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Abstract

The popular new economy theory argues that the U.S. economy can now grow at rates much greater than in the past without igniting higher levels of price inflation. At the core of the new economy paradigm is the belief that the U.S. economy experienced an innovation in the 1990s that raised its so-called constant-inflation trend growth rate. According to its advocates, evidence of the new economy comes from the fact that the U.S. economy experienced relatively strong output growth and low levels of price inflation over the 1990s. This paper evaluates the new economy theory by formally testing whether the growth rate of the constant-inflation trend changed significantly over the 1990s. I find that there is no evidence of the new economy when the constant-inflation trend is estimated using recent GDP and CPI data. My results suggest that the robust economic expansion of the 1990s was not due to a increase in the trend growth rate but rather a cyclical expansion and a level increase in the trend.

Key words: Business cycle; Constant-inflation trend; Unobserved components.

JEL classifications: E32; O47.

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1 Introduction

It is virtually impossible these days to avoid articles in the popular press hailing the dawn of the new economy in which all the old truths about the U.S. economy no longer hold. A major tenet of this theory is that the economy can now grow at rates much greater than in the past without igniting higher levels of price inflation. This stems from the belief that the U.S. economy experienced an innovation in the 1990s that raised its so-called constant-inflation trend growth rate.[1] Advocates claim that evidence of this change comes from the fact that the U.S. economy has been growing relatively fast while maintaining relatively low levels of price inflation. At the same time, others have argued against the new economy by pointing to recent events, such as the Asian crisis, that would have had a positive impact on the level of output and inflation, but not altered the trend growth rate of output. This paper adds to the debate by formally testing whether the growth rate of the constant-inflation trend of U.S. output changed significantly over the 1990s.

The debate over the new economy boils down to the age old problem of decomposing movements in macroeconomic time series into trend and cyclical components. The trend and cycle are latent variables, so their identification depends on the researchers definition of the trend and/or cycle. Prior to the 1980s it was common for applied economists to regard the trend as a deterministic function of time and the cyclical component as a stationary process that fluctuated around the trend. In this setting, all movements in a time series above or below its constant trend growth rate were assigned to the cycle component, so periods of high growth indicated a cyclical expansion. In other words, all output fluctuations were considered temporary. At around that time Nelson and Plosser (1982) discovered that one could not reject the hypothesis that most macroeconomic time series had a stochastic trend. In this setting, fluctuations in a time series might be due to innovations in the trend or the cycle. In other words, changes in output could signal a permanent shift in the level (an innovation in the trend) or a temporary fluctuation (an innovation in the cycle). This discovery (combined with renewed interest in the business cycle in the 1980s) spawned three different approaches for isolating trend and cycle components in data with stochastic trends: spectral analysis, ARIMA time series analysis and unobserved component techniques (UC).

The most popular approach is spectral analysis. Its appeal comes the fact that it attacks the problem of trend-cycle decomposition in the frequency domain, rather than the more typical time domain used by the ARIMA and UC methods. Identification is achieved by simply specifying the frequencies that define the trend and cycle. These components are typically defined in the following way: the trend includes frequencies of 8 years or more, the cycle includes frequencies between 18 months to 8 years, while frequencies of less than 18 months are assigned to an economically

[1] See, for example, recent articles by Cooper and Madigan (1999), Mandel (1999), Shepard (1997), and Ullman, Cohen and Mandel (1999).

uninteresting irregular component. Another attraction of this approach is that the computational costs of capturing these frequencies is very low because practitioners use approximate band-pass filters (BPF) that are simple moving averages of the data (see, for example, Baxter and King 1995).

The ARIMA and UC methods are not as popular as BPFs simply because they require strong assumptions about the data generating process. In other words, they require a structural model to identify the trend and cycle. Plus, the computational costs of estimating these models is considerably higher than for BPFs. These approaches are, however, more attractive than the spectral approach in the context present study because I want to test hypotheses related to the time series properties of structural definitions of the trend.

The only restriction that economic theory appears to impose on trend-cycle decomposition is that these components be independent. This is an outgrowth of the independent study of growth and the business cycle; independence implying that innovations driving the trend and cycle are independent. I use the UC approach rather than the ARIMA approach to address the question of whether the trend growth rate has changed because the latter does not allow for independent trend-cycle decomposition sought by growth and business cycle researchers.[2]

My application builds on well-known UC models developed by Watson (1986) and Kuttner (1994). Watson's model is a parsimonious univariate model of output growth. The natural logarithm of output is modeled as an additive trend and cycle. The trend is modeled as a unit root with drift, while the independent cycle is assumed to be a second order autoregression. The trend growth rate in Watson's model is captured by the trend drift term, which is a assumed to be constant. Watson's model relied on only output data to identify the trend and cycle. Kuttner on the other hand, developed a multivariate model that allows the trend and cycle to be influenced by fluctuations in the level of price inflation and output. Kuttner's model extends Watson's analysis by adding an equation that links fluctuations in price inflation to the cyclical component of output. Under appropriate restrictions the trend generated by Kuttner's specification is consistent with Gordon's (1990, p.10) definition of the trend as that level of output where inflation is constant. I refer to this as the constant-inflation trend. This is precisely the definition of trend output that the new economy advocates claim has been growing faster in the 1990s. With that in mind, Kuttner's model is better suited to testing inferences related to the new economy theory.

I adapt Watson and Kuttner's analysis to the current problem by adding time-varying drift terms to their models. This allows me to test whether the trend growth rate of output has changed significantly over the 1990s. I do this in two ways. First, I

[2] Watson (1986) has shown that these closely related time series methods can have very different implications for the trend and cycle. In particular, Watson revealed that the cycle estimate from a parsimonious UC model of output was more persistent than the cycle from a similarly parameterized ARIMA model proposed by Beveridge and Nelson (1981). One of the features of Watson's UC model was that it generated a cycle with turning points that matched NBER peaks and troughs.

introduce decade dummy variables that capture discrete jumps in the drift term from the 1950s to 1990s. I maintain the 1990s as the base year and test if the coefficients of the decade dummies are significantly different from zero. In this case, statistically significantly lower growth rates in the decades before the 1990s would be evidence in favor of the new economy. Second, a potential weakness of the discrete jump approach is that the choice of jump dates is arbitrary, so I also allow the trend to evolve smoothly over time by modeling it as a stationary first order autoregression. This allows me to compare recent movements in the growth rate against its long run mean. In this case, evidence in favor of the new economy would show up as a significant positive deviation of recent trend growth rates (that is, over the 1990s) from their long run mean.

I complete the analysis by comparing trend and cycle estimates from the UC analysis with those from the more popular BPF approach. I find that the UC models with smoothly varying drift terms yield cycle components that are highly correlated with the cycle generated by widely used BPFs that extract business cycle frequencies of 18 months to 8 years.

The remainder of the paper is structured as follows. Section 2 investigates the trend properties of the data used in the empirical analysis. Section 3 describes in detail the structural models underlying the unobserved component analysis. Section 4 discusses econometric issues. Section 5 reports estimates of the UC models and their associated trends, cycles and trend growth rates. The paper concludes in Section 6 with a summary of the main results.

2 Trend properties of output and inflation

An important assumption in Watson (1986) and Kuttner (1994) is that the natural logarithm of real output has a unit root. Kuttner's model goes one step further in assuming that price inflation also has a unit root. This section reports the results of Augmented Dickey-Fuller (ADF) tests for nonstationarity using quarterly U.S. real chain-weighted gross domestic product (GDP) and consumer price index (CPI) data from 1951:Q1 to 1999:Q2.

The left hand panel of Table 1 reports ADF t-statistics for cases with a constant and time trend, using various lags of first differences of the dependent variable, in this case the natural logarithm of real GDP. These test statistics do not allow me to reject the null of a unit root in the log of real GDP at typical levels of significance.

