Deterministic vs. Stochastic Trend in U.S. GNP, Yet Again

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Deterministic vs. Stochastic Trend in U.S. GNP, Yet Again

Almost fifteen years after the seminal work of Nelson and Plosser (1982), the question of deterministic vs. stochastic trend in U.S. GNP (and other key aggregates) remains open. This discouraging outcome certainly isn't due to lack of professional interest--the literature on the question is huge. Instead, the stalemate may be explained by low power of tests of stochastic trend (or "difference stationarity" in the parlance of Cochrane, 1988) against nearby deterministic-trend ("trend stationary") alternatives, together with the fact that such nearby alternatives are the relevant ones.

In an important development, Rudebusch (1993) contributes to the "we don't know" consensus by arguing that unit-root tests applied to U.S. quarterly real GNP per capita lack power even against *distant* alternatives. Rudebusch builds his case in two steps. First, he shows that the best-fitting trend-stationary and difference-stationary models imply very different medium- and long-run dynamics. Then he shows with an innovative procedure that, regardless of which of the two models obtains, the exact finite-sample distributions of the Dickey-Fuller (e.g., 1981) test statistics are very similar. Thus, unit root tests are unlikely to be capable of discriminating between the deterministic and stochastic trend.

The distinction between trend stationarity and difference stationarity is not critical in some contexts. Often, for example, one wants a broad gauge of the persistence in aggregate output dynamics, in which case one may be better informed by an interval estimate of the dominant root in an autoregressive approximation. Hence the importance of Stock's (1991) clever procedure for computing such intervals. But the distinction between trend stationarity and difference stationarity *is* potentially important in other contexts, such as economic forecasting, because the trend- and difference-stationary models may imply very different dynamics and hence different point forecasts, as argued by Stock and Watson (1988) and Campbell and Perron (1991).

Motivated by the potential importance of unit roots for the forecasting of aggregate output, as well as other considerations that we discuss later, we extend Rudebusch's analysis to several long spans of annual U.S. real GNP data. We examine both the Balke-Gordon (1989) and Romer (1989) pre-1929 real GNP series, in both levels and per capita terms, and we examine the robustness of all results to variations in the sample period. As we shall show, the outcome is both surprising and robust.

*Others who have found that the U.S. is TS but the rest of the world is DS:

de Haan and Zelhorst (1993, 1994 and another forthcoming in JMCB)

I. Construction of Annual U.S. Real GNP Series, 1869-1993

Three annual "raw" data series underlie the annual series used in this paper. We create the first two, which are real GNP series, by splicing the Balke-Gordon and Romer 1869-1929 real GNP series to the 1929-1993 real GNP series reported in Table 1.10 of the National Income and Product Accounts of the United States, measured in billions of 1987 dollars. The two historical real GNP series are measured in billions of 1982 dollars, which we convert to 1987 dollars by multiplying by 1.166, which is the ratio of the 1987 dollar value to the 1982 dollar value in the overlap year 1929, at which time both the Balke-Gordon and Romer series are in precise agreement.

The third series is the total population residing in the United States in thousands of people, as reported by the Bureau of the Census. For 1869-1970, we take the data from Table A-7 of *Historical Statistics of the United States*. For 1971-1993, we take the data from the Census Bureau's *Current Population Reports*, Series P-25.

From these underlying series we create and use:

GNP-BG ("GNP, Balke-Gordon"): Gross national product, pre-1929 values from Balke-Gordon;

GNP-R ("GNP, Romer"): Gross national product, pre-1929 values from Romer;

GNP-BGPC ("GNP, Balke-Gordon, per capita"): Gross national product per capita, pre-1929 values from Balke-Gordon;

GNP-RPC ("GNP, Romer, per capita"): Gross national product per capita, pre-1929 values from Romer.

In each case, of course, the post-1929 values are identical. In the earlier years, however, they differ because of the differing assumptions underlying their construction.

