, and this technique is repeated on a rolling basis with increasing sample sizes. As before, the root mean squared error is calculated. Again both lagged inflation and Livingston expectations are used in place of the π_t^e term. The root mean square errors for both the lagged inflation and the Livingston data cases are again calculated.

For the case of Adams and Coe's structural method, recall that the structural method generates estimates of actual and natural unemployment rates as a function of certain structural variables such as the relative minimum wage and the percentage of the labor force that is unionized. Consequently, all that is required in order to forecast the unemployment rates is to estimate the structural equation using data through the present period and again make use of univariate time series forecasts—this time of the structural determinants. Substituting such forecasts into the estimated structural equation yields forecasts of the unemployment rates which may then be substituted into an estimated version of the Phillips curve given in (6b). Root mean squared errors are again calculated incorporating either lagged inflation or Livingston survey information.

D. Results

In light of the superiority of the way in which the Kalman filter incorporates new information, one might reasonably wonder whether the Kalman filter might produce one-step-ahead errors that fall at a faster rate than those yielded by the other estimators so that the forecast errors given by the Kalman filter method are relatively large early in the analysis but relatively small later.

In order to gain insight into this possible superiority of the Kalman filter in forecasting inflation, again consider the differences between estimates of the NAIRU derived from a Phillips curve and the natural rate estimates produced by the Kalman filter. In a recursive least squares context, the Phillips curve delivers a slightly updated estimate of the natural rate each time new information becomes available. However, the updated value is arrived at by giving equal weight to all observations—including the new observation. For example, in modifying the estimated NAIRU as new data become available for 1997, the recursive least squares techniques give equal weight to the new observation, the prior year's observation, and the observation from, for example, 1953. In doing so, the technique ignores anything the policymaker might know about how the NAIRU may evolve over time.

The Kalman filter, on the other hand, gives more weight to more recent observations. Further, the Kalman filter lets the policymaker refer to her presuppositions about how the natural rate may evolve over time. Moreover, inasmuch as the Kalman filter constitutes a learning process, one might expect that forecast errors would be larger in the earlier stages of observation, estimation, and prediction than in later periods. That is, since the policymaker in the Kalman setting learns from past mistakes, her mistakes will, on average, grow smaller over time. Consequently, the mean forecast error may be relatively large due to larger errors quite early in the learning process, but grow quite small as learning continues. Therefore, it is indeed possible that while the mean forecast errors for the Kalman filter are larger than those yielded by other estimators, actual forecast errors for the Kalman filter become smaller in later periods. In fact, forecast errors for the Kalman filter might even grow smaller than other forecast errors given sufficient time for the policymaker to learn about her stochastic environment.

To investigate this possibility, I calculate the root mean squared forecast error for each of the forecasts, but do so over different intervals. The shortest interval includes only 1997, the next includes 1997 and 1996, the next includes 1997-95, and so forth. One would expect that the average forecast error becomes larger as the period becomes longer. The resulting series are plotted in Figures 4 and 5. Figure 4 consists of the forecasts that incorporate the Livingston data, and Figure 5 consists of the forecasts that incorporate lagged inflation.

Unsurprisingly, the mean forecast errors of all equations and estimates of the natural rate grow larger as the period lengthens to include earlier and earlier years. Further, in the case of forecasts incorporating the Livingston forecast of inflation, there is little variation in the root mean square error of the forecasts associated with the Kalman filter. However, it is the Hodrick-Prescott filter estimates of the natural rate that appear to produce the smallest RMSEs. While there is considerably more variation in the forecast errors associated with the equations incorporating lagged inflation rather than those incorporating the Livingston information, the natural rate estimates following from the Hodrick-Prescott filter again appear superior in forecasting.