A potential time-varying model of the trend growth rate of GDP is a unit root without drift (see, for example, Harvey and Todd's (1983) analysis of UK output and Clark's (1987) analysis of U.S. output). A time-varying trend growth rate with a unit root would require a unit root in the first difference of the log of real GDP. The right hand panel of Table 1 reports ADF t-statistics for the first difference of the natural logarithm of real GDP. I am able to reject the null of a unit root in the growth rate of GDP at conventional levels of significance when a constant is included in the regression. This implies that the trend growth rate of real GDP is a stationary process.

Table 2 repeats these experiments for inflation, measured as the first difference of the natural logarithm of the CPI. The left hand panel suggests that at conventional levels of significance I cannot reject the null of a unit root in inflation. The right hand panel suggests that I can reject the null of a unit root in the growth rate (first difference) of inflation at conventional levels of significance. This implies that the first difference of inflation is also a stationary process.

3 Unobserved Component Models

This section introduces notation and describes in detail the unobserved component models estimated in the paper. My starting point is a description of Watson's (1986) univariate stochastic trend model. Watson's model is parsimonious in assuming that the natural logarithm of GDP x_t can be additively decomposed into a stochastic trend τ_t and a stationary cyclical term c_t:

$$\begin{aligned} x_t &= \tau_t + c_t, & (1)\\ \tau_t &= \mu + \tau_{t-1} + \varepsilon_{\tau t}, & (2)\\ c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_{ct} & (3) \end{aligned}$$

and

$$\begin{bmatrix} \varepsilon_{\tau t} \\ \varepsilon_{ct} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_\tau^2 & 0 \\ 0 & \sigma_c^2 \end{pmatrix}\right)$$

Equation (2) describes the trend as a random walk with drift, which is consistent with the unit root tests of the last section. The constant drift term μ measures the steady state or trend growth rate (that is, the growth rate of output in the absence of shocks to the trend or cycle). Note that the overall growth rate of the trend differs from the steady state or trend growth rate by the error term $\varepsilon_{\tau t}$. In this setting, trend growth above μ indicates an increase in the level of the trend. The linear trend is a special case of (2) and corresponds to the restriction $\sigma_\tau^2 = 0$. Equation (3) describes the cyclical term, which is modeled as a second order autoregressive process.[3] The trend and cycle are independent in the sense that $\varepsilon_{\tau t}$ and ε_{ct-j} are uncorrelated for all j.

[3] Others such as Clark (1987) and Lam (1990) estimate richer time series models of the cycle. They find that increases in the value of the likelihood function over the second order autogressive process are small enough to allow them to reject the richer specifications.

3.1 Time-varying trend growth rate models

My first extension to Watson's model is to incorporate a time-varying drift term μ_t. I consider two cases, both are consistent with the unit-root tests results of the previous section. The first case assumes that changes in the trend growth rate of output take on discrete jumps. In particular, the trend growth rate is assumed to jump to a new level for a fixed interval ($t = i$ to $i + T$). Changes in the trend growth rate μ_t are measured as deviations μ_i from a base period trend growth rate μ. The discrete jump model is described by the following equations:

$$\begin{aligned} x_t &= \tau_t + c_t, && (4) \\ \tau_t &= \mu_{t-1} + \tau_{t-1} + \varepsilon_{\tau t}, && (5) \\ \mu_t &= \mu + \mu_i \text{ for } i \le t \le i + T && (6) \\ c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_{ct} && (7) \end{aligned}$$

and

$$\begin{bmatrix} \varepsilon_{\tau t} \\ \varepsilon_{ct} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_\tau^2 & 0 \\ 0 & \sigma_c^2 \end{pmatrix}\right)$$

I allow for five trend growth rate changes spanning the decades from the 1950s to 1990s. I take the 1990s as the base year and test whether there are significant deviations from the 1990s trend growth rate in the other decades. Within the context of this set up the new economy theory implies that the $\mu_i's$ spanning the decades of the 1950s to 1980s are significantly less than zero.

The second case assumes that the trend growth rate follows a stable markov process. The advantage of this model over the discrete jump model is that the persistence and timing of fluctuations in the trend growth rate are determined by the data. I limit the analysis to a stable first order autoregressive process. I do this for two reasons. First, the model is not identified for higher order specifications. Second, the analysis of the previous section ruled out a unit root in the trend growth rate. Under this assumption the model is described by the following equations:

$$\begin{aligned} x_t &= \tau_t + c_t, && (8) \\ \tau_t &= \mu_{t-1} + \tau_{t-1} + \varepsilon_{\tau t}, && (9) \\ \mu_t &= \mu(1-\rho) + \rho\mu_{t-1} + \varepsilon_{\mu t}, && (10) \\ c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_{ct} && (11) \end{aligned}$$

and

$$\begin{bmatrix} \varepsilon_{\tau t} \\ \varepsilon_{\mu t} \\ \varepsilon_{ct} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_\tau^2 & 0 & 0 \\ 0 & \sigma_\mu^2 & 0 \\ 0 & 0 & \sigma_c^2 \end{pmatrix}\right)$$

In this setting, fluctuations in the trend can come from two sources: a persistent innovation $\varepsilon_{\mu t}$ that acts through the trend growth rate μ_t, and a noise term $\varepsilon_{\tau t}$. The persistence of these trend growth rate fluctuations is determined by ρ. The steady state or long run trend growth rate is given by μ. The new economy theory suggests μ_t has been significantly higher than μ over the 1990s.

3.2 A model of the constant-inflation trend

New economy advocates argue that strong domestic demand over the 1990s has not ignited higher levels of price inflation because an innovation to the U.S. economy caused the growth rate of the constant-inflation trend of output to rise. One way to evaluate this hypothesis is to estimate a structural model that embodies this notion of the trend and test whether the trend growth rate has changed over the 1990s. A convenient starting point is Kuttner's (1994) model. This model extends Watson's univariate stochastic trend model by allowing the trend and cycle of output to be influenced by price inflation:

$$\begin{aligned}
\pi_t &= \alpha + \pi_{t-1} + \gamma_1 \Delta x_{t-1} + \gamma_2 c_{t-1} + \varepsilon_{\pi t} + \delta_1 \varepsilon_{\pi t-1} + \delta_2 \varepsilon_{\pi t-2} + \delta_3 \varepsilon_{\pi t-3}, && (12) \\
x_t &= \tau_t + c_t, && (13) \\
\tau_t &= \mu + \tau_{t-1} + \varepsilon_{\tau t}, && (14) \\
c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_{ct} && (15)
\end{aligned}$$

and

$$\begin{bmatrix} \varepsilon_{\pi t} \\ \varepsilon_{\tau t} \\ \varepsilon_{ct} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_\pi^2 & 0 & \sigma_{\pi c} \\ 0 & \sigma_\tau^2 & 0 \\ \sigma_{\pi c} & 0 & \sigma_c^2 \end{pmatrix}\right)$$

where π_t denotes the level of price inflation, Δx_{t-1}denotes the lagged first difference of the natural log output, and c_{t-1} represents the lagged cycle.

This model links changes in inflation and output in two ways. Equation (12) models changes in the level of inflation as a function of lagged output growth and the lagged cycle. Inflation and the cycle are further linked by allowing innovations to inflation $\varepsilon_{\pi t}$ to be contemporaneously correlated with innovations to the cycle ε_{ct}. The correlation coefficient of these innovations is denoted by $\rho_{\pi c} = \sigma_{\pi c}/(\sigma_\pi \sigma_c)$. Kuttner argues that this specification is consistent with expectations-augmented Phillips curve models in which the expected rate of inflation is set equal to the lagged inflation rate. The other terms in equation (12) model serial correlation in the innovations to inflation. I follow Kuttner in modelling the innovations as a third order moving average. This specification is successful in removing the serial correlation present in the error term. The remaining equations (13–15) are the same as Watson's constant drift stochastic trend model.