As a guide to subsequent specification, we report here the results of conventional Dickey-Fuller tests of difference stationarity. The augmented Dickey-Fuller regression is

$$y_t = \hat{\mu} + \hat{\gamma}\, t + \hat{\delta}\, y_{t-1} + \sum_{j=1}^{k-1} \hat{\phi}_{t-j}\, \Delta y_{t-j} + \hat{\epsilon}_t,$$

and a unit root corresponds to $\delta = 1$. The Dickey-Fuller statistic is $\hat{\tau} = (\hat{\delta} - 1)/SE(\hat{\delta})$, where $SE(\hat{\delta})$ is the standard error of the estimated coefficient, $\hat{\delta}$.

We give particular care to the determination of k, the augmentation lag order, and we examine the sensitivity of test results to variation in k, because it's well-known that the results of Dickey-Fuller tests may vary with k. A number of authors have recently addressed this important problem, exploring the properties of various lag-order selection criteria. For example, Hall (1994) establishes conditions under which the Dickey-Fuller test statistic converges to the Dickey-Fuller distribution when data-based procedures are used to select k, and he verifies that the conditions are satisfied by the popular Schwarz information criterion. Ng and Perron (1995), however, argue that t and F tests on the augmentation lag coefficients in the Dickey-Fuller regression are preferable, because they lead to less size distortion and comparable power.

We report estimates of the augmented Dickey-Fuller regressions in Table 1. The analysis is conducted for the four real GNP variables discussed above and for k=1 through k=6. The common sample period for all variables and for all values of k is 1875 to 1993. The selected lag order in the Dickey-Fuller regression for all four variables is k=2, regardless of whether we use the Schwarz criterion, the Akaike criterion, or conventional hypothesis-testing procedures to determine k. More precisely, all diagnostics indicate that k=1 is grossly inadequate and that k>2 is unnecessary and therefore wasteful of degrees of freedom. Thus, in terms of a "reasonable range" in which to vary k, we focus on k=2 through k=4, and our attention centers on k=2. Throughout the relevant range of k values, and for each series, we consistently reject the unit-root hypothesis at significance levels better than one percent, strongly supporting the trend-stationary model.

III. Evidence From Rudebusch's Exact Finite-Sample Procedure

Now we perform a Rudebusch-style analysis. In Table 2 we display the full-sample estimates of the selected trend-stationary and difference-stationary models for each of the four GNP series. For each series, the two models fit about equally well, but they imply very different dynamics, as can be seen by comparing the forecasts shown in Figure 1, in which we graph GNP per capita using Romer's pre-1929 values (GNP-RPC), 1869-1933, followed by the forecasts from the best-fitting trend- and difference-stationary models, 1934-1993, made in 1933. 1932 and 1933 are of course years of severe recession, so the forecasts are made from a position well below trend. The forecasts from the trend-stationary model revert to trend quickly, in sharp contrast to those from the difference-stationary model, which are permanently lowered.

For each series, we compute the exact finite-sample distribution of $\hat{\tau}$ under the best-fitting difference-stationary model and the best-fitting trend-stationary model, and then we check where the value of $\hat{\tau}$ actually obtained (call it $\hat{\tau}_{sample}$) lies relative to those distributions. This information is summarized in the p-values $Prob(\hat{\tau} \leq \hat{\tau}_{sample} | f_{DS}(\hat{\tau}))$ and $Prob(\hat{\tau} \leq \hat{\tau}_{sample} | f_{TS}(\hat{\tau}))$, where $f_{DS}(\hat{\tau})$ is the distribution of $\hat{\tau}$ under the difference-stationary model and $f_{TS}(\hat{\tau})$ is the distribution of $\hat{\tau}$ under the trend-stationary model. In Table 3 we show the p-values for k=2 through k=4. The results provide overwhelming support for the trend-stationary model. For each value of k and each aggregate output measure, the p-value associated with $\hat{\tau}$ under the difference-stationary model is very small, while that associated with $\hat{\tau}$ under the trend-stationary model is large. In the leading case of k=2, to which all diagnostics point, the p-value under the difference-stationary model is consistently less than .01, while that under the trend-stationary model is consistently greater than .59.