Since the series correspond so closely in Figures 4 and 5, Table 2 contains the RMSE values underlying the figures. Under both the Livingston and lagged-inflation versions, the lowest RMSE of the four estimators for each subperiod is given in **bold**. In the Livingston case, the Hodrick-Prescott filter yields the lowest RMSE for all but one subperiod. In the case of lagged-inflation, however, the results are considerably more varied. While the Hodrick-Prescott filter again yields the lowest RMSE for the longest subperiod, the Kalman filter has the lowest RMSE for the period beginning immediately following the first OPEC oil embargo. The Phillips curve appears to provide the lowest RMSE for the forecasts from the second OPEC price hike forward. The structural determinants method is best only from the recession of the early 1990s forward.

Examination of Table 2 reveals several additional points of interest. First, evidence regarding the usefulness of the Livingston data is unclear. While incorporating the Livingston survey information yielded a larger average forecast error, the differences were only slight. Hence, it is unclear whether policymakers would do well to consider the Livingston data in formulating their inflation forecasts. The Livingston survey forecast of inflation may contain information regarding future inflation beyond that given by oil price shocks and unemployment rates alone, but that is unclear in the present analysis.

Second, no single estimator—NAIRU or otherwise—appears to enjoy an advantage when the average forecast error is considered over the entire out-of-sample forecasting period. In fact, the root mean squared errors are nearly identical across all estimators, with the only exception being the slightly smaller RMSE for the HP estimator in the specification incorporating lagged inflation. Hence, no estimator appears superior.

Finally, recall that forecasting inflation via the Phillips curve required no specific knowledge of the NAIRU implicit in the regression equation given in (6a). Thus it appears that, no matter which estimate of the natural rate of unemployment one employs, such estimates add no value in forecasting inflation.

IV. CONCLUSION

This paper considers how well various estimators of the natural rate of unemployment perform in their ability to forecast inflation in a future period relative to the NAIRU. Specifically, a Phillips-curve is used to estimate NAIRU; following Staiger, Stock, and Watson (1997b), recursive least squares is applied to a Phillips curve in order to estimate NAIRU and to generate one-step-ahead predictions of inflation. The forecast errors at each step are saved and the root mean squared forecast error is calculated.

Alternatively, the Kalman filter, the Hodrick-Prescott filter, and a structural determinants method are used to estimate the natural rate of unemployment. These estimates are then *substituted* into the Phillips curve to be estimated. In order to simulate the real-time forecasting problem faced by a policymaker, the Phillips curve is estimated on a rolling basis using each estimator of the natural rate. One-step-ahead inflationary forecasts are generated and saved; the root mean forecast error is calculated.

The analysis reveals that the overall inflation-forecasting performance of all estimators of the natural rate of unemployment relative to the NAIRU forecasts is not very different. This result provides additional support for the claim by Grant (2002) that the NAIRU offers no better utility in inflation forecasting than does the natural rate. Moreover, the present analysis—in examining three estimators of the natural rate beyond Okun's Law—confirms this hypothesis in a more exhaustive manner. As a result, the hypothesis appears to be quite robust to various estimators of the natural rate. An additional degree of robustness might be attained via examination of the hypothesis using data from nations other than the United States.

