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Author(s): Kenneth N. Kuttner

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Estimating Potential Output as a Latent Variable

Kenneth N. KUTTNER

Research Department, Federal Reserve Bank of Chicago, Chicago, IL 60604

This article proposes a new method for estimating potential output in which potential real gross domestic product (GDP) is modeled as an unobserved stochastic trend, and deviations of GDP from potential affect inflation through an aggregate supply relationship. The output and inflation equations together form a bivariate unobserved-components model which is estimated via maximum likelihood through the use of the Kalman-filter algorithm. The procedure yields a measure of potential output and its standard error and an estimate of the quantitative response of inflation to real growth and the output gap.

KEY WORDS: Inflation; Kalman filter; Phillips curve; Stochastic detrending; Unobserved-components models.

Potential output figures prominently in a wide range of macroeconomic models. At the most abstract level, it represents the steady-state level of output associated with the long-run aggregate supply curve—the level to which gross domestic product (GDP) reverts as the transitory effects of macroeconomic disturbances dissipate. Besides capturing the underlying trend in real GDP, potential output is also an important component of models of price determination built on the Phillips curve. According to this view, output in excess of potential leads to rising inflation; similarly, disinflation requires output to fall below potential. Although the microeconomics of this mechanism are unclear, the “systematic relationship between the rate of change of prices and the level of real output” is a central feature of the modern business cycle (Lucas 1972, p. 103).

Because it represents “the maximum production without inflationary pressure... or more precisely... the point of balance between more output and greater stability” (Okun 1970, pp. 132–33), potential output is a natural target for macroeconomic policy (Boschen and Mills 1990). The main obstacle to its use in policy is the inability to observe it directly, forcing policymakers to rely on imperfect estimates. Occasionally, as in the productivity slowdown of the 1970s, flawed estimates of potential output have led to inappropriate policy targets. This has not, however, eliminated the need for such a guide.

The underlying determinant of potential output is the supply side of the economy. It is “the amount of output that would have been produced had the economy been in neither boom nor recession... from the existing capital stock and labor force” (Hall and Taylor 1991, p. 16), which depends in turn on such microeconomic fundamentals as technology and preferences. In principle, therefore, it should be possible to produce an estimate of potential output based on these fundamentals. The large cyclical fluctuations in productivity and labor supply, however, make this strategy very difficult to implement empirically.

This article proposes a new method for estimating potential

output using inflation and real output data. Its primary innovation is to model potential real GDP as a latent stochastic trend, linking deviations from the trend to inflation through a simple reduced-form Phillips curve equation. That is, instead of analyzing the supply side directly, it uses the joint behavior of output and inflation to “back out” an estimate of potential. The output and inflation equations together form a bivariate unobserved-components model, an example of the dynamic multiple indicator multiple cause specification described by Watson and Engle (1983). The model is estimated by maximum likelihood through the use of the Kalman-filter algorithm.

Although this method represents a shortcut relative to a comprehensive supply-side analysis, it does offer three distinct advantages over existing, traditional measures of potential output. First, its explicit dependence on inflation endows it with more economic content than measures derived from purely univariate methods. Second, the stochastic trend specification allows for continuous, smooth adjustment of the estimate in real time as new data become available. Its third and perhaps most important feature is its ability to estimate the uncertainty associated with the potential output series.

The results turn up two additional findings of economic interest. First, the estimation procedure yields a relatively precise measure of the speed of inflation’s response to deviations from potential, essentially a dynamic version of the so-called “sacrifice ratio.” The second implication of the bivariate model is that the estimated unit root in real GDP is considerably larger than indicated by a univariate stochastic trend model.

The remainder of the article proceeds as follows. To motivate the proposed technique, Section 1 surveys and critiques a variety of existing potential output measures. Section 2 conducts a preliminary analysis of the time series properties of output and inflation relevant to the specification of the bivariate unobserved-components potential output model, which Section 3 develops. Section 4 concludes.