To illustrate the starkness of the results, we graph in Figure 2 the exact distributions of

$\hat{\tau}$ for the best-fitting difference-stationary and trend-stationary models for GNP-RPC with k=2. It is visually obvious that $\hat{\tau}_{sample}$ is tremendously unlikely relative to $f_{DS}(\hat{\tau})$ but very likely with respect to $f_{TS}(\hat{\tau})$.

All of our results are robust to reasonable variation in the sample's beginning and ending dates. We subjected every part of our empirical analysis to extensive robustness checks, varying both the starting and endings date over a wide range, with no qualitative change in any result. In Figure 3, for example, we show the exact finite-sample p-values of $\hat{\tau}$ under the best-fitting difference-stationary model for GNP-RPC and k=2, computed using the Rudebusch procedure over samples ranging from t_1 through t_T, with t_1 = 1875, ..., 1895 and t_T = 1973, ..., 1993. The p-value is always below .05 and typically below .01.

Finally, it is of interest to reconcile our results with those of Nelson and Plosser. In Figure 4, we show U.S. real GNP per capita, using the Romer pre-1929 values (GNP-RPC), together with a fitted linear trend, 1869-1993. Nelson and Plosser used only the shaded subsample, 1909-1970. Two issues are relevant. First, the Nelson-Plosser sample is obviously much shorter than ours, and on that ground alone Nelson and Plosser had less power to detect deviations from difference stationarity. Second, Figure 4 makes clear that the only prolonged, persistent deviation of output from trend is the depression and the ensuing World War II, which sits squarely in the center of the Nelson-Plosser sample. If we restrict our analysis to the Nelson-Plosser years, we obtain $\hat{\tau}$= -3.26 and we would not reject the difference-stationary model at conventional levels. If we trim fifteen years from each end of the Nelson-Plosser sample, using only 1924-1955, we obtain $\hat{\tau}$= -2.71, corresponding to even less evidence against the difference-stationary model. Conversely, as we expand the sample to include years both earlier and later than those used by Nelson and Plosser, the evidence against difference-stationarity grows quickly, because the earlier and later years included in our sample are highly informative with respect to the question of interest, as output clings tightly to trend. By the time we use the full sample, 1875-1993, we obtain $\hat{\tau}$= -4.57 and we reject difference-stationarity at any reasonable level.

IV. Concluding Remarks

There is no doubt that unit root tests *do* suffer from low power in many situations of interest. Rudebusch's analysis of postwar U.S. quarterly GNP illustrates that point starkly. We have shown, however, that both Rudebusch's and more conventional procedures produce very different results on long spans of annual data -- the evidence distinctly favors trend-stationarity. Interestingly, the same conclusion has been reached by very different methods in the Bayesian literature (e.g., DeJong and Whiteman, 1992) and in out-of-sample forecasting competitions (e.g., Geweke and Meese, 1984; DeJong and Whiteman, 1993). And of course, allowing for trend breaks in the spirit of Perron (1989) would only strengthen our results. Thus, the U.S. aggregate output data are not so uninformative as many believe.

We have already stressed the importance of our results for forecasting aggregate output. They are also important for macroeconometric modeling more generally. For example, recent important work by Elliott (1995) points to the non-robustness of cointegration methods to deviations of variables from difference-stationarity. More precisely, even very small deviations from difference-stationarity can invalidate the inferential procedures associated with conventional cointegration analyses. Our results suggest that, at least for U.S.

aggregate output, deviations from difference stationarity are likely to obtain -- the dominant autoregressive root is likely close to, but less than, unity. This points to the desirability of additional work on inference in macroeconometric models with dynamics that are either short-memory with roots local to unity, as in Elliott, Rothenberg and Stock (1992), or long-memory but mean-reverting, as in Diebold and Rudebusch (1989).