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Year	Unemployment Rate (%)	Smoothed Estimates: Natural Rate (%)	Smoothed Estimates: Cyclical Rate (%)	Year	Unemployment Rate (%)	Smoothed Estimates: Natural Rate (%)	Smoothed Estimates: Cyclical Rate (%)
1949	5.9	4.99	0.91	1974	5.6	5.66	-0.06
1950	5.3	4.98	0.31	1975	8.5	5.79	2.71
1951	3.3	4.94	-1.64	1976	7.7	5.80	1.90
1952	3.0	4.94	-1.94	1977	7.1	5.82	1.28
1953	2.9	4.96	-2.06	1978	6.1	5.81	0.29
1954	5.5	5.06	-0.43	1979	5.8	5.83	-0.03
1955	4.4	5.06	-0.66	1980	7.1	5.90	1.20
1956	4.1	5.07	-0.97	1981	7.6	5.94	1.66
1957	4.3	5.11	-0.81	1982	9.7	6.02	3.68
1958	6.8	5.22	1.58	1983	9.6	6.03	3.57
1959	5.5	5.20	0.30	1984	7.5	5.96	1.54
1960	5.5	5.23	0.27	1985	7.2	5.95	1.25
1961	6.7	5.29	1.41	1986	7.0	5.94	1.06
1962	5.5	5.28	0.22	1987	6.2	5.91	0.29
1963	5.7	5.30	0.39	1988	5.5	5.87	-0.37
1964	5.2	5.31	-0.11	1989	5.3	5.86	-0.56
1965	4.5	5.31	-0.81	1990	5.6	5.86	-0.26
1966	3.8	5.31	-1.51	1991	6.8	5.89	0.91
1967	3.8	5.34	-1.54	1992	7.5	5.90	1.59
1968	3.6	5.36	-1.76	1993	6.9	5.87	1.03
1969	3.5	5.39	-1.89	1994	6.1	5.83	0.27
1970	4.9	5.48	-0.58	1995	5.6	5.80	-0.20
1971	5.9	5.55	0.35	1996	5.4	5.78	-0.38
1972	5.6	5.58	0.02	1997	4.9	5.75	-0.85
1973	4.9	5.60	-0.70	1998	4.5	5.73	-1.23

Table 1. *Actual Unemployment Rates and Smoothed Natural Rate Estimates, 1949-1998*

	Livingston				Lagged Inflation			
	Kalman	*Structural*	*HP*	*Phillips Curve*	*Kalman*	*Structural*	*HP*	*Phillips Curve*
1966	0.029995	0.030276	**0.029699**	0.030061	0.025018	0.024762	**0.023636**	0.025291
1967	0.030449	0.030735	**0.030141**	0.030514	0.025378	0.025116	**0.023997**	0.025659
1968	0.030948	0.031238	**0.030638**	0.031013	0.025631	0.025369	**0.024208**	0.025927
1969	0.031456	0.031726	**0.031151**	0.031521	0.026053	0.025802	**0.024558**	0.026357
1970	0.032003	0.032279	**0.031680**	0.032072	0.026402	0.026163	**0.024743**	0.026735
1971	0.032590	0.032868	**0.032260**	0.032659	0.026676	0.026516	**0.024795**	0.027062
1972	0.033151	0.033472	**0.032791**	0.033219	0.027142	0.027019	**0.025106**	0.027532
1973	0.033681	0.033978	**0.033302**	0.033751	0.027679	0.027531	**0.025603**	0.028077
1974	0.034354	0.034646	**0.033960**	0.034423	0.028195	0.027993	**0.026062**	0.028590
1975	0.034610	0.034899	**0.034176**	0.034677	0.027232	0.027103	**0.025194**	0.027675
1976	0.014453	0.014387	**0.012561**	0.015112	**0.017322**	0.018346	0.018258	0.017590
1977	0.014630	0.014641	**0.012780**	0.015095	**0.017528**	0.018190	0.018349	0.017785
1978	0.014899	0.014941	**0.012969**	0.015429	0.017425	0.018036	**0.017119**	0.017480
1979	0.014982	0.015052	**0.012965**	0.015630	**0.017391**	0.018127	0.017552	0.017442
1980	0.015137	0.015217	**0.013079**	0.015889	0.017531	0.018289	0.018006	**0.017419**
1981	0.015059	0.015119	**0.013093**	0.015918	0.016669	0.017597	0.017913	**0.016077**
1982	0.014574	0.014269	**0.012700**	0.015480	0.017182	0.018086	0.018330	**0.016507**
1983	0.014423	0.014062	**0.012619**	0.015374	0.013597	0.014966	**0.012016**	0.013005
1984	0.014899	0.014034	**0.012948**	0.014411	0.014056	0.014398	**0.010082**	0.013355
1985	0.012846	0.013540	**0.011581**	0.014107	0.014314	0.014832	**0.008760**	0.013838
1986	0.012931	0.014047	**0.011840**	0.014568	0.011866	0.009860	**0.008548**	0.011388
1987	0.013403	0.014664	**0.012277**	0.015204	0.011796	0.009913	**0.008928**	0.011065
1988	0.013625	0.014269	**0.012655**	0.014066	0.009850	0.009687	**0.008261**	0.010108
1989	0.011517	0.012254	**0.010988**	0.012134	0.009243	0.008545	**0.008350**	0.008717
1990	0.012211	0.012997	**0.011643**	0.012869	0.007586	0.006085	0.006390	**0.006052**
1991	0.011876	0.012510	**0.011489**	0.012487	0.007956	**0.006436**	0.006830	0.006445
1992	0.012234	0.012585	**0.011851**	0.012781	0.008319	**0.006243**	0.007373	0.006958
1993	0.012646	0.012957	0.012704	**0.012635**	0.008768	**0.006640**	0.006728	0.007317
1994	0.013539	0.014304	**0.013285**	0.013974	0.009461	**0.007214**	0.007314	0.008098
1995	0.015597	0.016516	**0.015281**	0.016127	0.005923	0.004780	**0.004395**	0.004947
1996	0.017708	0.019134	**0.017151**	0.018715	0.006356	0.004323	**0.004250**	0.004359
1997	0.021795	0.023472	**0.020959**	0.023219	0.008978	0.005918	0.005024	**0.004258**