Table 1. Unit-Root Tests for Real GDP

Lags	ADF <i>t</i> statistics		Lags	Autocorrelations			
	Constant	Constant, trend		Correlation coefficient			
2	-1.45	-2.42	1-2	.31	.17		
4	-1.32	-1.66	3-4	.01	-.02		
8	-1.19	-1.22	5-8	-.07	.02	-.02	-.14
12	-1.33	-1.11	9-12	-.06	.07	-.01	-.12

NOTE: Results are based on 156 quarterly observations from 1954:1 through 1992:4.

1. A SURVEY OF EXISTING POTENTIAL OUTPUT MEASURES

One class of potential output measures relies entirely on the univariate properties of real GDP. The simplest in this class is a linear trend, which was widely used until the early 1970s. Over time, the linear trend gave way to techniques that allowed the growth rate of potential to vary, such as the segmented-trend mid-expansion real-GDP series published by the Bureau of Economic Analysis. The Hodrick–Prescott filter (1980) and the latent variable models of Watson (1986) and Clark (1989) are more recent examples of univariate procedures that have been used to generate something resembling potential output. The main drawback to all of these measures is the lack of substantive economic content, much less the links to inflation and employment that are central to the definition of potential output.

A second approach rests on an aggregate production function. Substituting full-employment levels of productivity and labor and capital inputs into a production function yields an estimate of the economy's output under conditions of full employment. Despite the formidable task of constructing cyclically adjusted measures of labor hours, labor-force participation, capacity utilization, and productivity, this method saw widespread use in the late 1970s. Examples include Perry (1977), Clark (1979), and Perloff and Wachter (1979). It was also the basis of the series published in the *Economic Report of the President* until 1982.

A third approach uses the empirical relationship between output and the unemployment rate known as Okun's law,

$$X^* = X[1 + .032(U - U^*)], \quad (1)$$

where X^* and X represent potential and actual output, U is the unemployment rate, and U^* is the "natural" rate of unemployment. Conditional on an estimate of U^* , computing X^* is trivial. The problem comes when U^* is unobserved and varies over time, as it would with changing levels of structural employment (Lilien 1982; Rissman 1986). Clark (1983) and Braun (1990) used versions of this procedure, combined with time-varying estimates of the natural rate, to construct time series for potential output.

Finally, a fourth class of measures uses a modification to the Hodrick–Prescott filter. This involves specifying inflation, say, as a function of the filter's cyclical component and including the equation's squared error in the filter's objective function. Laxton and Tetlow (1992) and Hostland and Côté (1993) applied this multivariate filter to Canadian data

to extract measures of potential GDP linked to inflation and unemployment fluctuations.

In evaluating alternative measures of potential output as guides to macroeconomic policy, two considerations are especially important. First, it should be easy to construct and update in real time and sufficiently flexible to adjust rapidly to local variations in the trend. This is a challenge for the production-function and Okun's law methods because changes in productivity or the natural rate are rarely apparent at the time. Any measure based on a segmented trend is also vulnerable to this problem, with new breakpoints typically inserted only after hindsight shows the previous trend to be untenable. A second key feature is an estimate of the uncertainty associated with the potential output series. None of the traditional methods provides such an estimate, although the multivariate filtering technique can address the issue through Monte Carlo procedures. The latent-variable approach described in this article resolves both of these issues, while incorporating economic content that is absent from the univariate measures.

2. PROPERTIES OF OUTPUT AND INFLATION

Before specifying a complete model describing the relationship between output and inflation, it is useful first to examine the individual time-series properties of real GDP and inflation. This section reports the results of unit-root tests and estimates univariate time series models for the two series using data from 1954–1992.

2.1 Real GDP

The first step in the analysis is to determine an appropriate structure for the underlying trend component of real output. The stochastic trend specification of Watson (1986), which decomposes a difference-stationary series into an integrated trend and a stationary cycle, is a natural choice for the univariate representation of real GDP.