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Table 1
Studentized Statistics from Dickey-Fuller Regressions

	GNP-R Augmentation Lag Order (k)						**GNP-RPC** Augmentation Lag Order (k)					
Regressor	k=1	**k=2**	k=3	k=4	k=5	k=6	k=1	**k=2**	k=3	k=4	k=5	k=6
c	3.02	**4.86**	4.47	4.17	3.64	3.58	-2.62	**-4.53**	-4.14	-3.81	-3.19	-3.14
t	2.73	**4.66**	4.26	3.94	3.39	3.32	2.64	**4.50**	4.13	3.80	-3.20	3.16
y(-1)	-2.83	**-4.74**	-4.34	-4.02	-3.47	-3.41	-2.69	**-4.57**	-4.19	-3.86	-3.25	-3.20
Δy(-1)	**6.46**	6.01	5.81	5.53	5.39		**6.37**	5.92	5.76	5.46	5.34	
Δy(-2)		-0.05	0.05	-0.13	-0.11			-0.00	0.03	-0.16	-0.11	
Δy(-3)			0.29	-0.10	0.14				-0.10	0.23	0.29	
Δy(-4)				-1.15	-1.16					-1.13	-1.18	
Δy(-5)					0.24						0.36	
SIC	-5.91	**-6.18**	-6.14	-6.10	-6.07	-6.03	-5.90	**-6.16**	-6.12	-6.08	-6.05	-6.02
AIC	-5.98	**-6.27**	-6.25	-6.24	-6.23	-6.22	-5.97	**-6.26**	-6.24	-6.22	-6.22	-6.20

	GNP-BG Augmentation Lag Order (k)						**GNP-BGPC** Augmentation Lag Order (k)					
Regressor	k=1	k=2	k=3	k=4	k=5	k=6	k=1	**k=2**	k=3	k=4	k=5	k=6
c	3.15	**4.42**	4.57	3.96	3.61	3.30	-2.84	**-4.18**	-4.38	-3.73	-3.33	-3.00
t	2.87	**4.20**	4.36	3.73	3.37	3.04	2.85	**4.16**	4.36	3.73	3.35	3.02
y(-1)	-2.96	**-4.29**	-4.44	-3.81	-3.45	-3.13	-2.91	**-4.24**	-4.43	-3.78	-3.39	-3.06
Δy(-1)	**4.62**	4.25	4.14	3.83	3.58		**4.58**	4.21	4.11	3.80	3.56	
Δy(-2)		1.20	1.33	1.29	1.10			1.30	1.41	1.37	1.20	
Δy(-3)			-0.88	-0.77	-0.80				-0.80	-0.71	-0.74	
Δy(-4)				-0.51	-0.38					-0.48	-0.39	
Δy(-5)					0.69						-0.51	
SIC	-5.71	**-5.84**	-5.82	-5.78	-5.75	-5.71	-5.71	**-5.84**	-5.81	-5.78	-5.74	-5.70
AIC	-5.78	**-5.94**	-5.93	-5.92	-5.91	-5.90	-5.78	**-5.93**	-5.93	-5.92	-5.90	-5.89

Notes to table: The dependent variable is Δy. c is a constant term, t is a linear trend, and y is the log of Romer's GNP (GNP-R), the log of Romer's GNP per capita (GNP-RPC), the log of Balke and Gordon's GNP (GNP-BG), or the log of Balke and Gordon's GNP per capita (GNP-BGPC). All series are annual, 1875 to 1993. Entries in the table are the studentized statistics associated with the estimated coefficients. The last two rows report the Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC). The results corresponding to the selected augmentation lag orders are shown in boldface.

