Temporal instability of the unemployment–inflation relationship

Robert G. King, James H. Stock, and Mark W. Watson

Econometric modeling of the relationship between inflation and unemployment has been a central topic in macroeconomics since the investigation of Phillips (1958), who documented a negative correlation between these variables in a half-century of U.K. data. Since the simultaneous occurrence of high inflation and high unemployment in the United States and other countries during the 1970s, there has been general agreement that this econometric relationship is unstable. Indeed, the instability has been so great that Lucas and Sargent characterized it as "econometric failure on a grand scale."[1] This article summarizes some results from our recent work that documents various dimensions of this instability.[2]

We display econometric instability in three alternative and complementary ways. First we look at the simple correlation coefficient linking the unemployment rate and inflation, which initially attracted the attention of Phillips (1958) in U.K. data and Samuelson and Solow (1960) in U.S. data. We show that this correlation has changed in an important way since World War II, so that over the entire 1954-94 period the correlation is essentially zero. However, we also show that this largely reflects the changing trend behavior of the two series: When we eliminate trends and high-frequency components of inflation and unemployment so as to focus on the business cycle behavior of the two series, we find that there has been a remarkably stable negative correlation.

This combined pattern of stability and instability suggests the value of investigating the stability and performance of inflation and unemployment forecasting rules over various sample periods and horizons. Accordingly, our second approach is to investigate instability in the parameters of a reduced-form bivariate forecasting model—a vector autoregression (VAR)—for the two series. We document instability in the parameters of the forecasting model, particularly for the coefficients in the inflation equation. However, a closer examination suggests that this statistically significant time variation in parameters has a relatively small effect on the accuracy of forecasts.[3]

The inflation-unemployment relationship in major macroeconometric models is governed in large part by the econometrics of the "price equation" or "wage-price block," which specifies that the inflation rate is a negative function of the level of unemployment. Typically, these specifications imply that there is a rate of unemployment at which inflation is stable—a nonaccelerating inflation rate of unemployment (NAIRU), or "natural" rate of unemployment.[4] One potential

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Robert G. King is a professor of economics at the University of Virginia and a consultant to the Federal Reserve Bank of Richmond. James H. Stock is a professor of public policy at the Kennedy School of Government, Harvard University. Mark W. Watson is a professor of economics at Northwestern University and a consultant to the Federal Reserve Bank of Chicago. The authors wish to thank Charles Evans, Robert Gordon, Ken Kuttner, and Doug Staiger for comments.

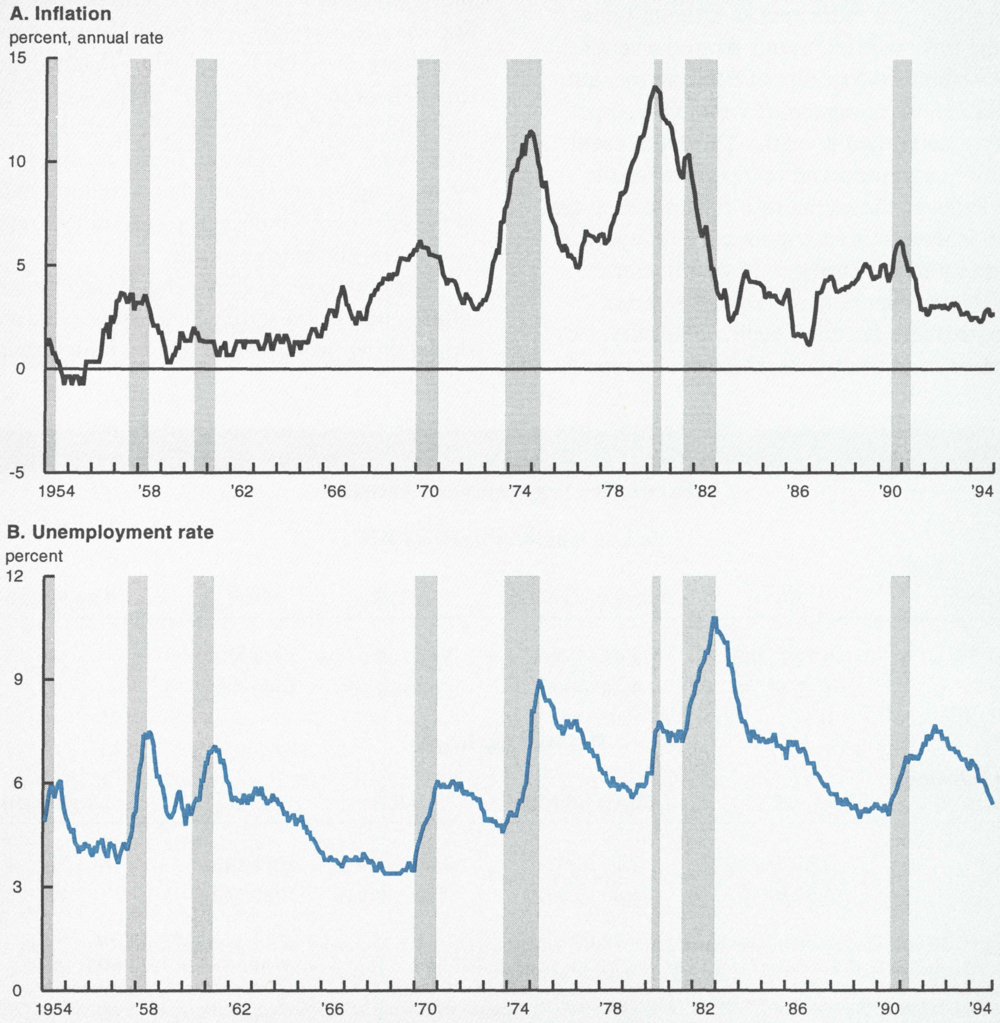
source of instability in the observed unemployment-inflation relationship in major econometric models is time variation in the NAIRU; our third approach is to study the extent of this form of instability in a conventional price equation. We find that while there may be time variation in the NAIRU, it is very hard to estimate precisely the extent of this time variation and the level of the NAIRU at any point in time. For example, in the econometric model with the most precise NAIRU estimate, the 95 percent confidence interval for the current value of the NAIRU ranges from 4.9 to 7.6 percentage points.[5]