The advantage of this model over Watson's is that under the restriction that $\alpha = -\mu\gamma_1$ the trend of this model matches Gordon's (1990) definition of trend output as the level of output at which inflation is constant. I refer to this as the constant-inflation trend. This is the definition of trend output that the new economy theorists argue has been growing faster in the 1990s. With that in mind, Kuttner's model is better suited to testing the new economy theory.

I adapt this model (as I did the univariate model) to the new economy analysis by allowing the trend growth rate to vary by discrete jumps and a stable markov process. I also modify the restriction on the constant in the inflation equation α_t to ensure that the trend measure is consistent with the constant-inflation definition. The multivariate time-varying growth rate models are described by the following equations:

$$\begin{aligned}
\pi_t &= \alpha_t + \pi_{t-1} + \gamma_1 \Delta x_{t-1} + \gamma_2 c_{t-1} + \varepsilon_{\pi t} + \delta_1 \varepsilon_{\pi t-1} + \delta_2 \varepsilon_{\pi t-2} + \delta_3 \varepsilon_{\pi t-3}, && (16) \\
x_t &= \tau_t + c_t, && (17) \\
\tau_t &= \mu_{t-1} + \tau_{t-1} + \varepsilon_{\tau t}, && (18) \\
c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_{ct} && (19)
\end{aligned}$$

where

$$\left.\begin{array}{l} \mu_t = \mu_i, \\ \alpha_t = -\gamma_1 \mu_i, \end{array}\right. \text{for } i \leq t \leq i+T \quad \textit{Discrete jump}$$

$$\left.\begin{array}{l} \mu_t = \mu(1-\rho) + \rho\mu_{t-1} + \varepsilon_{\mu t}, \\ \alpha_t = -\gamma_1 \mu, \end{array}\right. \quad \textit{Stable markov}$$

and

$$\begin{bmatrix} \varepsilon_{\pi t} \\ \varepsilon_{\tau t} \\ \varepsilon_{\mu t} \\ \varepsilon_{ct} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_\pi^2 & 0 & 0 & \sigma_{\pi c} \\ 0 & \sigma_\tau^2 & 0 & 0 \\ 0 & 0 & \sigma_\mu^2 & 0 \\ \sigma_{\pi c} & 0 & 0 & \sigma_c^2 \end{pmatrix}\right)$$

4 Econometric issues

I estimate these UC models using maximum likelihood (MLE). In each case the likelihood function is evaluated by using the Kalman filter on the model's state space representation.[4] I simplify the estimation by transforming the models so that they

[4] I use the Nedler-Mead simplex routine of Matlab (fmins) to search the parameter space. This procedure is slower but argued to be more reliable than other procedures typically used for non-linear optimization.

are specified in first differences rather than levels of the observables. In addition, I rewrite the unobserved component describing the time-varying trend growth rate in the stable markov model so that it represents the demeaned growth rate. For example, the constant-inflation trend model with stable markov drift is estimated using the following structure:

$$\begin{aligned}
\Delta\pi_t &= -\gamma_1\mu + \gamma_1\Delta x_{t-1} + \gamma_2 c_{t-1} + \varepsilon_{\pi t} + \delta_1\varepsilon_{\pi t-1} + \delta_2\varepsilon_{\pi t-2} + \delta_3\varepsilon_{\pi t-3}, \\
\Delta x_t &= \mu + \mu_{t-1} + c_t - c_{t-1} + \varepsilon_{\tau t}, \\
\mu_t &= \rho\mu_{t-1} + \varepsilon_{\mu t}, \\
c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \varepsilon_{ct},
\end{aligned}$$

and

$$\begin{bmatrix} \varepsilon_{\pi t} \\ \varepsilon_{\tau t} \\ \varepsilon_{\mu t} \\ \varepsilon_{ct} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_\pi^2 & 0 & 0 & \sigma_{\pi c} \\ 0 & \sigma_\tau^2 & 0 & 0 \\ 0 & 0 & \sigma_\mu^2 & 0 \\ \sigma_{\pi c} & 0 & 0 & \sigma_c^2 \end{pmatrix}\right)$$

The advantages of this approach are twofold. First, the computation costs are lower because the state vector is reduced to current and lagged values of the cycle, demeaned growth rate and inflation innovation. Second, these components are assumed to be stationary so the initial values of the state vector and the initial mean square error matrix of the state vector can simply be written in terms of the population moments of the state vector:

$$\begin{bmatrix} c_t \\ c_{t-1} \\ \mu_t \\ \mu_{t-1} \\ \varepsilon_{\pi t} \\ \varepsilon_{\pi t-1} \\ \varepsilon_{\pi t-2} \\ \varepsilon_{\pi t-3} \end{bmatrix} \sim NID\left(0, \begin{pmatrix} \sigma_c^{*2} & \frac{\phi_1\sigma_c^{*2}}{(1-\phi_2)} & 0 & 0 & \sigma_{\pi c} & a_1\sigma_{\pi c} & a_2\sigma_{\pi c} & a_3\sigma_{\pi c} \\ \frac{\phi_1\sigma_c^{*2}}{(1-\phi_2)} & \sigma_c^{*2} & 0 & 0 & 0 & \sigma_{\pi c} & a_1\sigma_{\pi c} & a_2\sigma_{\pi c} \\ 0 & 0 & \frac{\sigma_\mu^2}{1-\rho^2} & \frac{\rho\sigma_\mu^2}{1-\rho^2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\rho\sigma_\mu^2}{1-\rho^2} & \frac{\sigma_\mu^2}{1-\rho^2} & 0 & 0 & 0 & 0 \\ \sigma_{\pi c} & 0 & 0 & 0 & \sigma_\pi^2 & 0 & 0 & 0 \\ a_1\sigma_{\pi c} & \sigma_{\pi c} & 0 & 0 & 0 & \sigma_\pi^2 & 0 & 0 \\ a_2\sigma_{\pi c} & a_1\sigma_{\pi c} & 0 & 0 & 0 & 0 & \sigma_\pi^2 & 0 \\ a_3\sigma_{\pi c} & a_2\sigma_{\pi c} & 0 & 0 & 0 & 0 & 0 & \sigma_\pi^2 \end{pmatrix}\right).$$

where $\sigma_c^{*2} = \frac{\sigma_c^2}{1-\phi_1^2-\phi_2^2-2\phi_1\phi_2^2/(1-\phi_2)}$, $a_j = \phi_1^j + (j-1)\phi_1^{j-2}\phi_2$ and $\sigma_{\pi c} = \rho_{\pi c}\sigma_\pi\sigma_c$. This avoids the many problems associated with estimating the models in levels, such as, the unobserved components estimates depending critically on initial values of the state vector and its associated mean square error matrix.

5 Empirical findings

This section reports MLE estimates of the univariate and multivariate UC models described in the previous section using quarterly chain-weighted real GDP and CPI data from 1951:Q1 to 1999:Q2. I present the results in the following way. First, I report parameter estimates for the univariate model under the three growth rate assumptions. Next, I compare parameter estimates of the univariate model with those of the multivariate model. This allows me to contrast the cycle and time-varying growth rate components estimated with and without inflation data.

I use the following conventions when reporting parameters estimates or plotting the unobserved components. The trend growth rate μ and the standard deviation of the innovation to the trend σ_τ and cycle σ_c are expressed as annualized rates. Plots of the unobserved components refer to the smooth or two-sided estimate generated by the Kalman smoother. Confidence intervals for the unobserved components are calculated via the Monte Carlo method described in Hamilton (1994, p.397–399) using 1000 draws. In the case of the cycle c_t it is expressed as quarterly percentage deviations from the trend. The time varying trend growth rate μ_t is expressed as an annualized rate.

One of the secondary goals of this paper is to compare structural and spectral trend-cycle decomposition methods. I fulfil this objective by using the cycle (and trend) generated by Baxter and King's (1995) quarterly business cycle BPF and NBER peak-to-trough dates as reference series in plots of the UC cycles (and trends). You should note that this BPF is approximated by a two-sided moving average, with a lag length of 12 quarters, so I am unable to report BPF estimates for the first and last 12 observations. Note also that the NBER dates begin with a peak in 1953:Q3 and end with a trough in 1991:Q1.