Table 2
Selected Trend- and Difference-Stationary Models

Variable	c	t	y(-1)	y(-2)	Δy(-1)	SER
<u>Trend-Stationary</u> (Dependent variable is y.)						
GNP-R	.879	.577	1.330	-.514	--	.043
	(.181)	(.124)	(.080)	(.079)		
GNP-RPC	-1.072	.309	1.332	-.510	--	.043
	(.237)	(.069)	(.080)	(.080)		
GNP-BG	.900	.586	1.206	-.393	--	.050
	(.204)	(.139)	(.085)	(.085)		
GNP-BGPC	-1.139	.328	1.202	-.392	--	.051
	(.272)	(.079)	(.086)	(.085)		
<u>Difference-Stationary</u> (Dependent variable is Δy.)						
ΔGNP-R	.018	--	--	--	.427	.046
	(.005)				(.084)	
ΔGNP-RPC	.010	--	--	--	.421	.046
	(.004)				(.084)	
ΔGNP-BG	.023	--	--	--	.303	.054
	(.006)				(.088)	
ΔGNP-BGPC	.012	--	--	--	.297	.054
	(.005)				(.088)	

Notes to table: c is a constant term, t is a linear trend, and y is the log of Romer's gross national product (GNP-R), the log of Romer's gross national product per capita (GNP-RPC), the log of Balke and Gordon's gross national product (GNP-BG), or the log of Balke and Gordon's gross national product per capita (GNP-BGPC). All series are annual, 1875-1993. Standard errors are given in parentheses.

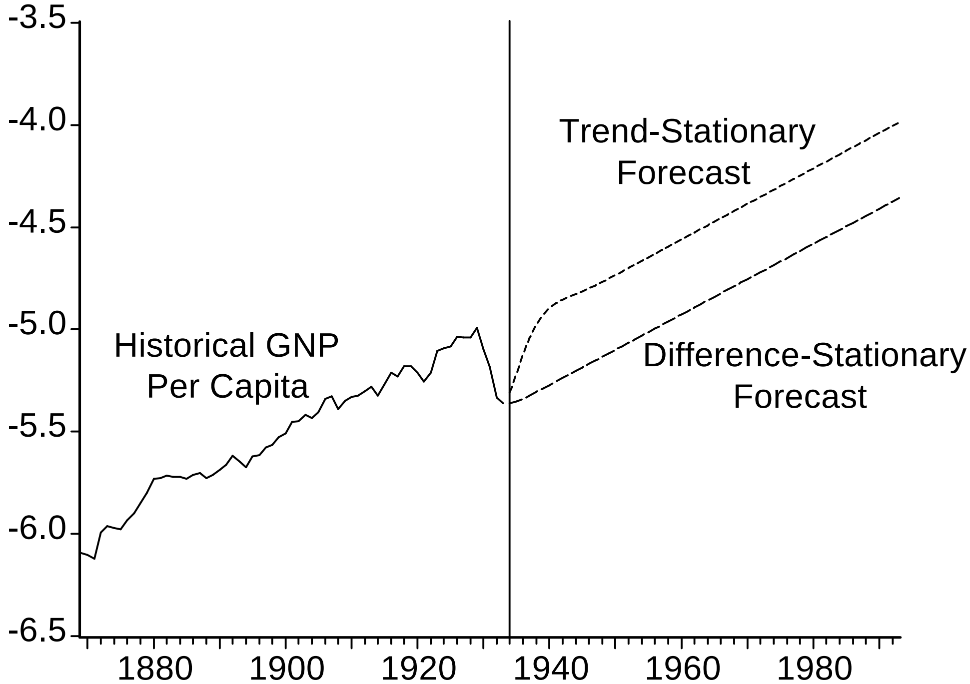
For the trend-stationary models, the trend coefficients and their standard errors have been multiplied by 100. The last column reports the standard error of the regression (SER).

Table 3
p-value of $\hat{\tau}_{sample}$ Under $f_{TS}(\hat{\tau})$ and $f_{DS}(\hat{\tau})$ for Different Lag Orders

k =	2	3	4
Variable:			
GNP-R			
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{TS}(\hat{\tau}))$	<u>.625</u>	.690	.592
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{DS}(\hat{\tau}))$	<u>.001</u>	.005	.012
GNP-RPC			
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{TS}(\hat{\tau}))$	<u>.668</u>	.673	.695
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{DS}(\hat{\tau}))$	<u>.001</u>	.007	.017
GNP-BG			
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{TS}(\hat{\tau}))$	<u>.651</u>	.616	.657
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{DS}(\hat{\tau}))$	<u>.005</u>	.002	.020
GNP-BGPC			
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{TS}(\hat{\tau}))$	<u>.692</u>	.656	.711
$Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{DS}(\hat{\tau}))$	<u>.006</u>	.003	.021