Instability in the correlation between the unemployment rate and inflation

Figure 1 plots the unemployment and inflation data used in this paper over the 1954-94 period.[6] The characteristics of the data evident in the figure suggest that a single correlation coefficient will do a poor job summarizing the relation between the two series. For example, both inflation and the unemployment rate are lower in the first half of the sample than in the second half. This suggests a positive correlation between the series. On the other hand, during business cycle recessions (shown as shaded areas in the figure), inflation tends to fall and unemployment increases; the opposite occurs

FIGURE 1

Inflation and unemployment



Note: Shaded areas indicate NBER-designated recessions.

during business cycle expansions. This suggests a negative correlation between the series of the sort summarized in the Phillips curve.

Table 1 shows the correlation coefficient calculated over the entire sample period and over two subsamples. When computed over the entire sample period, the two forces discussed in the last paragraph essentially cancel one another, yielding a correlation coefficient of 0.08. However, when we crudely adjust the data for time-varying trends by splitting the sample, the negative business cycle correlation is apparent. The sample correlations over the first half and second half of the sample are –0.28 and –0.26, respectively.

Figure 2 is a more careful attempt to extract the time-varying trends from the series. Panel A shows the results of filtering the data to isolate those components with cyclical periodicity greater than 8 years. These represent the slowly varying trend components of the data. Panel B shows the results of filtering the data to isolate those components with cyclical periodicity between 6 months and 8 years.[7] This isolates the components of the series associated with business cycle variability. As is evident from the figure, there is no apparent systematic relationship between the trend components, but there is a clear and apparently stable negative relationship between the business cycle components. These correlations are summarized in the last two columns of table 1. The sample correlation between the trend components of the table is unstable: –0.12 in the first half of the sample, 0.01 in the second half, and 0.43 over the entire sample period. On the other hand, the correlation of the business cycle components is remarkably stable: –0.60 in the first half, –0.64 in the second half, and –0.61 over the entire sample.

This analysis suggests that it may be possible to uncover a stable forecasting relationship linking inflation and the unemployment

TABLE 1

Sample correlation of unemployment and inflation

Sample period	Raw data	Trend component	Cyclical component
1954-94	0.08	0.43	–0.61
1954-73	–0.28	–0.12	–0.60
1974-92	–0.26	0.01	–0.64

Notes: The raw data correspond to the unemployment rate and the monthly percentage change in prices. The trend and cyclical components are the bandpass-filtered values of the raw data using a trend (with periods > 96 months) and a business cycle (with periods between 6 and 96 months) filter. See text for additional details.