5.1 Univariate model

Table 3 reports parameter estimates of Watson's (1986) univariate model with a constant drift term. Despite additional data and the move to chain-weighted real quantity indices the parameter estimates in Table 3 are very close to those reported by Watson. The annualized trend growth rate of real GDP is estimated at 3.14 percent. This is somewhat higher than the trend growth rate typically quoted by business economists of around 2.25 percent.[5] Innovations to the trend have an annualized standard deviation of 2.42 percent, while innovations to the cycle have an annualized standard deviation of 2.59 percent. The autoregressive coefficients of the cyclical term are 1.48 and -0.54 respectively, which suggests the cycle is persistent.

Figure 1A plots the smoothed UC cyclical term (solid line) against the business cycle frequency component of GDP extracted using a Baxter-King business cycle BPF (dashed line) and the NBER peak-to-trough dates (light vertical lines). The UC and BPF cycles have similar turning points, which line up with NBER dates. However, the series have different amplitudes. The BPF estimate tends to oscillate around zero, while the UC estimate tends to lie above or below the zero for longer periods. For example, in the period following the most recent trough, 1991:Q1, the

[5] See, for example, the estimates reported in Cooper and Madigan (1999) and Shepard (1997).

BPF suggests that U.S. output has been at or close to trend, while the univariate UC model indicates that U.S. output has been below trend. Figure 2A provides a different view of the trend-cycle decomposition by comparing the UC trend (solid line) and BPF trend (dashed line). The UC trend tends to be more linear than the BPF trend. In contrast to the cycle, the UC trend has been above the BPF trend since the last trough.

Table 4 reports estimates of the univariate model with time-varying growth rates. I turn your attention first to the results for the discrete jump model reported in the upper panel. Estimates of the difference between the trend growth rate of the 1990s and the preceding four decades are reported in the upper row. The estimates suggest that the 1990s trend growth rate was not significantly higher than in the earlier decades. In fact, the point estimates suggest that the growth rate of the 1990s was below that of the other decades. This is especially true for the 1960s. The point estimate of the difference between the 1960s trend growth rate and that of the 1990s is a statistically significant 1.88 percent. Figure 3A reveals that the trend growth rates from the UC model (thin solid line) take on the same pattern as the decade average GDP growth rates (thick solid line). Overall, these findings suggest that there is no evidence of a significant positive increase in the trend growth rate over the 1990s, which rejects the new economy theory.

One consequence of the discrete jump assumption is that the standard deviation of the trend innovation in considerably lower. This means that the trend is essentially a series of linear trends (see Figure 2B). Figure 1B describes the cycle under the discrete jump assumption. The obvious implication is that the UC cycle (solid line) has greater amplitudes than the BPF business cycle component (dashed line). Another implication of the discrete jump assumption is that it suggests U.S. output is currently well above its trend.

The lower panel of Table 4 reports estimates of the stable markov drift model which allows for the trend growth rate to vary according to a stable first order autoregressive process. The estimates of the direction change and the size of the shifts in the growth rate are reported in the upper row of the panel. The point estimates suggest that innovations to the demeaned trend growth rate are large with a standard deviation of 1.06 percent, while the deviations from the mean growth rate are persistent with an autoregressive coefficient of 0.67. However, these estimates are imprecise which suggests there has not been significant variation in the growth rate over the sample. The lack of precision in the direction of change and the size of innovations to the growth rate is revealed in Figure 3B by the volatility of the smoothed time-varying trend growth rate (thin solid line).

The remainder of the panel reveals that the point estimates of the trend and cycle parameters are slightly different to the model with a constant mean. The annualized trend growth rate is unchanged at 3.15 percent, while the standard deviation of innovations to the trend remain at 2.43 percent. The changes are confined to the cycle component. The cycle has a smaller innovation standard deviation of 2.19

percent, down from 2.42 percent in the constant case. The autoregressive coefficients suggest the cycle is less persistent. These differences are evident in plots of the cycle. Figures 1C and 1D plot the smoothed UC stable markov cycle (solid line) against the BPF cycle (dashed line) and UC constant drift cycle (dashed line), respectively. In contrast to the constant growth rate model the UC cycle from the stable markov model has a smaller amplitude than the BPF cycle. Notice also that the correlation between the BPF and UC cycle components has risen from 0.81 in the constant growth model to 0.99 in the markov model.

Figure 2C reveals that the stable markov model and BPF trend are quite similar. This is not surprising after looking at Figure 3B, which plots the markov model trend growth rate (thin solid line) against the BPF estimate (thick solid line). The stable markov model displays growth rate fluctuations that have a similar amplitude to the BPF trend growth rate series. Focusing on the results over the 1990s, the stable markov model suggests that the trend growth rate of GDP rose over that period but only to levels that had been experienced in the 1970s and 1980s. More importantly the estimates suggests the growth rate has been constant over the last three years (the period when most advocates argue the new economy was apparent in the data) at close to the annualized long run mean of 3.15 percent. These findings suggest that there is currently no evidence of the new economy in real GDP data.

5.2 Multivariate model

Table 5 reports estimates of Kuttner's (1994) constant-inflation trend model using recent real GDP and CPI data that cover the period from 1951:Q1 to 1999:Q2. Despite numerous methodological changes to the data the parameter estimates are essentially unchanged from Kuttner's original estimates. The parameters describing the trend and cycle components of output differ slightly from the univariate estimates. The annualized trend rate of growth is roughly similar at 3.10 percent, while the standard deviation of the innovations to the trend are higher at 2.87 percent. There are subtle differences in the parameters describing the cyclical term. The autoregressive coefficients are larger in absolute value, while the standard deviation of the innovations to the cycle is smaller. Visually the differences are more noticeable. The smoothed cycle from the constant-inflation trend model (solid line) is virtually identical to the business cycle component generated by a BPF (dashed line) in Figure 4A. The correlation of the BPF and constant trend UC cycle has risen from 0.81 in the univariate model to 0.96 in the multivariate case, while the amplitudes of the series are closer. The BPF cycle is slightly more volatile. Not surprisingly, Figure 5A reveals that the constant inflation and BPF trend are also closely related.

Fluctuations in the multivariate cycle match the movements in the BPF business cycle component over the early 1990s. I noted above that the BPF cycle suggested that U.S. output was close to its trend over this period, the multivariate cycle component suggests that this pattern continued over the last three years of the sample.

Recall that the univariate model suggested that the U.S. was operating below its trend, so the introduction of information on changes in the level of inflation has actually lowered the level of the trend over the 1990s (see Figures 6A and 6B). Note also, that while the overall growth rate of the multivariate trend is higher than the overall growth rate of the univariate trend in the early to mid 1990s, their overall grow rates converge over the last three years of the sample. One way to see this is by comparing the cycle estimates; parallel movements in the cycle imply parallel movements in the trend or a common growth rate. These results work against the new economy theory since the theory suggests that recent movements in inflation should have had a positive impact on the overall growth rate of trend output.

Figures 7A and 7B provide another measure of the effect of inflation information on the parameter estimates of the cycle. These figures show that information on inflation greatly improves the precision of the unobserved component by substantially lowering the size of the 95 percent confidence intervals of the cycle.

The next step is to relax the assumption of a constant trend growth rate. I do this by allowing for discrete jumps in the trend growth rate over decade long intervals and by allowing the trend growth rate to be a smoothly evolving first order autoregressive process. The parameter estimates are reported in Table 6. I report the findings for the discrete jump model in the upper panel. The results are similar to the univariate case. I find that the growth rate of the constant-inflation trend over the 1990s is not significantly different from estimates of the trend growth rates of the 1950s, 1970s and 1980s, while it is significantly lower than the growth rate experienced in the 1960s. Figure 3A reveals two pieces of information. First, the estimated trend growth rates from the univariate (thin solid line) and multivariate (dashed line) discrete jump models are similar, which suggests that incorporating information on inflation has little impact on the results. Second, the multivariate discrete jump model generates trend growth rate estimates that are similar to the decade average growth rates of GDP (thick solid line). These findings suggest that there is no evidence of the new economy in GDP and CPI data.