Notes to table: $\hat{\tau}$ is the Dickey-Fuller statistic, $f_{TS}(\hat{\tau})$ is the empirical distribution of $\hat{\tau}$ conditional on the trend-stationary model, $f_{DS}(\hat{\tau})$ is the empirical distribution of $\hat{\tau}$ conditional on the difference-stationary model, k is the augmentation lag order in the Dickey-Fuller regression, and $Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{TS}(\hat{\tau}))$ and $Prob(\hat{\tau} \le \hat{\tau}_{sample} \mid f_{DS}(\hat{\tau}))$ are the probabilities of obtaining $\hat{\tau} \le \hat{\tau}_{sample}$ under the trend-stationary and the difference-stationary models. The variables are the log of Romer's gross national product (GNP-R), the log of Romer's gross national product per capita (GNP-RPC), the log of Balke and Gordon's gross national product (GNP-BG), or the log of Balke and Gordon's gross national product per capita (GNP-BGPC). All series are annual, 1875-1993. The underlined entries correspond to the augmentation lag orders selected by the Schwarz and Akaike criteria.

Figure 1
GNP Per Capita, Historical and Two Forecasts



Notes to figure: Pre-1930 GNP values are from Romer (1989).

Figure 2
Exact Distributions of $\hat{\tau}$ in Best-Fitting
Trend-Stationary and Difference-Stationary Models
U.S. Real GNP per Capita (pre-1929 from Romer)