TABLE 2

Predictive regression F-statistics

A. Lag lengths chosen by BIC

Forecasting equation	GC	Chow(73:M12)	QLR	QLR_{date}	Lag length
$\Delta\pi$	3.74 (0.00)	3.46 (0.00)	3.66 (<0.01)	1974:M8	8
Δu	1.85 (0.16)	0.76 (0.58)	4.08 (0.03)	1960:M1	2

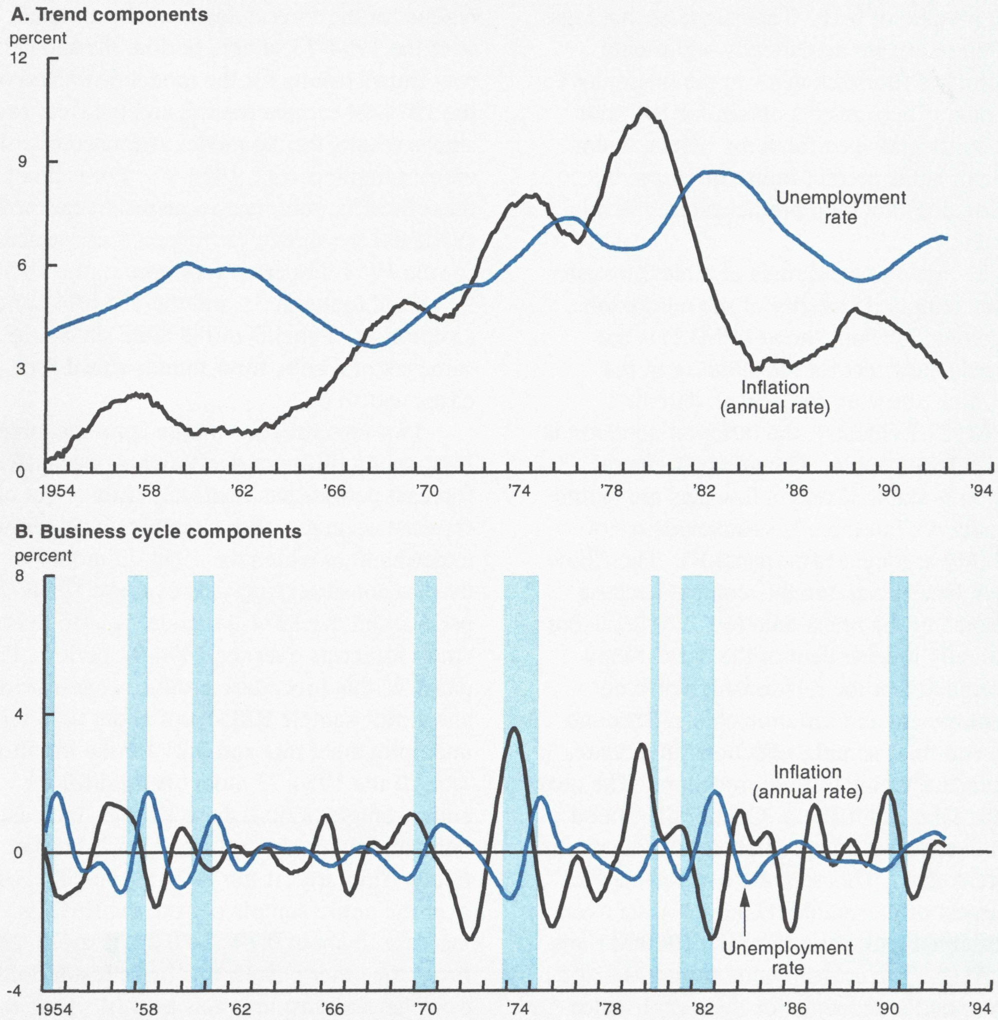
B. Fixed lag length

Forecasting equation	GC	Chow(73:M12)	QLR	QLR_{date}	Lag length
$\Delta\pi$	3.55 (0.00)	2.24 (0.00)	2.60 (<0.01)	1974:M8	12
Δu	1.37 (0.17)	1.81 (0.01)	2.46 (<0.01)	1960:M3	12

Notes: GC refers to the Granger-causality F-statistic testing the null hypothesis of no Granger-causality. Chow (73:M12) is the Chow test for instability in all of the coefficients with a single break allowed in 1973:M12. QLR is the Quandt likelihood ratio statistic (expressed here in F-statistic form) for a single break at an unknown time period between 1960:M1 and 1988:M12 (the middle 70 percent of the sample). QLR_{date} is the date at which the QLR statistic is maximized. Lag length refers to the number of lags included in the regression. The numbers in parentheses are p-values for the statistics under the null hypothesis.

FIGURE 2

Trend and cyclical components



Note: Shaded areas indicate NBER-designated recessions.

rate, but that the specification must focus on the shorter-run variation in the series and mask longer-run trend variation.

Instability in the bivariate VAR

Trending behavior in the series can be masked if the forecasting model is specified using the first differences of the variables.[8] Accordingly, we consider forecasts constructed from a bivariate VAR that incorporates $\Delta\pi_t$ and Δu_t, where π_t is the inflation rate and u_t is the unemployment rate.

