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WORLDWIDE PERSISTENCE, BUSINESS CYCLES, AND ECONOMIC GROWTH

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ABSTRACT

We study the time series properties of aggregate data drawn from the Penn World Tables using numerical Bayesian procedures which facilitate inference with small samples. We find substantial persistence in world aggregates, and some evidence for a world business cycle. Across economies, there is great dispersion in our measure of persistence of shocks to real gross domestic product. That we also find no evidence of a relationship between growth and persistence sheds light on which of two competing models of endogenous growth is likely to be able to explain the PWT data.

We thank Patty Brislin for helping us organize the PWT4 data.

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1. INTRODUCTION

Empirical studies of the causes, characteristics, and consequences of international economic growth and business cycles have been hampered by two data problems: data sets are short, and they are not useful for many purposes. The shortness of international data sets will plague researchers for another generation or two: most comprise annual data and date from the end of World War II. In fact, many countries did not exist in their present form prior to 1960; for these countries there are at best thirty years of data.

A second problem with international data is that variables are measured in home currency units, making comparisons across countries problematic. Kravis, Heston, and Summers (1982) demonstrated that using official exchange rates to make such comparisons for per capita incomes across countries results in a systematic understatement of income in poor countries. These errors are quite significant, in many cases resulting in measures of per capita income that understate real per capita income by a factor of two or three.

Two recent developments make these problems sufficiently manageable that aggregate international time series analysis seems fruitful. First, the development of practical, numerical Bayesian procedures (Kloeck and van Dijk, 1978; Geweke, 1989; DeJong and Whiteman, 1989a,b,c) facilitate analyses which condition on the available data. These procedures provide ready made exact finite sample (Bayesian) distribution theory, and allow us to determine what, if anything, the existing data have to say about hypotheses of interest.

The second development is an alternative exchange rate measure given in the Penn World Tables (Summers and Heston, 1988). Their purchasing power indices more accurately reflect relative income across countries. While these data were constructed expressly to facilitate point-in-time cross-country comparisons and calculations of the worldwide distribution of income, we use these data for studying the time series properties of worldwide aggregates.

We have two broad interests in the data: to discover the properties of the world aggregate time series in output, consumption, investment, government spending, and international trade; and comparisons of individual countries' time series for these variables. Our goal is to discover the nature of the temporal movements of the international aggregates and the country-specific aggregates from which they are constructed.

We first construct world aggregate time series for real and nominal GDP, consumption, investment, government spending, population, imports and exports. The first part of our investigation suggests that with the exception of aggregate real world government spending, aggregate international time series are highly persistent; i.e., aggregate international secular trends seem to arise from underlying random walks. This suggests that in studying the cyclical properties of world output, for example, it is appropriate to remove the trend via differencing. We do so, and estimate the spectrum of (differenced) world output; the result is suggestive of the presence of a world business cycle.

The second major part of our investigation concerns the relationship between individual countries' time series. We discover that there is a surprisingly large dispersion across countries in the persistence of shocks. Like the existence of dispersion in growth rates, dispersion in persistence is troubling for endogenous growth models (Lucas, 1988) which predict no dispersion. Yet our results suggest a further puzzle for one class of recently developed multiple equilibrium endogenous growth models (Aghion and Howitt, 1989; Azariadis and Drazen, 1988; Tamura, 1989) which account for disparate growth *by* disparate persistence: we find no relation in the data between growth and persistence. This finding does not conflict with the predictions of another class of multiple equilibrium endogenous growth models, the locally interacting systems of Durlauf (1989).

2. DATA

One way to facilitate cross-county comparisons involves using purchasing power indices of the different national currencies in place of the exchange rate weights. The recently released Penn World Tables Mark 4 (PWT4; Summers and Heston, 1988) are constructed using purchasing power weights, and report time series for real GDP and other country-specific aggregates in 1980 international prices for 130 countries. A sketch of the data construction procedures is provided in an Appendix; details are provided in Summers and Heston (1988).

Roughly, the data were constructed in four steps: first, detailed purchasing power indices were estimated for each country and each commodity group for a base year (1975 or 1980). Second, the price data were used to create an international unit of account (the international dollar, I$) by taking a weighted average of the various price indices, with weights given by the country's relative production share of that commodity. Third, the unit of account was extrapolated to other years by using constant price series from national accounts to compute growth rates of consumption, investment, and government spending. Current price series were used to compute the growth rates for PPP and price levels. Finally, the individual country data were converted to I$ using the implicit exchange rate. These implicit exchange rates constructed in this fashion more accurately reflect real purchasing power of individual country GDP and thus facilitate international comparisons.