Letting x^* denote the unobserved trend component of log

Table 2. Estimated Univariate Model for Real GDP [Eq. (2)]

Parameter estimates					Estimation statistics	
μ_x	ϕ_1	ϕ_2	σ_e	σ_u	SE	Q(16)
.0069 (.0006)	1.44 (.16)	-.47 (.16)	.0052	.0069	.0088	13.62

NOTE: Results are based on 156 quarterly observations from 1954:1 through 1992:4. Standard errors are in parentheses. The mean log-likelihood for the model is 4.22653.

Table 3. Unit-Root Tests for CPI Inflation

Lags	ADF <i>t</i> statistics		Lags	Autocorrelations			
	Constant	Constant, trend		Correlation coefficient			
2	-2.23	-2.09	1-2	-.20	-.39		
4	-2.56	-2.42	3-4	.26	.11		
8	-2.51	-2.52	5-8	-.08	-.08	.07	-.06
12	-1.62	-1.49	9-12	-.03	-.06	-.06	.05

NOTE: Results are based on 156 quarterly observations from 1954:1 through 1992:4.

real GDP and z_t its cycle, Watson's model can be written as

$$\begin{aligned}\Delta x_t^* &= \mu_x + e_t \\ z_t &= \phi_1 z_{t-1} + \phi_2 z_{t-2} + u_t \\ x_t &= x_t^* + z_t.\end{aligned}\quad (2)$$

Observed output, x_t , is the sum of trend and cycle components. The trend term follows a random walk; the drift term μ_x captures the average growth rate over the sample. The cycle is assumed to be a stationary (autoregressive) AR(2) process with coefficients ϕ_1 and ϕ_2 . The white-noise e_t and u_t represent permanent and transitory shocks to real output.

An important property of this model is that it implies a unit root in real GDP. Although this is consistent with the augmented Dickey-Fuller tests for nonstationarity reported in Table 1, Christiano and Eichenbaum (1990), among others, demonstrated the fragility of such tests. Leaving aside these inference issues, the nonstationary stochastic trend specification is a useful way to capture low-frequency movements or "variable trends" (Stock and Watson 1988) in real GDP. Moreover, unobserved components models usually deliver smaller estimates of the size of the unit root than the autoregressive moving average (ARMA) specifications used by Campbell and Mankiw (1987).

Another attractive feature of the stochastic trend specification is its adaptability to linear statistical methods, unlike Hamilton's (1989) nonlinear procedure. In any case, because Hamilton's two-state model empirically captures the difference between recession and nonrecession growth rates, it is inappropriate for modeling low-frequency fluctuations in potential output. An additional advantage relative to the segmented-trend specification of Braun (1990) is that it does

not require the selection of breakpoints prior to estimation.

Table 2 reports the estimate of the stochastic trend specification (2), estimated via maximum likelihood, with the Kalman filter used to evaluate the likelihood function as described in Section 3. The results are similar to those reported by Watson (1986). The estimated drift term of .007 implies an average annualized growth rate of 2.8%. The ϕ 's are indeed consistent with a stationary (but rather persistent) cycle component. In term of standard deviations, shocks to the cycle are on average 30% larger than the shocks to the trend component, implying a relatively larger role for the transitory disturbances in real output fluctuations.

2.2 Inflation

The rate of inflation used here is based on the Consumer Price Index (CPI) because its relationship to real GDP at cyclical frequencies is more pronounced than it is for other series, such as the implicit deflator. The insignificant augmented Dickey-Fuller statistics reported in Table 3 suggest treating CPI inflation as an integrated series.

The next step is to find an appropriate ARMA specification for capturing the short-run dynamics of inflation. The size of the first four autocorrelations reported in the table suggest beginning with fourth-order models; the (unreported) partial autocorrelations provide no clear indication in favor of either an AR or an MA specification. Estimates of pure AR and MA models appear in Tables 4 and 5. In both cases, the fourth lag is insignificant at 5% level, and in the AR specification, only the first two lags are significant. The Q statistics, however, show somewhat more higher-order residual autocorrelation in the AR specifications than in the MA models. ARMA specifications do no better than the pure AR and MA models.