Table 2 summarizes a variety of F-statistics constructed from each of the equations in the model. Panel A of the table shows the results for a VAR with lag lengths chosen by the Bayesian Information Criterion (BIC, a standard model-selection model), and panel B shows results when the lag lengths are set equal to 12 (a common specification for monthly models). The first column of the table identifies the equation considered, and the second column reports the Granger-causality F-statistic for the equation. This statistic tests the hypothesis that the other variable does not help predict the dependent variable in this equation. For example, from panel A, the Granger-causality F-statistic in the $\Delta\pi$ equation is 3.74, and this tests the null hypothesis that lags of unemployment do not help predict future inflation. Since the p-value (shown in parentheses) is very small, the test suggests that lags of unemployment do help predict future inflation. On the other hand, the Granger-causality statistic for the Δu equation is 1.85 with a p-value of 0.16. This suggests that lags of inflation are not statistically significant predictors of future changes in the unemployment rate. These results obtain for BIC and fixed-lag-length specifications. Thus, unemployment helps predict future inflation, but inflation does not help predict future unemployment.

The next three columns of table 2 investigate the temporal stability of the regressions. The column labeled Chow(73:M12) is the standard Chow test for the stability of the regression, allowing for a break date in 1973:M12. Evidently, the inflation equation is statistically unstable. The unemployment equation is stable if only a few lags are included (panel A), but there is some evidence of instability at longer lags (panel B). The Chow test can be criticized in this context because the choice of the break date (1973:M12) is not statistically independent of the data: Many have argued that the relationship between unemployment and inflation changed around 1973, and this "sample selection" invalidates the standard Chow testing procedure. The next statistic labeled QLR (for Quandt likelihood ratio) overcomes this problem by endogenizing the break date. This statistic is calculated as the largest of the standard Chow F-tests over all possible break dates between 1960:M1 and 1988:M12. The critical value for the statistic now explicitly accounts for the sample selection associated with choosing the largest of this sequence of statistics. Using the QLR test, one sees instability in both the $\Delta\pi$ and Δu equations regardless of the lag-length specification. The column labeled QLR_{date} shows the break date that yielded the largest F-statistic. If there is only one break in the process, this serves as an estimate of that break date. Notice that the inflation process appears to have undergone a shift in the middle of the sample (in 1974), while the apparent shift in the unemployment process occurred much earlier (in 1960).

While the evidence suggests some instability in the inflation and unemployment processes, table 2 says little about the magnitude of the shift. This is addressed in table 3, which shows how forecasting performance is affected by three factors: the forecasting horizon, the sample period used to estimate the model, and the sample period for the forecasts. For example, panel A shows results for 1-month-ahead forecasts. The first row of each panel shows results for the forecasting model estimated over the 1954-73 sample period, the second row shows results for the model estimated over the 1974-94 sample period, and the final row shows results for the model estimated over the entire sample period, 1954-94. For each of these models, root mean square forecast errors (RMSEs) are shown for forecasts constructed for the 1954-73 period (column 2), the 1974-94 period (column 3), and the 1954-94 period (column 4). Panel B of the table shows the same set of results for 6-month-ahead forecasts, and so on.

Two conclusions emerge from the table. First, using different coefficients over different forecast periods has relatively little effect on forecast accuracy. For example, consider an experiment in which the 1954-73 model is used to construct forecasts over the 1954-73 period, and the 1974-94 model is used to construct forecasts over the 1974-94 period. From panel A, this procedure produces one-month-ahead full-sample RMSEs of about 0.18 for the unemployment rate and 0.21 for the inflation rate. If the 1954-73 model is used for the entire sample period, these RMSEs increase only slightly to about 0.19 and 0.24, respectively. Similarly, if the 1974-94 model is used over the entire sample period, the RMSEs increase to about 0.19 and 0.22, respectively. From the other panels, this basic result holds for other forecast intervals as well. Thus there is only a small gain from changing the coefficients of the forecasting model over different forecast periods. The second conclusion that follows from table 3 is that inflation became more difficult to forecast over long horizons in the second half of the sample. For example, at the twelve-month horizon, the in-sample RMSE from 1954-73 is about 1.13, and this increases to 1.86 in the second period.

In summary, the results presented in tables 2 and 3 suggest that statistically significant changes occurred in the unemployment-inflation processes during the sample period. This change had little effect on the best choice of a bivariate forecasting model but did have an effect on the accuracy of inflation forecasts. Regardless of the forecasting model used, inflation became more difficult to forecast in the second half of the sample.