The lower panel of Table 6 reports parameter estimates for the multivariate model with stable markov drift. In contrast to the univariate model the direction of change in the demeaned trend growth rate term is slightly larger at 0.84, while the estimated standard deviation of the innovation to the demeaned trend growth rate is considerably smaller at 0.43 percent. Both parameters have smaller standard errors than the univariate estimates. The other parameters of the model are virtually unchanged from the constant growth model (see Table 5). This observation is reinforced by Figure 4D which shows that the cycle from the stable markov model (solid line) is virtually identical to the constant growth rate cycle (dashed line). A comparison of standard deviations suggest that the constant growth model has a slightly more volatile cycle. This comes about because some of the temporary fluctuations are passed to the constant-inflation trend growth rate.

Figure 3B reveals that the multivariate trend growth rate shares common turning points with the univariate and BPF trend growth rates. Although, the multivariate estimate has a smaller amplitude than the other estimates. The multivariate model also suggests that the trend growth rate has been increasing over the 1990s. The estimates from the constant-inflation trend model also imply that the trend growth rate has merely returned to levels experienced in the 1970s and 1980s. Over the last three years the constant-inflation trend has been constant at around its long run mean of 3.1 percent. These results suggest that there is no evidence of a significant increase in the trend growth rate of U.S. output over the 1990s in real GDP and CPI data, which rejects the new economy theory.

Figures 6C and 6D compare the trends and cycles of the univariate and multivariate models with stable markov drift. This comparison gives a measure of the impact of incorporating information on inflation on the trend and cycle. In contrast to the constant drift case, presented in Figures 6A and 6B, incorporating information on inflation appears to have a small impact on the point estimates of the trend and cycle. Figures 7C and 7D reveal that while information on inflation appears to have a negligible impact on the point estimates of the trend growth rate it does improve the precision of the estimates by substantially lowering the size of the 95 percent confidence intervals. However, the point estimates remain imprecise. This suggests that there is no evidence of significant variation in the trend growth rate over the sample.

6 Conclusion

The popular press has hailed the dawn of a new paradigm in which the U.S. economy can expand at rates much greater than the past without igniting higher levels of price inflation. Underlying this theory is the belief that the U.S. experienced structural change in the 1990s that raised its constant-inflation trend growth rate. New economy advocates argue that evidence of the structural change is embodied in the low rates of price inflation and high output growth rates of the 1990s. I respond to this by formally estimating the constant-inflation trend using these price and output data. I estimate models that allow for two types of variation in the trend growth rate. In the first model the trend growth rate is allowed to vary by discrete jumps. The other model allows for smooth changes in the growth rate by modeling it as a first order autoregression. Estimates from both these models suggest that the trend growth rate of the 1990s is not significantly different from the trend growth rates the 1970s and 1980s. Overall, the statistical models suggests that the robust performance of the U.S. economy over the 1990s was due to factors that permanently raised its productive capacity, but did not change its trend growth rate.

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Table 1

Unit-Root Tests for Real GDP

	$x_t = \ln(GDP_t)$	$\Delta x_t = x_t - x_{t-1}$
Lags	**Constant, Trend**	**Constant**
2	-2.14	-7.12
4	-1.87	-6.93
8	-1.48	-4.97
12	-1.62	-4.52

Source: Author's calculations based on GDP data from 1951:Q1 to 1999:Q2.

Table 2

Unit-Root Tests for CPI Inflation

	$\pi_t = \ln(CPI_t) - \ln(CPI_{t-1})$	$\Delta\pi_t = \pi_t - \pi_{t-1}$
Lags	**Constant, Trend**	**Constant**
2	-2.12	-8.69
4	-2.57	-6.90
8	-2.67	-5.74
12	-1.84	-5.52

Source: Author's calculations based on CPI data from 1951:Q1 to 1999:Q2.

Table 3

Estimated Univariate Model for Real GDP

Parameter estimates					Summary Statistics		
μ	ϕ_1	ϕ_2	σ_τ	σ_c	SE	Q(16)	LLF
3.14	1.48	-0.54	2.42	2.59	0.94	13.79	-82.11
(0.21)	(0.15)	(0.17)	(0.63)	(0.70)			

Notes: Standard errors in parenthesis. SE denotes equation standard error.

Q(n) is the Box-Ljung test for randomness of the errors distributed χn.

LLF denotes the log of the likehood function.

Source: Author's calculations based on GDP data from 1951:Q1 to 1999:Q2.

Table 4

Estimated Univariate Model for Real GDP with Time-Varying Drift

Discrete Jump

Parameter estimates					Summary Statistics		
μ_{50}	μ_{60}	μ_{70}	μ_{80}				
0.31	1.88	0.17	0.21				
(0.61)	(0.58)	(0.54)	(0.78)				
μ	ϕ_1	ϕ_2	σ_τ	σ_c	SE	Q(16)	LLF
2.56	1.26	-0.39	0.00	3.52	0.91	15.49	-73.89
(0.53)	(0.07)	(0.08)	(270.59)	(0.23)			

Stable Markov

Parameter estimates					Summary Statistics		
ρ	σ_μ						
0.67	1.06						
(4.94)	(15.69)						
μ	ϕ_1	ϕ_2	σ_τ	σ_c	SE	Q(16)	LLF
3.15	1.43	-0.58	2.43	2.19	0.94	12.16	-81.38
(0.30)	(0.38)	(0.50)	(0.71)	(5.82)			

Notes: Standard errors in parenthesis. SE denotes equation standard error.

Q(n) is the Box-Ljung test for randomness of the errors distributed χn.

LLF denotes the log of the likehood function.

Source: Author's calculations based on GDP data from 1951:Q1 to 1999:Q2.

Table 5

Estimated Multivariate Model for Real GDP

Parameter estimates						**Summary Statistics**		
μ	ϕ_1	ϕ_2	σ_τ	σ_c	$\rho_{\pi c}$	SE	Q(16)	
3.10	1.54	-0.68	2.87	1.96	0.15	0.95	13.56	
(0.24)	(0.12)	(0.11)	(0.32)	(0.45)	(0.16)			
γ_1	γ_2	δ_1	δ_2	δ_3	σ_π	SE	Q(16)	LLF
0.06	0.05	-0.43	-0.44	0.49	1.58	0.44	18.70	-4.51
(0.02)	(0.01)	(0.08)	(0.07)	(0.06)	(0.07)			

Notes: Standard errors in parenthesis. SE denotes equation standard error.

Q(n) is the Box-Ljung test for randomness of the errors distributed χn.

LLF denotes the log of the likehood function.

Source: Author's calculations based on GDP and CPI data from 1951:Q1 to 1999:Q2.

Table 6

Estimated Multivariate Model for Real GDP with Time Varying-Drift

Discrete Jump

Parameter estimates						**Summary Statistics**		
μ_{50}	μ_{60}	μ_{70}	μ_{80}					
-0.06	1.88	0.23	0.18					
(0.41)	(0.41)	(0.34)	(0.52)					
μ	ϕ_1	ϕ_2	σ_τ	σ_c	$\rho_{\pi c}$	SE	Q(16)	
2.56	1.27	-0.40	0.12	3.54	0.07	0.93	15.59	
(0.34)	(0.07)	(0.07)	(2.76)	(0.20)	(0.07)			
γ_1	γ_2	δ_1	δ_2	δ_3	σ_π	SE	Q(16)	LLF
0.06	0.03	-0.39	-0.43	0.48	1.61	0.45	19.38	4.51
(0.02)	(0.01)	(0.07)	(0.07)	(0.06)	(0.07)			

Stable Markov

Parameter estimates						**Summary Statistics**		
ρ	σ_μ							
0.84	0.43							
(0.49)	(1.09)							
μ	ϕ_1	ϕ_2	σ_τ	σ_c	$\rho_{\pi c}$	SE	Q(16)	
3.09	1.50	-0.65	2.67	2.08	0.16	0.95	12.03	
(0.31)	(0.13)	(0.13)	(0.38)	(0.52)	(0.15)			
γ_1	γ_2	δ_1	δ_2	δ_3	σ_π	SE	Q(16)	LLF
0.07	0.05	-0.42	-0.44	0.48	1.58	0.45	19.26	-3.72
(0.02)	(0.02)	(0.09)	(0.08)	(0.06)	(0.07)			

Notes: Standard errors in parenthesis. SE denotes equation standard error.