Table 4. Estimated Univariate MA Inflation Models

	Parameter estimates							Estimation statistics	
	μ_π	δ_1	δ_2	δ_3	δ_4	γ_1	γ_2	SE	Q(16)
(1)	†	-.25 (.08)	-.37 (.08)	-.40 (.08)	.05 (.08)			.0044	12.60
(2)	†	-.27 (.07)	-.36 (.07)	-.41 (.07)				.0043	14.11
(3)	-.0008 (.0003)	-.31 (.07)	-.46 (.07)	-.47 (.07)		.11 (.03)	.01 (.03)	.0041	14.04
(4)	-.0008 (.0003)	-.30 (.07)	-.46 (.07)	-.47 (.07)		.11 (.02)		.0041	14.15

NOTE: Estimated equations are of the form $\Delta \pi_t = \mu_\pi + \delta(L)\pi_t + \gamma(L)\Delta x_{t-1}$. Results are based on 156 quarterly observations from 1954:1 through 1992:4. Standard errors are in parentheses. † denotes estimates less than .0001.

Table 5. Estimated Univariate AR Inflation Models

	Parameter estimates							Estimation statistics	
	μ_π	θ_1	θ_2	θ_3	θ_4	γ_1	γ_2	SE	Q(16)
(1)	†	-.26 (.08)	-.43 (.08)	.06 (.08)	.02 (.08)			.0044	20.21
(2)	†	-.29 (.07)	-.45 (.07)					.0044	22.14
(3)	-.0008 (.0003)	-.34 (.07)	-.51 (.07)			.08 (.03)	.04 (.03)	.0042	18.79
(4)	-.0007 (.0003)	-.34 (.07)	-.50 (.07)			.11 (.03)		.0042	20.26

NOTE: Estimated equations are of the form $\Delta\pi_t = \mu_\pi + \theta(L)^{-1}v_t + \gamma(L)\Delta x_{t-1}$. See also note to Table 4.

Next, two lagged real growth terms are added to yield a set of transfer function models capturing the positive correlation between inflation and lagged real output growth. In both AR and MA specifications, only one lag of real growth is significant. The fourth lines of Tables 4 and 5 report the estimates of the AR(2) and MA(3) specifications augmented with one lag of Δx . Despite its slightly less parsimonious representation, the MA(3) specification,

$$\Delta\pi_t = \mu_\pi + \gamma\Delta x_{t-1} + v_t + \delta_1 v_{t-1} + \delta_2 v_{t-2} + \delta_3 v_{t-3}, \quad (3)$$

is preferable to the AR(2) on the basis of its smaller residual autocorrelation and standard error.

3. THE POTENTIAL OUTPUT MODEL

The essence of Phillips curve models of price adjustment is that the *level* of output relative to potential is systematically related to inflation. A model with this feature can be constructed by including the (lagged) cycle component from the stochastic trend model (2) as an additional explanatory variable in the inflation equation (3). Using the MA(3) specification yields

$$\Delta\pi_t = \mu_\pi + \gamma\Delta x_{t-1} + \beta z_{t-1} + v_t + \delta_1 v_{t-1} + \delta_2 v_{t-2} + \delta_3 v_{t-3}, \quad (4)$$

which can now be interpreted as a dynamic aggregate supply relationship involving the output “gap,” defined in this article as the deviation of (log) real GDP from potential output.

By specifying the change in the inflation rate as a function of the output gap, the equation matches Gordon’s (1990, p. 10) definition of potential as the level of output at which the inflation is constant. The potential output series extracted from this specification is, therefore, a “constant-inflation” measure. As others (e.g., Laxton and Tetlow 1992, p. 17) have noted, such “accelerationist” specifications are consistent with expectations-augmented Phillips curve models in which the expected rate of inflation is set equal to the lagged inflation rate. Of course, there is no guarantee that this reduced-form equation, with its ad hoc treatment of expectations, represents a genuine output–inflation trade-off for policymakers; see Lucas (1976).