TABLE 3

Root mean square error for models estimated over different sample periods

A. 1-month-ahead forecast error RMSE

	Forecasting period					
	1954:M1-73:M12		1974:M1-94:M12		1954:M1-94:M12	
Estimation period	Unemp.	Infl.	Unemp.	Infl.	Unemp.	Infl.
1954:M1-73:M12	0.177	0.213	0.205	0.262	0.193	0.235
1974:M1-94:M12	0.208	0.250	0.174	0.213	0.192	0.224
1954:M1-94:M12	0.185	0.226	0.181	0.220	0.184	0.224

B. 6-month-ahead forecast error RMSE

	Forecasting period					
	1954:M1-73:M12		1974:M1-94:M12		1954:M1-94:M12	
Estimation period	Unemp.	Infl.	Unemp.	Infl.	Unemp.	Infl.
1954:M1-73:M12	0.566	0.554	0.725	1.007	0.658	0.811
1974:M1-94:M12	0.657	0.699	0.607	0.901	0.635	0.796
1954:M1-94:M12	0.591	0.589	0.632	0.929	0.617	0.796

C. 12-month-ahead forecast error RMSE

	Forecasting period					
	1954:M1-73:M12		1974:M1-94:M12		1954:M1-94:M12	
Estimation period	Unemp.	Infl.	Unemp.	Infl.	Unemp.	Infl.
1954:M1-73:M12	0.964	1.126	1.271	2.052	1.141	1.643
1974:M1-94:M12	1.120	1.328	1.095	1.864	1.116	1.585
1954:M1-94:M12	0.988	1.158	1.151	1.910	1.083	1.585

D. 24-month-ahead forecast error RMSE

	Forecasting period					
	1954:M1-73:M12		1974:M1-94:M12		1954:M1-94:M12	
Estimation period	Unemp.	Infl.	Unemp.	Infl.	Unemp.	Infl.
1954:M1-73:M12	1.196	2.287	1.754	5.214	1.525	4.126
1974:M1-94:M12	1.300	2.750	1.661	4.680	1.512	3.904
1954:M1-94:M12	1.199	2.270	1.705	4.844	1.498	3.904

Notes: The entries in the table refer to the root mean square forecast error for unemployment and inflation for the forecasting period shown. The inflation forecast corresponds to price inflation over the forecast period and is expressed as the annual percentage rate. For example, the 6-month forecast error for inflation dated 1954:M1 is the forecast error for the rate of change in prices over the period 1953:M7-54:M1 using the forecast constructed in 1953:M7 and expressed in percent at an annual rate. The forecasts were formed using VAR(12) models (including a constant) estimated over the periods given in the first column of the table.

Instability in estimates of the NAIRU

One important characteristic of the forecasting relation linking unemployment and inflation is the NAIRU—that value of the unemployment rate, which if maintained, would forecast no long-run changes in the inflation rate. This NAIRU can be estimated as the parameter $\bar{u}$ in a regression specification of the form

$$(1)\quad \Delta\pi_t = \Sigma_{i=1}^{p}\beta_i(u_{t-i} - \bar{u}) + \Sigma_{i=1}^{k}\gamma_i\Delta\pi_{t-i} + a_t,$$

where a_t is a regression error. If it is postulated that $u_\tau = \bar{u}$ for $\tau > t$, and if the lag polynomial

$1-\gamma_1 L - \ldots \gamma_k L^k$ is stable, then this equation produces long-run forecasts of $\Delta\pi$ that are equal to zero, so that inflation is unchanging.[9]

Equation 1 differs from the VAR used above in one important way: The level of u enters equation 1, while the VAR is specified using the first difference of u. If the VAR is correctly specified (and we argue that it is, given the trend behavior in the unemployment rate evident in figure 2), then equation 1 can be correct only if the distributed lag of u's entering the equation can be written entirely in terms of first differences of u. This is possible only if $\Sigma_{i=1}^{p}\beta_i=0$. This constraint has important implications for estimation of the NAIRU. Notice that the NAIRU, $\bar{u}$, enters equation 1 only as $\bar{u}\,\Sigma_{i=1}^{p}\beta_i$. Thus, if $\Sigma_{i=1}^{p}\beta_i=0$, then $\bar{u}$ does not enter the equation, so that the inflation equation contains no information about $\bar{u}$. This implies that the value of the NAIRU is econometrically unidentified from equation 1. Alternatively, the NAIRU has no meaning in an equation when only changes in the unemployment rate help predict future inflation.