Q(n) is the Box-Ljung test for randomness of the errors distributed χn.

LLF denotes the log of the likehood function.

Source: Authors calculation's based on GDP and CPI data from 1951:Q1 to 1999:Q2.

Figure 1

Univariate Cycle Component of GDP

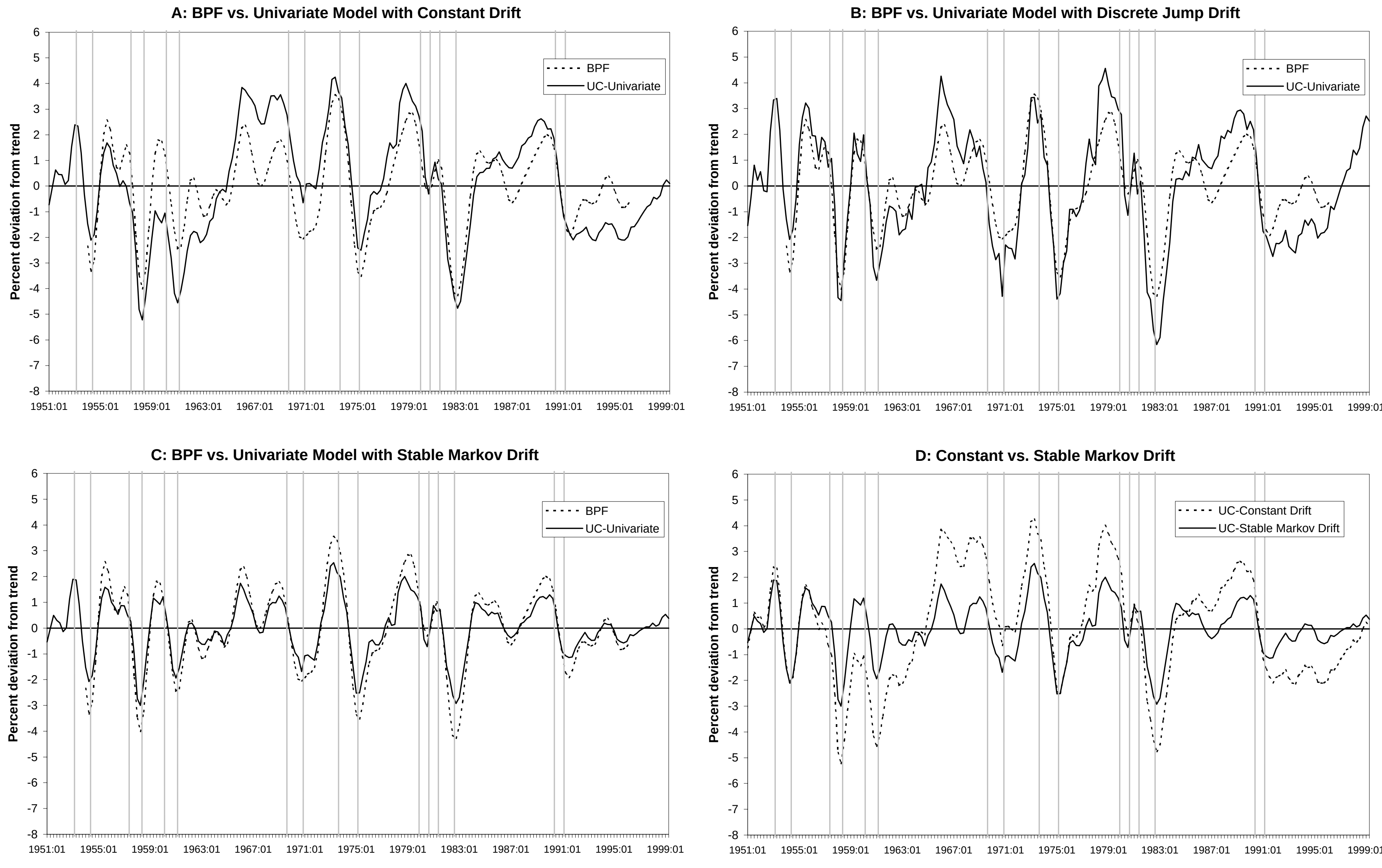

Figure 2