Table 2. *Root Mean Square Error of Four Estimators of the NAIRU over Different Subperiods*

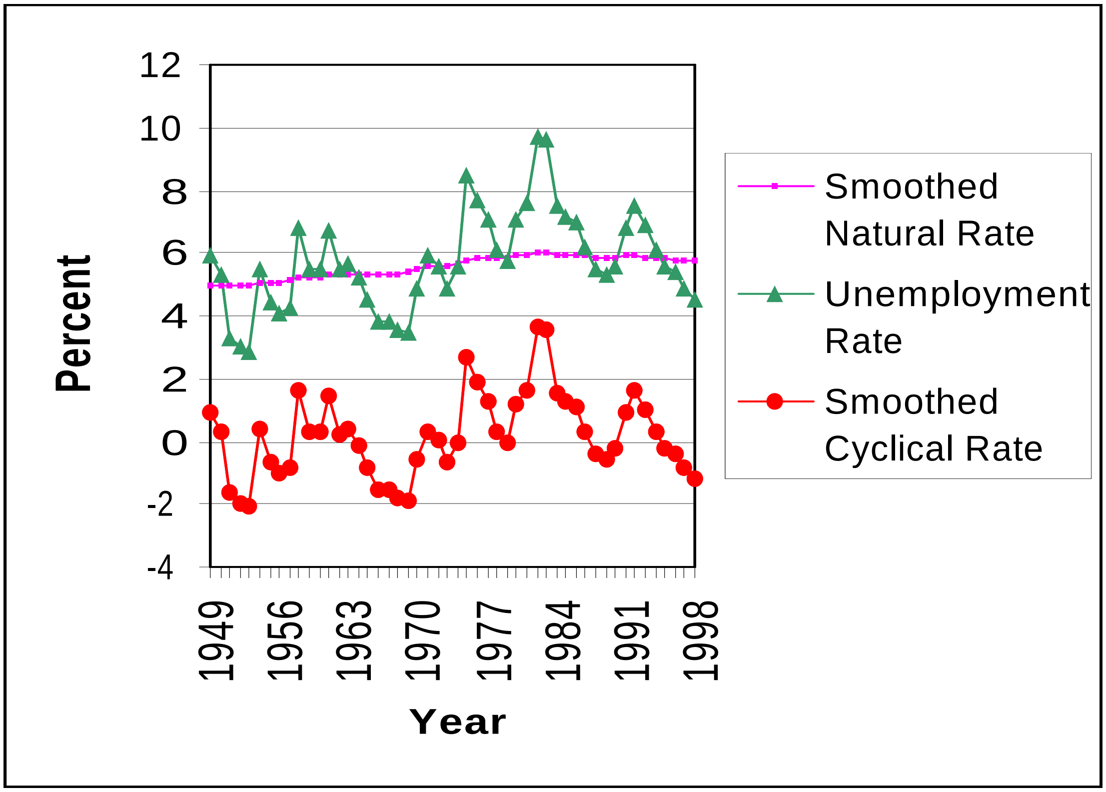

Figure 1. *The Unemployment Rate and the Smoothed Estimates of the Natural Rate and Cyclical Rate, 1949-1998*