There are two ways around this criticism. The first is simply to assume that $\Sigma_{i=1}^{p}\beta_i \neq 0$, and use equation 1 to estimate $\bar{u}$. Since the β_i's are estimated as part of this process, if $\Sigma_{i=1}^{p}\beta_i=0$, then this will be true approximately for the estimates as well. This in turn will lead to estimates of $\bar{u}$ that are very imprecise, which should be apparent from large standard errors for the estimate of $\bar{u}$. Equivalently, the problem should surface as wide confidence intervals for $\bar{u}$. An alternative is to specify equation 1 allowing the parameter $\bar{u}$ to vary through time, capturing the time-varying trend in the unemployment data. This will obviate the need to first-difference u in the equation.

Here we use a model that incorporates both of these possibilities. Specifically we estimate a model of the form

(2) $\Delta\pi_t = \Sigma_{i=1}^{p}\beta_i(u_{t-i} - \bar{u}_t) + \Sigma_{i=1}^{k}\gamma_i\Delta\pi_{t-i} + a_t$

(3) $\bar{u}_t = \bar{u}_{t-1} + e_t$,

TABLE 4

Estimated parameters for time-varying NAIRU model

	σ_e			
Parameter	**0.00**	**0.05**	**0.10**	**0.15**
$u(-1)$	−0.724 (0.659)	−0.723 (0.638)	−0.728 (0.635)	−0.727 (0.630)
$u(-2)$	−0.377 (1.433)	−0.373 (1.375)	−0.361 (1.362)	−0.341 (1.342)
$u(-3)$	0.729 (1.585)	0.721 (1.515)	0.704 (1.500)	0.679 (1.483)
$u(-4)$	0.115 (1.481)	0.110 (1.425)	0.102 (1.429)	0.079 (1.433)
$u(-5)$	0.190 (1.585)	0.194 (1.521)	0.223 (1.521)	0.267 (1.521)
$u(-6)$	1.529 (1.617)	1.532 (1.557)	1.525 (1.558)	1.493 (1.554)
$u(-7)$	−0.831 (1.538)	−0.822 (1.481)	−0.816 (1.482)	−0.792 (1.478)
$u(-8)$	−0.478 (1.522)	−0.481 (1.465)	−0.480 (1.468)	−0.452 (1.466)
$u(-9)$	−2.215 (1.620)	−2.198 (1.549)	−2.191 (1.546)	−2.189 (1.539)
$u(-10)$	2.725 (1.532)	2.701 (1.492)	2.669 (1.490)	2.605 (1.484)
$u(-11)$	−1.267 (1.367)	−1.309 (1.321)	−1.321 (1.319)	−1.320 (1.319)
$u(-12)$	0.560 (0.652)	0.605 (0.626)	0.633 (0.628)	0.663 (0.634)
$\Delta\pi(-1)$	−0.009 (0.049)	−0.015 (0.048)	−0.020 (0.051)	−0.029 (0.057)
$\Delta\pi(-2)$	0.024 (0.057)	0.020 (0.055)	0.018 (0.057)	0.014 (0.060)
$\Delta\pi(-3)$	−0.124 (0.055)	−0.124 (0.053)	−0.120 (0.054)	−0.114 (0.056)
$\Delta\pi(-4)$	−0.010 (0.055)	−0.101 (0.053)	−0.095 (0.054)	−0.086 (0.055)
MA(1)	−0.831 (0.037)	−0.827 (0.039)	−0.838 (0.046)	−0.854 (0.060)
σ_ε	0.278 (0.104)	0.260 (0.123)	0.247 (0.136)	0.226 (0.136)
Log-likelihood	−711.73	−712.19	−712.74	−713.20

Notes: These are estimates of the parameters in equations 2 through 4 of the text. They are estimated by Gaussian maximum likelihood using data from 1953:M1–94:M12.

where e_t is an *iid* error term with a mean of zero and standard deviation of σ_e. Since $\bar{u}_t = \bar{u}_0 + \Sigma_{s=1}^{t} e_s$, then $\bar{u}_t$ is constant when $\sigma_e = 0$, so that equation 2 collapses to equation 1. When $\sigma_e \neq 0$, the model allows the NAIRU to change by e_t in each period. To complete the model, we set the lag lengths as $p=12$ and $k=4$, and allow the error term a_t to follow an MA(1) process:

$$(4) \quad a_t = \varepsilon_t - \Theta\, \varepsilon_{t-1},$$

with ε_t an *iid* error term with mean zero, variance σ_ε^2, and uncorrelated with e_t at all leads and lags. (The MA(1) specification turned out to be a parsimonious way to model persistence in the inflation process.) The model summarized by equations 2-4 is a standard stochastic time-varying parameter regression model that can be estimated using Gaussian maximum likelihood methods as described in Harvey (1989) or Hamilton (1994).[10]