Univariate Trend Component of GDP

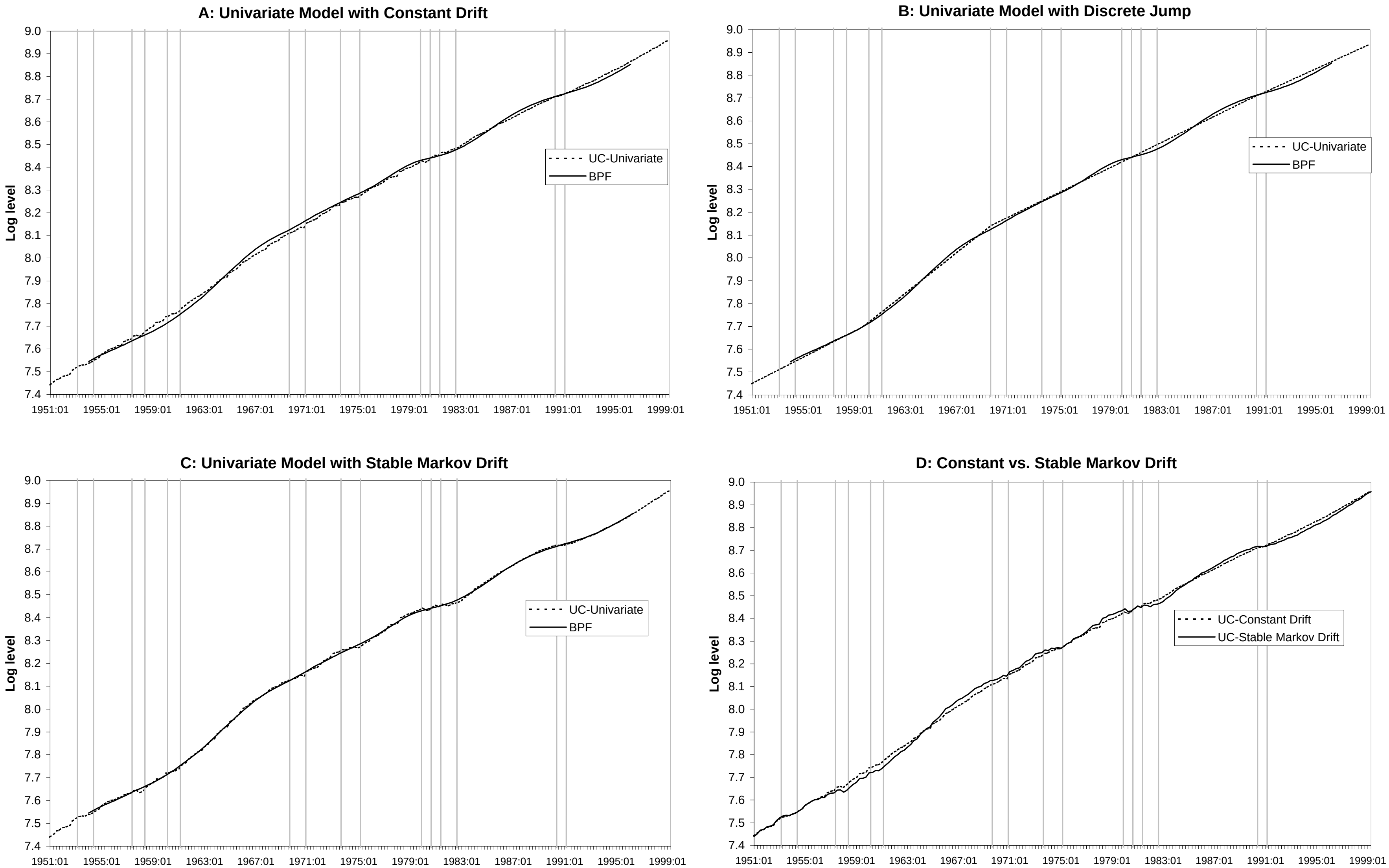

Figure 3

Trend Growth Rate

A: Decade Average vs. UC Models with Discrete Jumps

B: BPF vs. UC Models with Stable Markov Drift

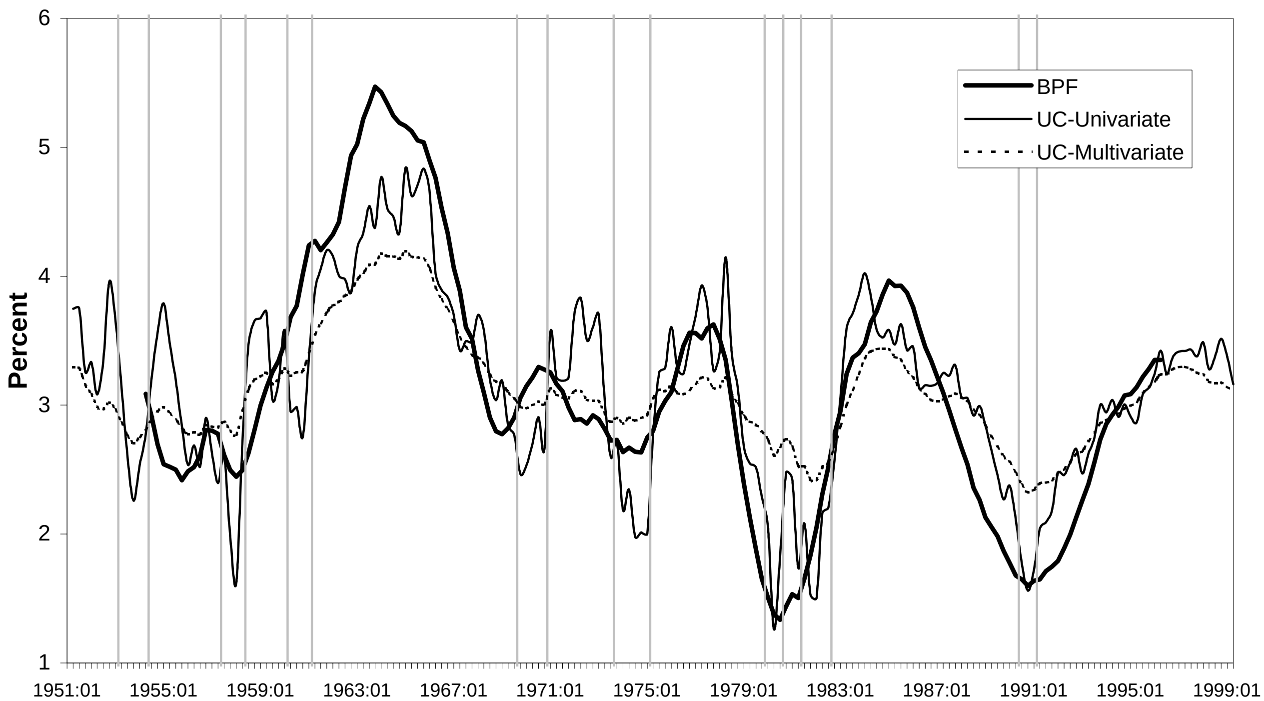

Figure 4

Multivariate Cycle Component of GDP