The dependence of output and inflation on a common unobserved output gap suggests that the joint estimation of (2) and

(4) should provide more information on the output gap (and the level of potential output) than (2) alone. Loosely speaking, estimating the model amounts to choosing the unknown parameters to yield the z_t most consistent with observed inflation, subject to the smoothness restrictions implicit in the stochastic trend specification for GDP. In this way, the bivariate potential output model adds an element of economic content that is absent from the univariate detrending methods discussed earlier.

One convenient technique for estimating unobserved-components models is to use the Kalman filter on the model’s state-space representation to evaluate a normal likelihood function; details were given by Harvey (1981, 1989). This method can be applied to the potential output model by rewriting (2) and (4) in state-space format, with current and lagged values of x^* , z , and v (potential output, the output gap, and the inflation error term) appearing in the state vector. The measurement equation expresses real GDP and the differenced CPI inflation rate as a function of these variables, lagged output growth, and a constant.

Parameter estimates are computed by maximizing the likelihood function with respect to the 13 unknown parameters. Estimates of the initial state vector and its covariance matrix are computed by using the Kalman smoother to “backcast” the required latent variables, conditional on the data and starting values for the model parameters.

3.1 Model Estimates

The results from estimating the constant-inflation potential output model based on the MA(3) inflation specification appear in Tables 6 and 7. The parameter estimates generally resemble those of the univariate specifications in Tables 2,

Table 6. Estimated Output Equation From the Complete Model [Eq. (2)]

Parameter estimates					Estimation statistics	
μ_x	ϕ_1	ϕ_2	σ_e	σ_u	SE	Q(16)
.0070 (.0006)	1.57 (.12)	-.68 (.12)	.0071	.0045	.0088	14.72

NOTE: Results are based on 156 quarterly observations from 1954:1 through 1992:4. Standard errors are in parentheses. The mean log-likelihood for the model is 9.26123.

Table 7. Estimated Inflation Equation From the Complete Model [Eq. (4)]

Parameter estimates								Estimation statistics	
μ_π	γ	β	δ_1	δ_2	δ_3	σ_v	$\rho_{u,v}$	SE	Q(16)
-.0007 (.0003)	.11 (.02)	.04 (.02)	-.39 (.09)	-.52 (.09)	-.42 (.09)	.0038	.08	.0040	14.10

NOTE: See note to Table 6.

4, and 5. The diagnostic tests reported in Tables 8 and 9 show no evidence of residual correlation; nor do they suggest including additional lags of output growth or inflation. The absence of residual correlation at lag 4 confirms that the MA(3) specification is sufficient to capture short-run inflation dynamics and is consistent with the insignificant fourth order MA coefficient in Table 4. Unreported estimates of autoregressive specifications are similar, but suffer from marginally significant high-order residual serial correlation.

From an economic perspective, the most important results concern the relationship between real output and inflation. One aspect of this is the response of inflation to the output gap, as captured by the β coefficient in (4), whose 5% statistical significance confirms its importance even controlling for output growth. The point estimate of .04 indicates that an output gap of 1% (i.e., output in excess of potential) implies a .17% per quarter increase in the annualized inflation rate, an increase of .7% if maintained over an entire year. Negative output gaps yield symmetric effects.

The other feature of the relationship is the link between output growth and inflation embodied in γ . The statistically significant estimate of .11 is similar to the one obtained from the univariate model and says that when output growth exceeds its average by 1% the result is a .4% per quarter increase in the annualized inflation rate. Comparing the estimates of β and γ , it appears that the growth-rate effects would dominate the output-gap effects at a quarterly frequency. Because the gap is more persistent than the growth rate, however, the cumulative effects of the output gap are likely to be comparable.

The estimate of the output equation from the potential output model are broadly similar to the earlier results. The one notable exception is that the persistent shocks (i.e., the shocks to potential output) are now considerably larger than they were in the univariate specification, surpassing the standard deviation of the transitory shocks by 60%.