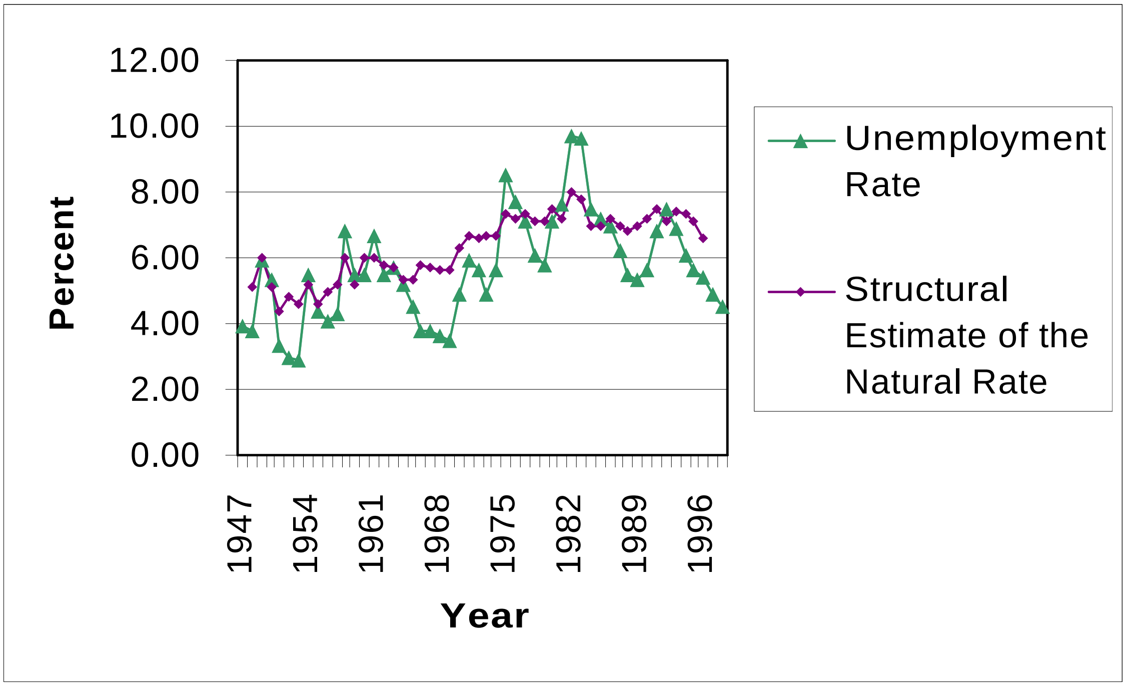

Figure 2. *The Unemployment Rate and the Structural Estimate of the Natural Rate of Unemployment, 1948-1996*