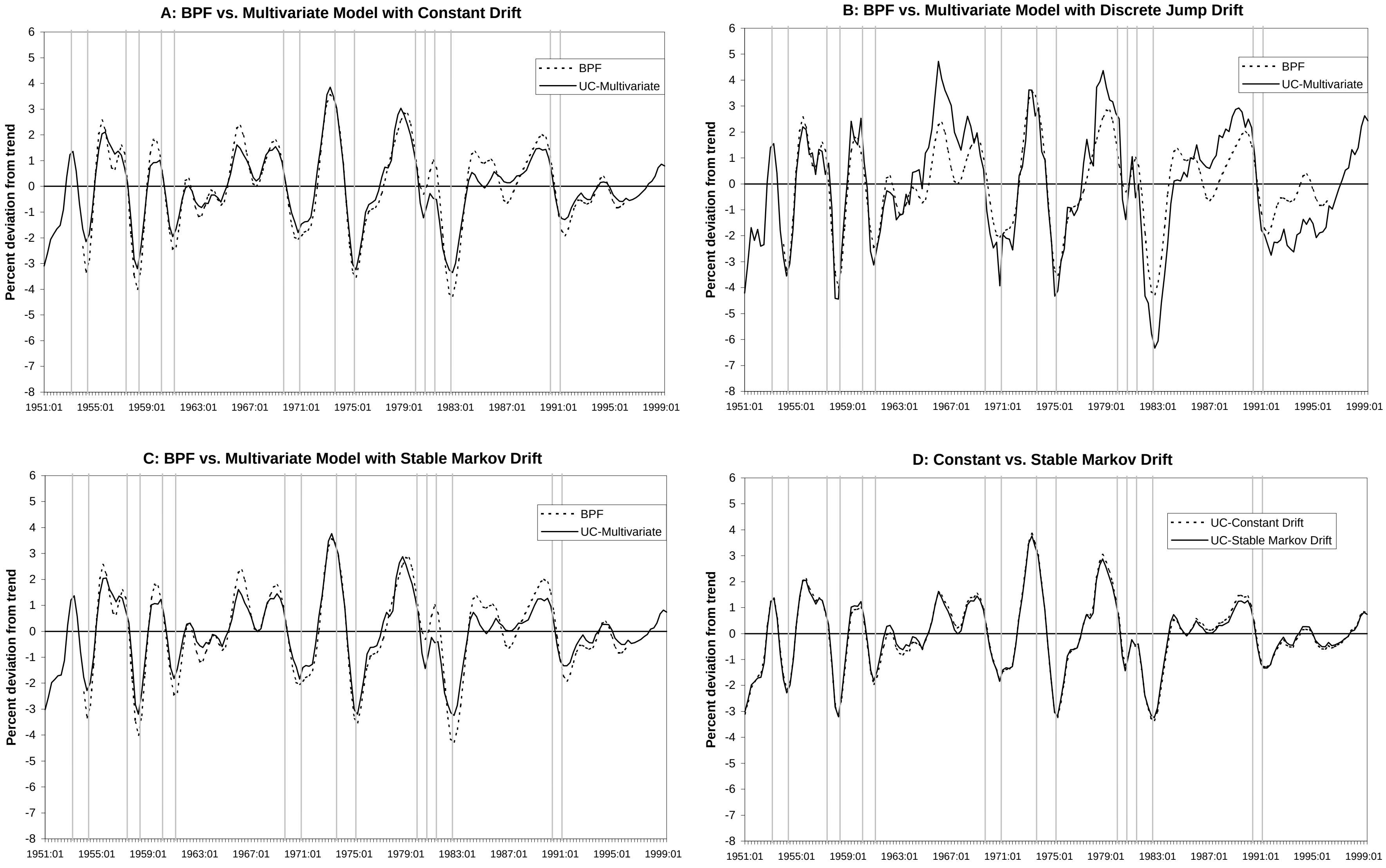

Figure 5

Multivariate Trend Component of GDP

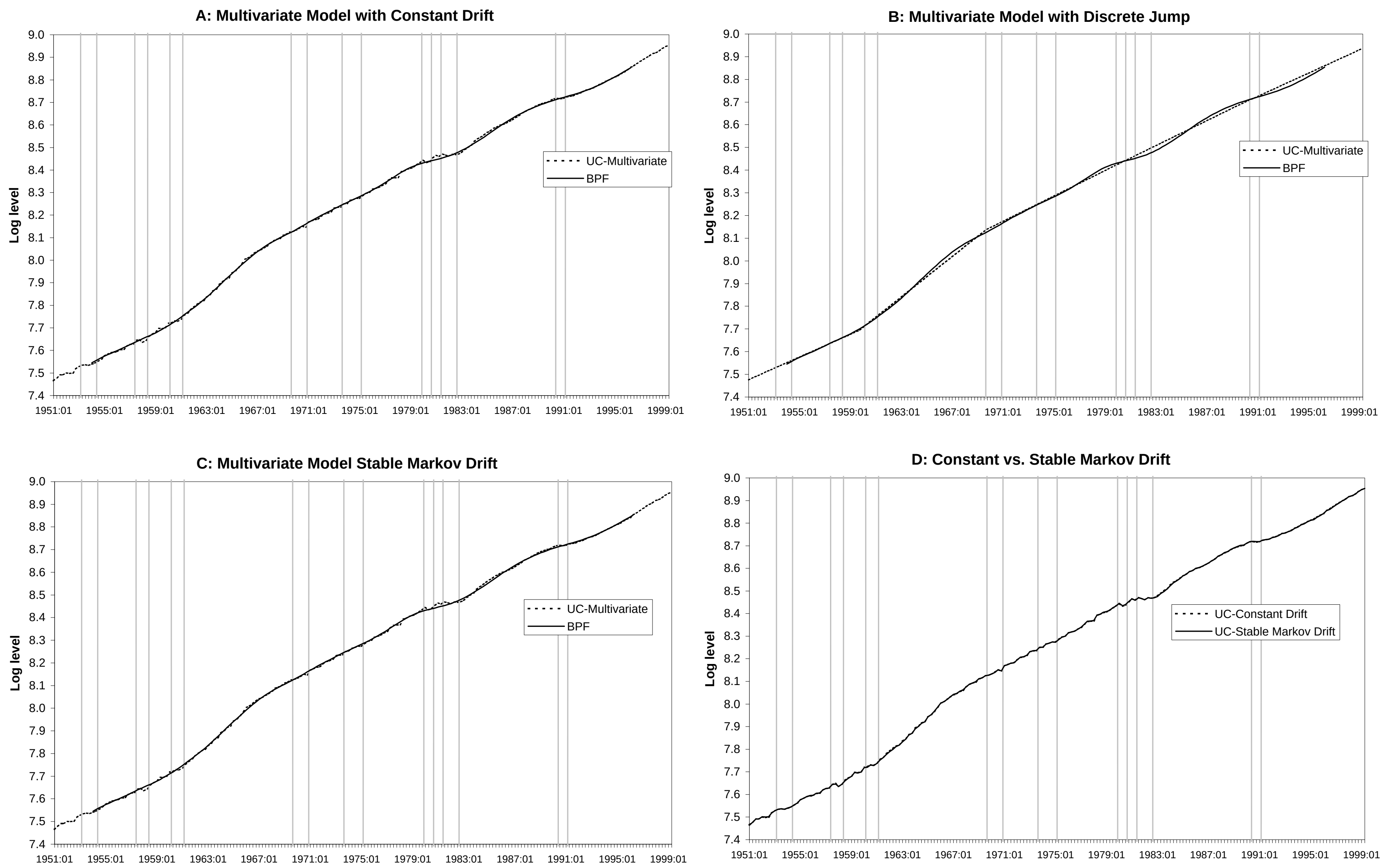

Figure 6

Comparison of Univariate and Multivariate UC Models

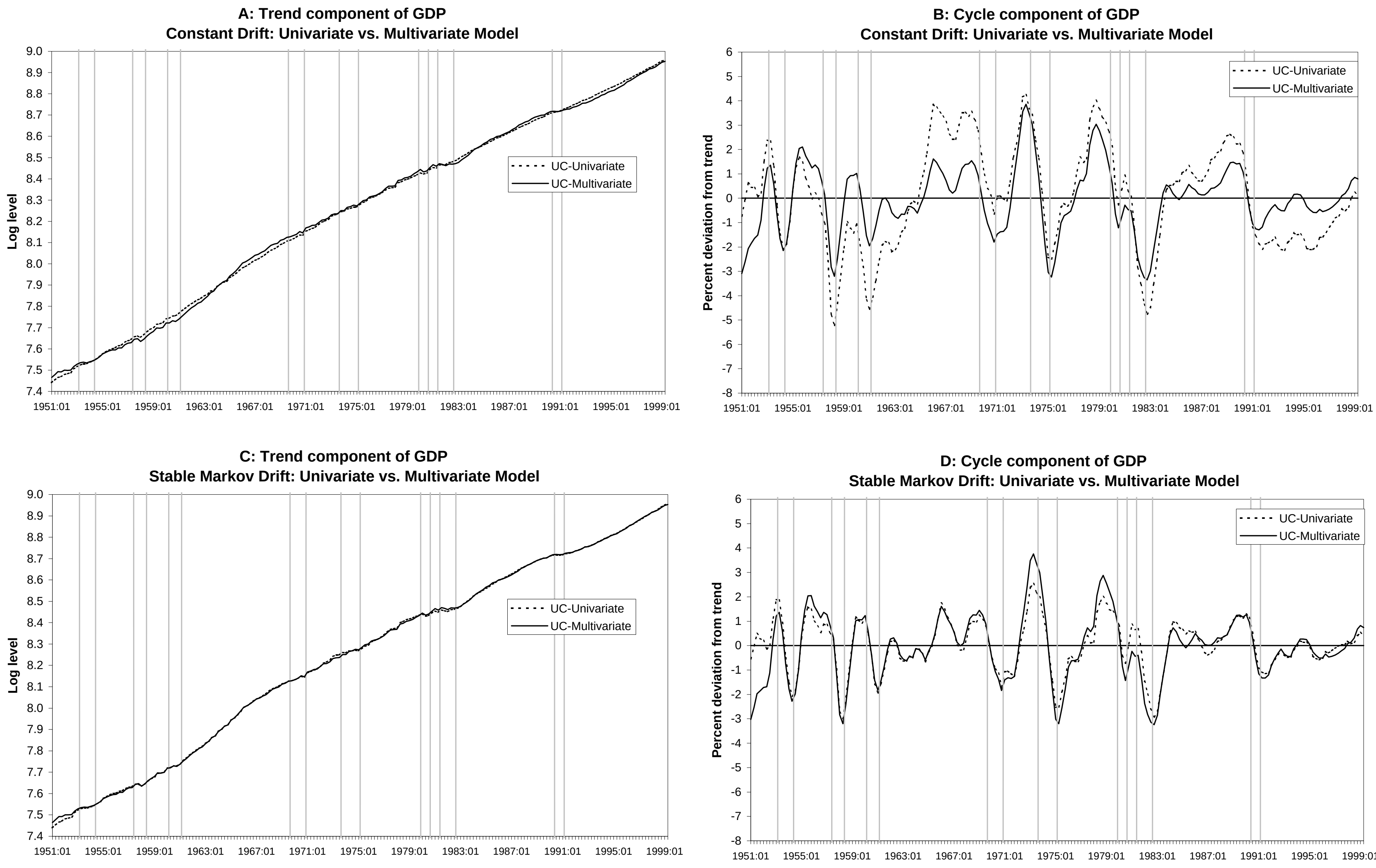

Figure 7

Confidence Intervals for Unobserved Components