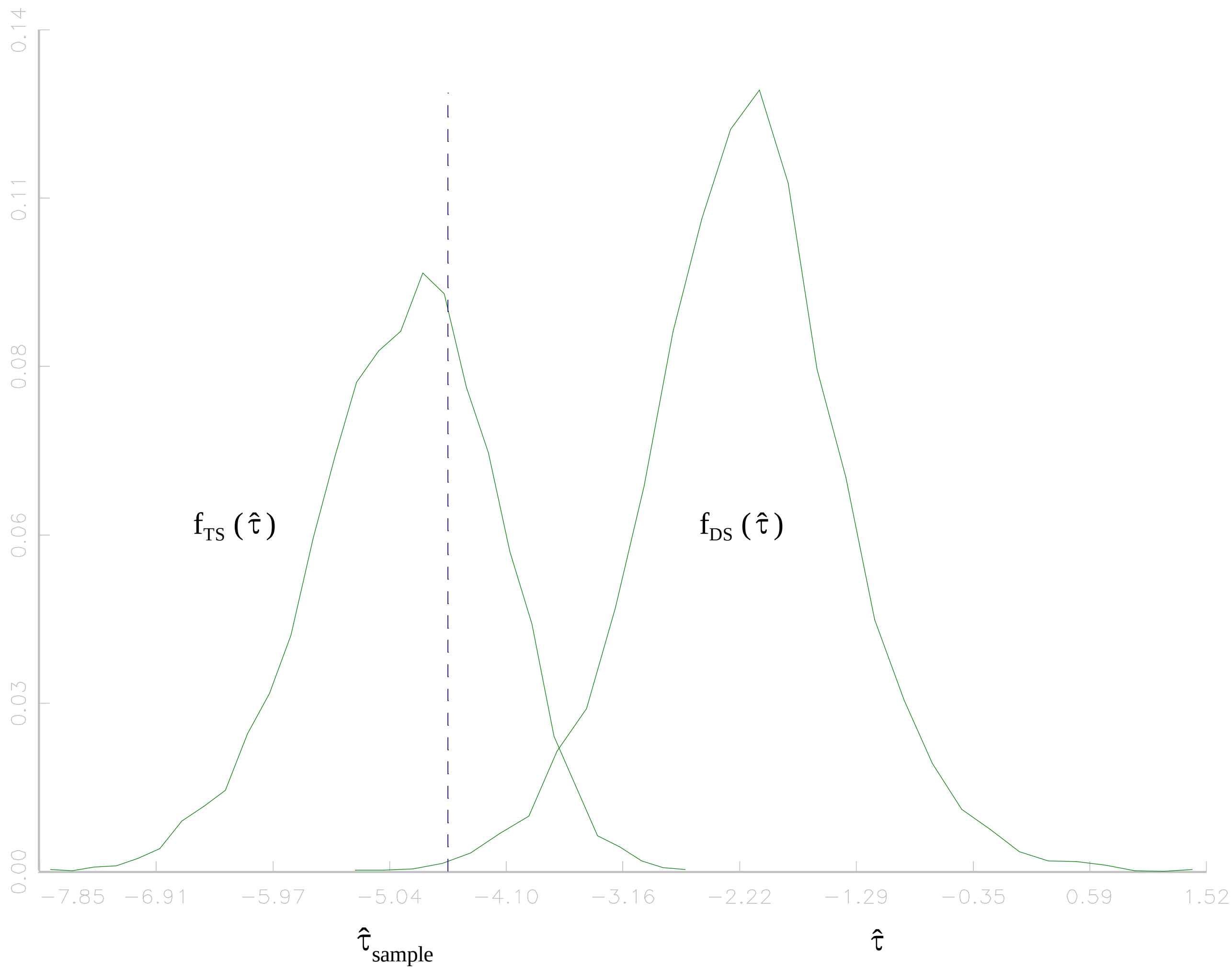


Figure 3
Exact p-values of the Dickey-Fuller Statistic Under the Difference Stationary Model, Various Starting and Ending Dates (Five Percent Plane Superimposed)