Table 4 shows the results obtained by estimating the model over a range of values of σ_e, the time variation allowed in $\bar{u}$. Notice that the model with $\sigma_e = 0$ results in the highest value of the log-likelihood and hence corresponds to the maximum likelihood estimate. However, models with larger values of σ_e produce log-likelihoods that are not significantly larger, at least using conventional rules of thumb.[11]

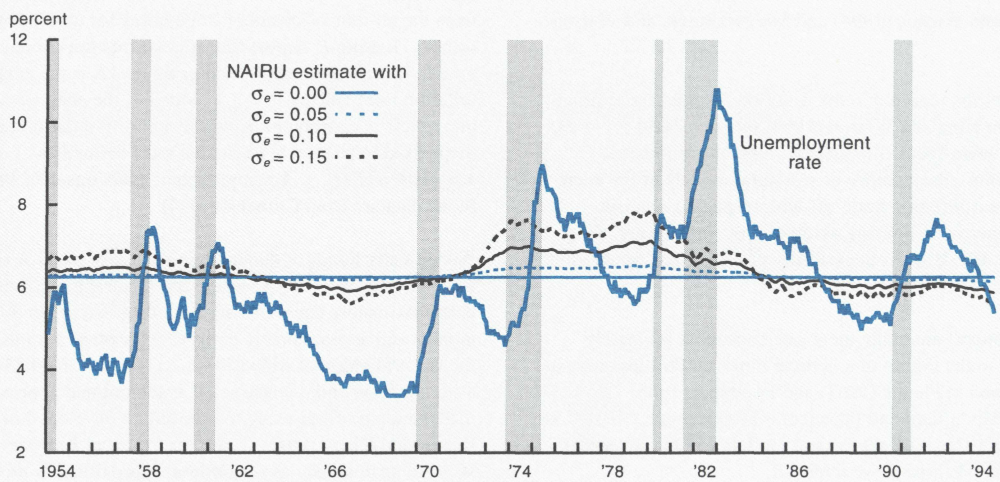
Figure 3 plots the estimates of $\bar{u}$ produced by each of the models, together with the actual unemployment rate.[12] When $\sigma_e = 0$, the NAIRU is constant with an estimated value of 6.26 percent. As σ_e increases, more variation is apparent in the estimated values of $\bar{u}_t$. For example, when σ_e is 0.15 (the largest value considered), the estimates of $\bar{u}_t$ vary from a high of 7.87 percent (in 1980:M1) to a low of 5.62 percent (in 1967:M2 and 1994:M12).

Table 5 presents estimates of $\bar{u}$ at five intervals for the each of the models. Also shown are the estimated standard errors of the estimates.[13] The most striking feature of this table is the size of these standard errors. For example, if it assumed that the NAIRU is constant, then the 95 percent confidence interval is 4.9 to 7.6 percentage points. If it is assumed that the NAIRU has significant time variation ($\sigma_e = 0.15$), then the 95 percent confidence interval for the NAIRU in 1994:M12 is 2.7 to 8.5 percentage points. The source of this uncertainty in the estimated value of $\bar{u}$ is the very small estimated value of $\Sigma_{i=1}^{p} \beta_i$. This is estimated as –0.04 in the $\sigma_e = 0$ model, and does not change appreciably as σ_e is allowed to take on non-zero values.[14]

In summary, while the data may be characterized by a model with a time-varying NAIRU, the value of this NAIRU is estimated very imprecisely from the data.

FIGURE 3

Estimates of the NAIRU



Note: Shaded areas indicate NBER-designated recessions.

TABLE 5

Selected values of the NAIRU

Date	Unemployment rate	NAIRU with σ_e 0.00	0.05	0.10	0.15
1954:M1	4.90	6.26 (0.67)	6.29 (1.28)	6.40 (1.99)	6.68 (2.63)
1960:M1	5.20	6.26 (0.67)	6.28 (1.17)	6.33 (1.72)	6.53 (2.07)
1965:M1	4.90	6.26 (0.67)	6.22 (1.10)	6.07 (1.58)	5.97 (1.80)
1970:M1	3.90	6.26 (0.67)	6.27 (1.04)	6.18 (1.46)	6.09 (1.64)
1975:M1	8.10	6.26 (0.67)	6.50 (0.98)	6.96 (1.30)	7.51 (1.47)
1980:M1	6.30	6.26 (0.67)	6.55 (0.95)	7.13 (1.23)	7.87 (1.38)
1985:M1	7.30	6.26 (0.67)	6.31 (0.94)	6.29 (1.17)	6.17 (1.30)
1990:M1	5.30	6.26 (0.67)	6.22 (0.95)	6.06 (1.17)	5.88 (1.33)
1994:M12	5.40	6.26 (0.67)	6.16 (0.98)	5.89 (1.24)	5.62 (1.48)

Notes: These are estimates of the NAIRU computed using the Kalman smoother applied to the model 2 through 4 with parameter values taken from table 4. The standard errors (in parentheses) were computed following Hamilton (1986).