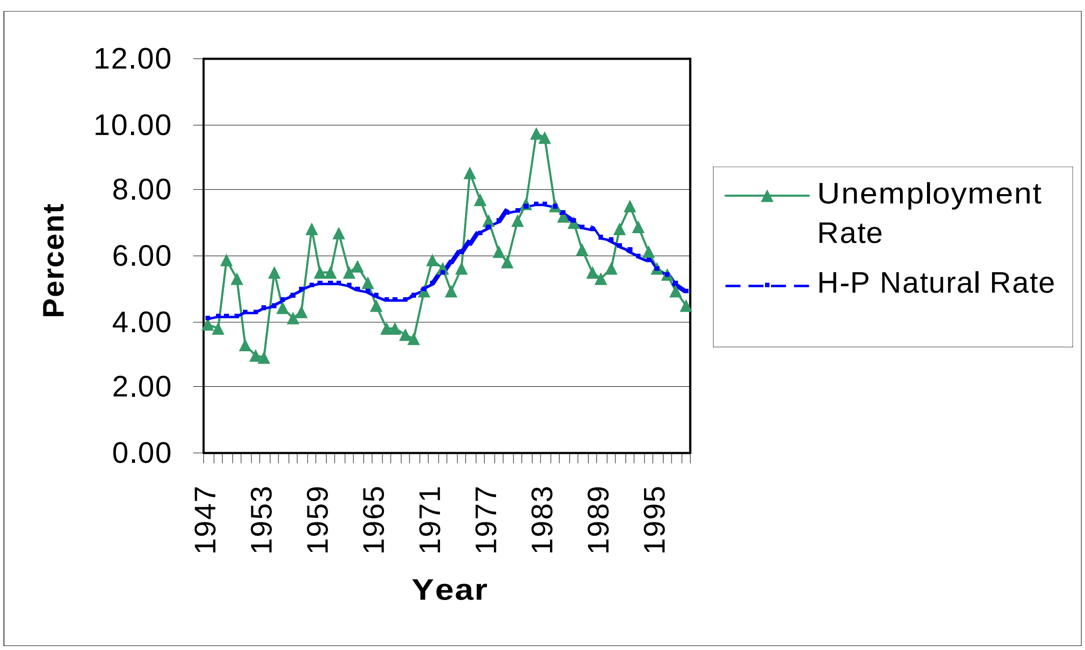

Figure 3. *The Unemployment Rate and the Hodrick-Prescott Filter Estimate of the Natural Rate of Unemployment, 1947-1998*

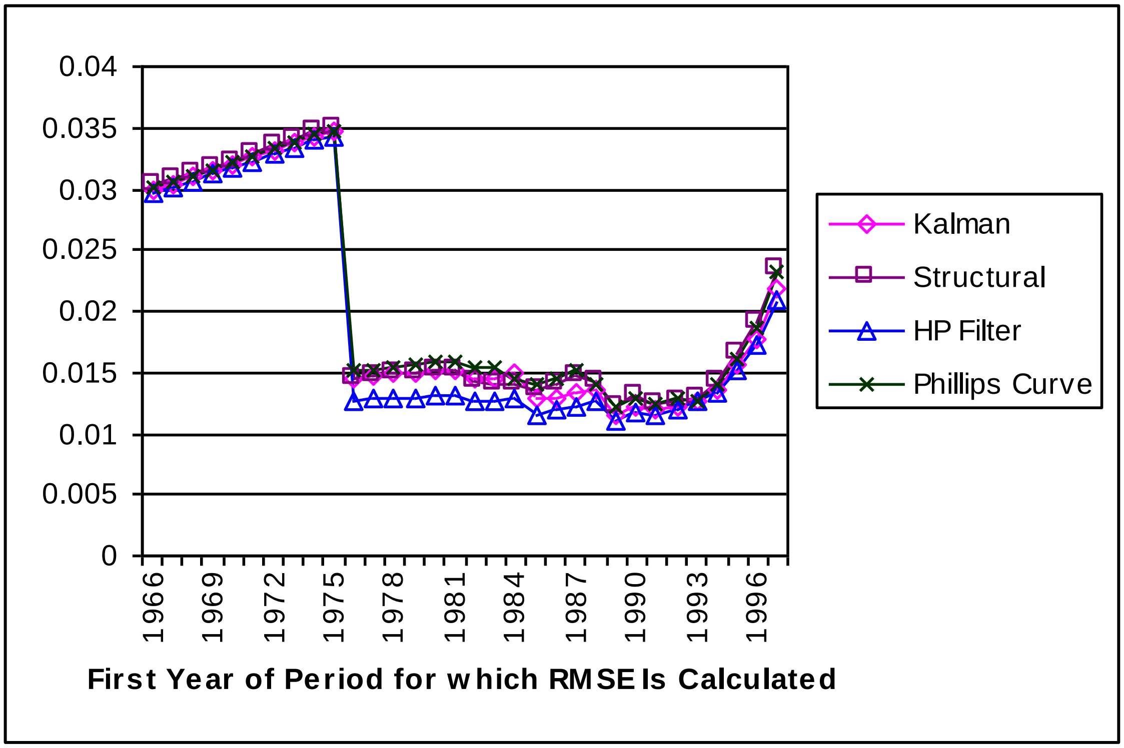

Figure 4. *Root Mean Square Error of Four Estimators of the NAIRU over Different Subperiods, Incorporating the Livingston Forecast*