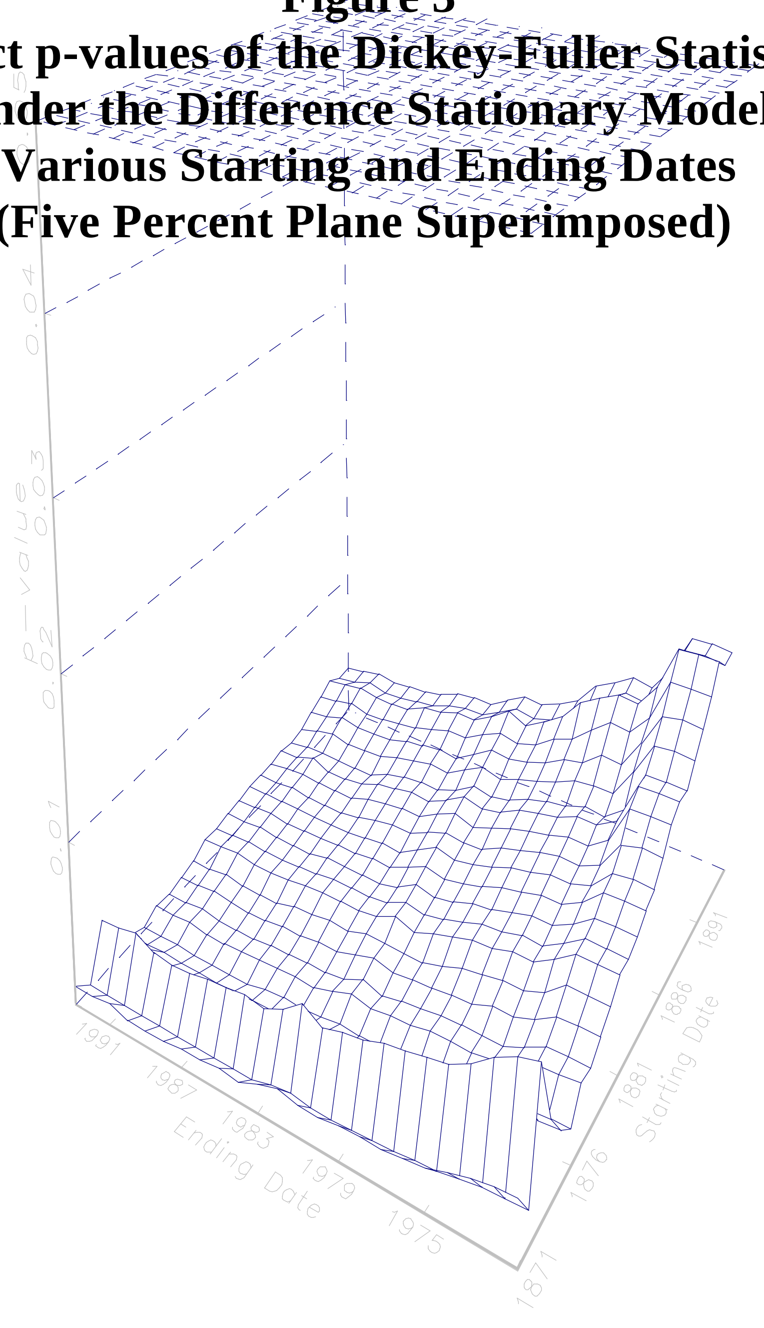
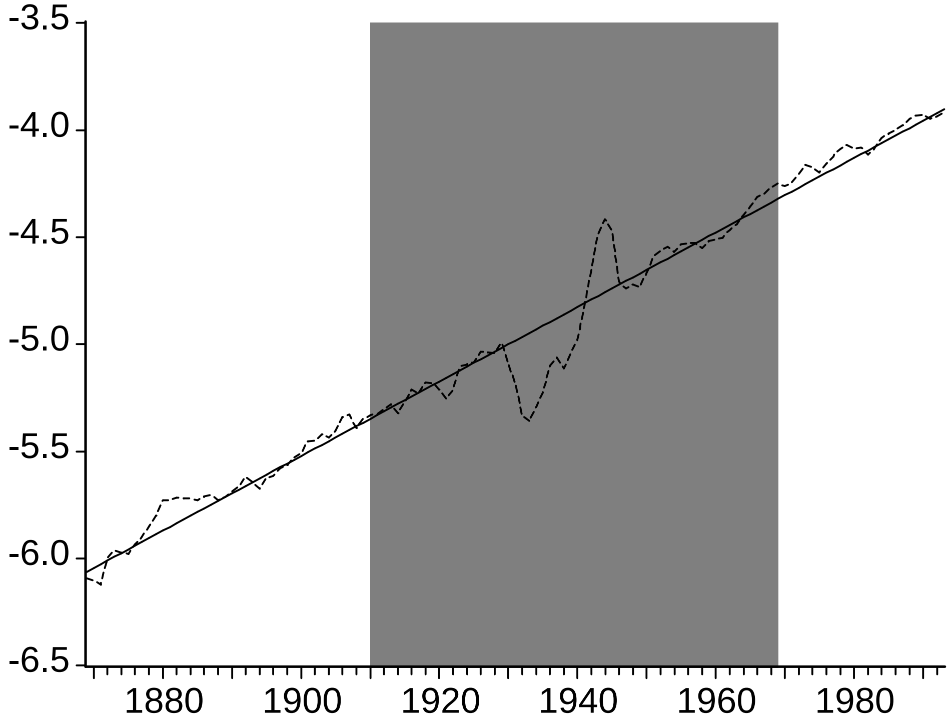


Figure 4
Log of GNP Per Capita, Actual and Trend



Abstract: A sleepy consensus has emerged that U.S. GNP data are uninformative as to whether trend is better described as deterministic or stochastic. Although the distinction is not critical in some contexts, it *is* important for point forecasting, because the two models imply very different long-run dynamics and hence different long-run forecasts. We show, using a variety of procedures, that the pessimistic "we don't know" consensus (e.g., Christiano and Eichenbaum, 1990; Rudebusch, 1993) is unwarranted. Specifically, long spans of U.S. GNP data *are* informative, and the evidence distinctly favors deterministic trend. This result accords with those of out-of-sample forecasting competitions, as well as Bayesian posterior odds computations.