3.2 Estimated Potential GDP and its Standard Errors

Extracting an estimate of the latent potential output series is straightforward. Conditional on the maximum likelihood parameter estimates, the Kalman filter generates a “one-sided” estimate of x^* . Similarly, applying the Kalman smoother yields a “two-sided” estimate that incorporates data through the end of the sample. As Okun (1970, p. 123) observed, however, potential output is “at best an uncertain estimate, and not a firm, precise measure.” One of the most useful results of this potential-output model is an estimate of this uncertainty.

The estimation process itself yields one ingredient, a measure of the uncertainty that comes from the fact that the underlying state variables are unobserved and must be inferred from their laws of motion and their noisy link to the data. In estimating the latent state vector, the Kalman filter computes its variance conditional on data through the current quarter. Similarly, the Kalman smoother estimates its variance conditional on data through the end of the sample.

If the model’s true parameters were known, this signal-extraction variance would be the only source of uncertainty. Because these parameters are estimated, however, another source of uncertainty is the variance associated with the unknown parameters. Hamilton (1986) described a method for computing this variance that decomposes the total variance of the state-vector element of interest. Letting $x_{t|T}^*$ denote the estimate of x_t^* conditional on information through the end of the sample (i.e., the estimate from the Kalman smoother), total variance can be decomposed into the signal-extraction or “filter” component,

$$E\{(x_t^* - x_{t|T,\psi_0}^*)^2 | Z_T, \psi_0\}, \quad (5)$$

and the parameter uncertainty,

$$E_\psi\{(x_{t|T,\psi}^* - x_{t|T,\psi_0}^*)^2 | Z_T\}, \quad (6)$$

where ψ_0 is the estimated parameter vector and Z_T represents the data through period T . The Kalman smoother yields the

Table 8. Diagnostic Tests for the Output Equation

Residual correlation				Omitted $\Delta\pi$ terms	
Lag 3	Lag 4	Lags 5–8	Lags 9–12	Lag 1	Lags 1–4
.10 (.75)	.24 (.63)	5.32 (.26)	5.43 (.25)	.07 (.79)	4.32 (.36)

NOTE: The LM test statistics reported are distributed as χ^2 random variables, with degrees of freedom equal to the number of restrictions. Probability values appear in parentheses. See also note to Table 6.

Table 9. Diagnostic Test for the Inflation Equation

Residual correlation			Omitted Δx and $\Delta\pi$ terms	
Lag 4	Lags 5–8	Lags 9–12	Δx_{t-2}	$\Delta\pi_{t-1}$
.29 (.59)	3.91 (.42)	3.57 (.47)	1.41 (.24)	.08 (.78)

NOTE: See notes to Tables 7 and 8.

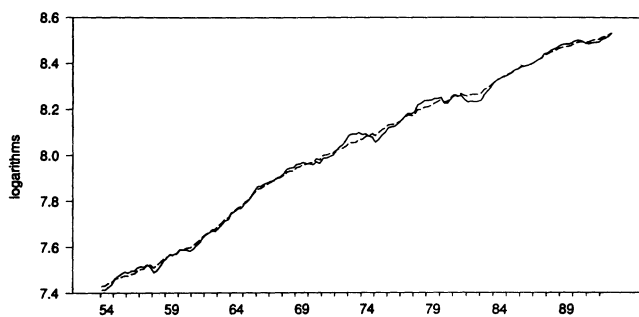


Figure 1. Real GDP and Two-Sided Potential Output: Potential Output, - - - -; Log Real GDP, ———.

filter uncertainty directly. The parameter uncertainty is computed via Monte Carlo: An artificial sample of ψ 's is drawn from a multivariate normal population, generating a sample of x_{it}^* series, which is then used to compute the sample variance of each observation in the series. A similar procedure can be used to compute the variance of the one-sided estimate.