Conclusion

In this article we investigated the temporal stability of the relationship between unemployment and inflation. We documented both stable and unstable characteristics of the relationship. The correlation between the two series over the business cycle is remarkably stable, but there appears to be no stable relationship over long horizons. We uncovered statistically significant changes in the forecasting relationship between the variables. However, splitting the sample to allow changes in the coefficients did little to improve the forecasts. The major unstable characteristic of the forecasting relationship is an increase in the long-horizon variance of inflation. Finally, we constructed models that allowed time variation in the NAIRU. The resulting estimates of the NAIRU were very imprecise, which is consistent with the theory that future inflation is better predicted by changes in the unemployment rate than by the size of the unemployment gap (the difference between unemployment and the NAIRU).

NOTES

[1]Lucas and Sargent (1979).

[2]King and Watson (1994) and Staiger, Stock, and Watson (1995).

[3]The results reported in the first two sections are abstracted from King and Watson (1994, sections 2 and 5.1–5.2), whose main focus is a different type of econometric instability: the stability of structural models of the unemployment-inflation trade-off with respect to specific econometric identifying assumptions. In addition, King and Watson discuss the stability of estimated structural trade-offs across different periods.

[4]The natural unemployment rate concept is intimately linked to the notion of a vertical long-run Phillips curve as explained in Phelps (1967) and Friedman (1968). However, as Modigliani and Papademos (1976) argue, NAIRU is an interesting concept even in models without a vertical long-run Phillips curve trade-off.

[5]The work described in this section reports preliminary results from Staiger, Stock, and Watson (1995).

[6]The unemployment rate is for all workers 16 years and older, seasonally adjusted. The inflation rate is computed from the all-items Consumer Price Index for urban consumers. Letting P_t denote the value of this price index at time t, the inflation rate plotted in figure 1A is the annual inflation rate: $100*ln(P_t/P_{t-12})$. Much of the analysis in this article is carried out using the monthly inflation rate (expressed in percent at an annual rate) defined as $\pi_t=1{,}200*ln(P_t/P_{t-1})$. Unemployment and Consumer Price Index data are from Citibank (1994).

[7]Specifically letting x_t denote the raw series, panel A of figure 2 plots $y_t = A(L)\, x_t$, where the spectral gain of $A(L)$ is approximately equal to 1 for periods greater than 96 months and approximately equal to 0 for other periods; the spectral phase of $A(L)$ is 0. $A(L)$ is a two-sided 24-term lag polynomial constructed as the optimal approximate bandpass filter using the procedure developed in Baxter and King (1994). The filter for panel B is constructed analogously as the optimal approximate 6-month to 96-month bandpass filter.

[8]Formally, this amounts to modeling the data as "integrated processes," so that they exhibit stochastic growth, but not "co-integrated," so that each series has its own distinct long-run trend.

[9]The essentials of this method for estimating the NAIRU or the natural unemployment rate can be traced back to Gordon (1972). In that original work and much subsequent work, Gordon has investigated nonlinearities, demographic and other shifts in the relationship, and their implied effect on estimates of the natural rate. Equation 1, however, captures the essential features of the relationship between the NAIRU and inflation.

[10]The econometric model represented by equations 2 through 4 is one version of Cooley and Prescott's (1973) adaptive regression model. Its use as a forecasting tool is surveyed in Engle and Watson (1988), and both Gordon (1994) and Staiger and Stock (1994) discuss the model's potential for estimating the natural unemployment rate.

[11]In typical situation, 2 times the log-likelihood ratio is approximately distributed as a χ^2 random variable. Since the models in table 4 differ by the choice of one parameter, and since the 95 percent critical value for the χ^2_1 is 3.84, this suggests log-likelihoods must differ by more than 1.92 to be statistically significant.

[12]These estimates are computed from a Kalman smoother, conditional on the parameter estimates shown in table 4.

[13]These standard errors were calculated using the procedure developed in Hamilton (1986).

[14]One possible modification to increase the precision of $\bar{u}_t$ is to use the unemployment equation in addition to the inflation equation to identify the NAIRU. This would explicitly link the NAIRU to the stochastic trend in the observed unemployment rate. Kuttner (1994) estimates "potential output" in such a framework.

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