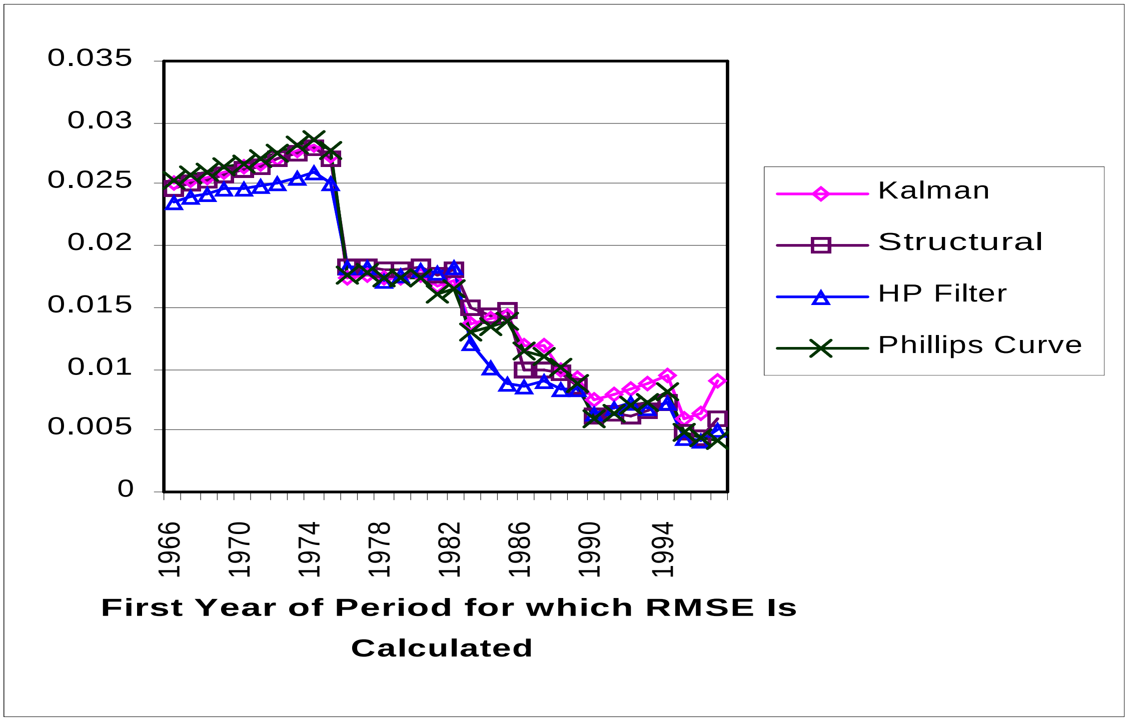

Figure 5. *Root Mean Square Error of Four Estimators of the NAIRU over Different Subperiods, Incorporating the Lagged CPI Inflation Rate*

NOTES

1. Recent citations of Blanchard and Quah appear in Mocan (1999) and Galí (1999).

2. I use annual data for frequency reasons that will become apparent later in the paper.

3. Zavodny (1999) gives a very recent indication of the difficulties inherent in collecting such unionization data, and the necessity of consulting a variety of sources and linearly interpolating missing points.

4. While Adams and Coe are quick to note that this assumption is somewhat simplistic, they offer no superior choice; note that this assumption implicitly posits that the cyclically neutral output gap is zero.

5. As in Roberts (1995), annual data are used in order to match the frequency of the Livingston data.