Figure 1 displays the two-sided estimated potential output series, along with the logarithm of real GDP. Although the potential real GDP series is indeed considerably smoother than actual output, it is nonetheless subject to a significant amount of low-frequency variability. This is especially apparent in its comparison to a linear trend fit through the logarithm of real GDP, depicted in Figure 2. Although real GDP does appear gradually to revert to the trend, the implicit speed of adjustment is quite low; large deviations (some in excess of 5%) persist for several years.

Figure 3 shows the estimated two-sided output gap (i.e., the amount by which output exceeds potential), along with the 1.00 and 1.69 standard error bounds, the latter corresponding to a 90% confidence interval. Although most cyclical fluctuations exceed the one-standard-deviation mark, only four episodes surpass the 90% bounds, the 1973 and 1978 expansions and the 1974–1975 and 1981–1982 recessions.

Figure 4 shows the one-sided output gap and its error bounds. Comparing it with Figure 3 is revealing in that the one-sided estimate corresponds approximately to the information that would have been available to policymakers at the time. Because of the one-sided estimate's larger variance, those output gaps are generally less significant in the one-sided estimate; the gap exceeds 90% interval only twice, during the 1974–1975 and 1981–1982 recessions. More recently, the gap exceeded the one-standard deviation bound

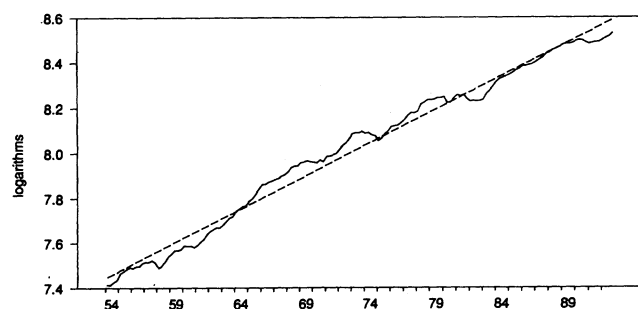


Figure 2. Real GDP and Linear Trend: Linear Trend, - - - -; Log Real GDP, ———.

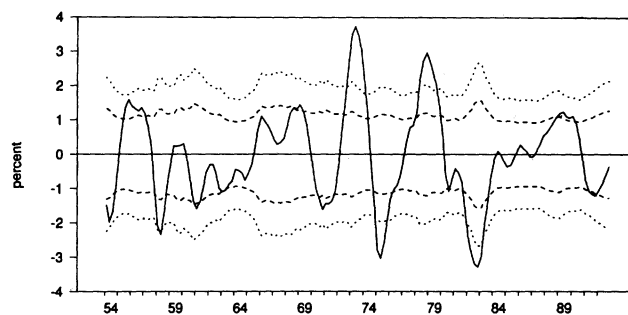


Figure 3. Two-Sided Output Gap, 1.00 and 1.69 Error Bounds.

during 1988–1989 in the two-sided estimate but failed to do so in the one-sided version. This is one example of how statistical “hindsight” can change one’s assessment of the economy. Kuttner (1992) discussed the policy implications of this uncertainty and how data revisions further complicate matters.

More data do not always result in more significant output gaps, however. During the 1966 expansion and again in the 1990 recession, the one-sided output gap exceeded one-standard-deviation bounds but fell short in the two-sided version. Apparently, it is also possible that subsequent data may lead to the conclusion that output fluctuations (measured as a deviation from potential) are *less* prominent than originally believed.

Table 10 reports the average size of the error attributable to filter and parameter uncertainty for both the one- and the two-sided estimates. For the one-sided results, the filter variance is almost twice the parameter variance. In the two-sided estimate, which incorporates information from the entire sample, the filter variance is only 60% of what it was in the one-sided case. The net effect of moving to the two-sided estimate is to reduce the overall standard error from 1.42% to 1.23%.

3.3 An Illustrative Comparison

How does the series proposed here compare with traditional estimates of potential output? Figure 5 plots the output gap implied by two-sided constant-inflation estimate of potential, along with the gap based on the “ Q^* ” series prepared by the Federal Reserve Board (FRB). This experimental estimate of potential output, constructed according to the method outlined by Braun (1990), is an ingredient in the P^* model (Hallman, Porter, and Small 1991).

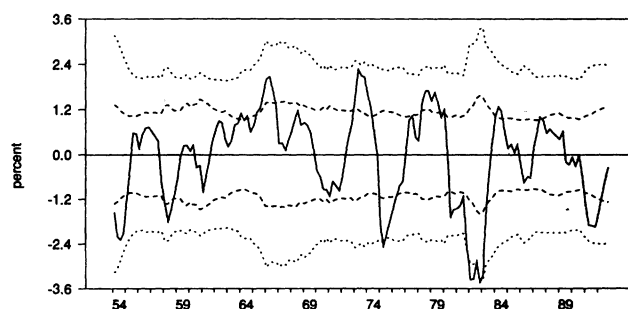


Figure 4. One-Sided Output Gap, 1.00 and 1.69 Error Bounds.

Table 10. Signal Extraction Statistics for Potential Output

	One-sided	Two-sided
Filter variance	1.41×10^{-4}	8.77×10^{-5}
Parameter variance	6.37×10^{-5}	6.76×10^{-5}
Overall standard error	1.42%	1.23%

NOTE: The parameter variances are estimated via Monte Carlo with 200 draws. The results exclude the first eight quarters of the sample to minimize the effects of the initial conditions.

Overall, the two alternative measures of the gap are qualitatively similar. The main difference between the two is in the size of the gaps, with the Q^* series generally yielding substantially larger output gaps. That is, the constant-inflation series tends to attribute a larger share of real GDP fluctuations to potential output shocks. According to the FRB series, for example, the output gap reached -6.8% , but according to the constant-inflation series, it reached a more modest -3.6% . Similarly, the 1990–1991 recession registered a -3.9% gap according to the Q^* series but only a -1.2% gap as measured by the constant-inflation series—a difference of roughly two standard deviations. The small size of the constant-inflation gap is largely a reflection of the meager reduction in inflation during this recession.

4. CONCLUSIONS

This article has described a new method for constructing a timely and economically sensible estimate of potential output by exploiting the cyclical relationship between inflation and the output gap. Estimating the bivariate model delivers a useful measure of potential output, as well as inflation's response to deviations from potential.

Generating a potential output series in this way has several significant advantages over the alternatives. First, it is readily updated as new output and inflation data are released, and unlike most existing methods, specification in terms of a stochastic trend allows for its continuous adjustment in light of current economic developments. Second, no independent measure of the natural rate of unemployment is needed, nor does it require any subjective judgment. A third important feature is its measure of the time-varying uncertainty associated with the potential output series—an essential ingredient for its use in policymaking.

Although the basic bivariate inflation-output model has

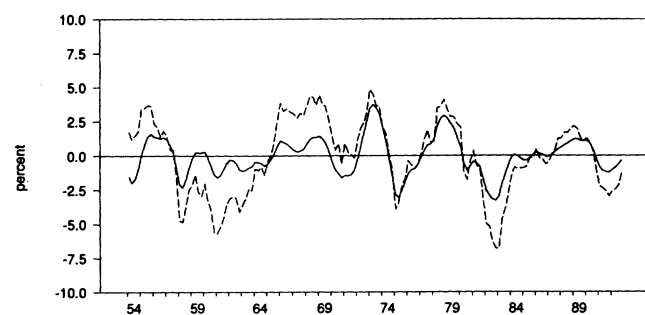


Figure 5. Comparing Alternative Output-Gap Measures: Two-Sided Gap, —; FRB Q^* Gap, ----.

delivered promising results, two extensions may yield additional refinements. One is to incorporate multiple measures of inflation, whose common dependence on the output gap would provide an even more reliable measure of underlying price pressures. In addition, this model could provide a framework for evaluating the distinct cyclical behavior of alternative price indexes. A second extension is to include suitable factor inputs as determinants of potential output, resulting in a hybrid measure embodying certain supply-side elements. Both of these extensions could easily be incorporated into the unobserved-components apparatus used here.

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