The PWT4 data involve 17 variables, to which we have added export and import data from the IMF International Financial Statistics. The annual data run from 1950-1985 for each variable, with a few exceptions. The centrally planned countries (there are nine of these) have only population and output data; for the most part we neglect these countries. For some countries, the data begin around 1960. These countries typically did not exist as independent political entities before this date.

3. INFERENCE WITH THE PWT4 DATA

It is unfortunate that the PWT4 are no exception to the rule for international data: the data set is quite short. Standard application of Classical time series analysis is not likely to be fruitful, for use of asymptotic distribution theory to judge statistical results is clearly unwarranted with 36 observations. We think it unproductive to wait the generation or so it would take to complete the collection of even a moderately-sized data set, and wish to proceed to learn as much as possible from the data which currently exist.

One way to deal with small samples is the Classical (sampling theory) finite sample approach. But working out finite sample distributions for test statistics associated with each hypothesis of interest is at minimum a formidable task. In many cases analytical progress is not likely to be forthcoming soon, and numerical methods must be relied upon: distributions are extremely sensitive to sample size and nuisance parameters, and small changes in hypothesized values of parameters of interest may cause huge changes in distributions of test statistics. Further, even when numerical or finite sample results are available, popular Classical procedures may have very low power against relevant alternatives. For example, DeJong, Nankervis, Savin, and Whiteman (1989a) report that for a sample size of 50, the size 5% Dickey-Fuller (1981) tests for unit roots have powers less than 20% against alternatives of interest. DeJong, Nankervis, Savin, and Whiteman (1989b) show that even for a sample of size 100, power drops to less than 10% when plausible autocorrelation is present.

In the Classical interpretation, parameters are viewed as fixed, and the data are viewed as being random. Thus the Classical approach begins with assumptions concerning the probability distributions of the data and the specification of values of parameters, i.e., the null hypothesis. Then, though it may be possible to proceed analytically, in effect many samples are generated from the null distribution. For each sample, statistics (functions of the sample values) are computed. The histograms of these artificially generated statistics are the sampling distributions for the statistics. Once these sampling distributions have been calculated, the statistics are computed using the actual data. There is evidence against the null hypothesis if the statistics look unusual when judged against their sampling distributions. As mentioned above this procedure does not work well if data sets are small.

An alternative, Bayesian view of parameters and data is that the data are fixed (they have been observed) and the parameters are random (they are unknown and subject to varying "degrees of belief".) Using the Bayesian approach, one does not average over unobserved samples, but rather *conditions* on the data. Then, given the data, the Bayesian asks what parameter values are most likely to have generated such observations. Given the short PWT4 data set, we think this approach is attractive, as it allows us to glean what we can from the data we have. If the data have little to say, we will not glean very much.

In fact, the practical difference between the approaches has to do with the interpretation of the likelihood function. To further develop the distinction, it is useful to proceed to a discussion of the likelihood function we employ for the PWT4 data.

Denote by y_t the natural logarithm of an international aggregate. We assume that y_t can be represented by

1) $y_t = \beta_0 + \beta(L)y_t + \delta t + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{IIDN}(0,\sigma^2)$,

where $\beta(L) = \beta_1 L + \beta_2 L^2 + \beta_3 L^3$; y_0, y_{-1}, and y_{-2} are fixed; and the lag operator L is defined by $L^n y_t = y_{t-n}$. Stacking the T observations in the standard fashion, we have

$$y = X\beta + \varepsilon,$$

where $y = (y_1, \ldots, y_T)'$, $X = (x_1', \ldots, x_T')'$ with $x_t = (1\ y_{t-1}\ y_{t-2}\ y_{t-3}\ t)$, and $\beta = (\beta_0\ \beta_1\ \beta_2\ \beta_3\ \beta_4)'$. Let $\theta \equiv (\beta'\ \sigma) \in \Theta \equiv R^5 \times R_+^1$, and define

2) $\lambda(z) \equiv 1 - \beta(z) = \Pi_{j=1}^{3}\ (1 - \lambda_j z)$.

We refer to the λ_j's as the "roots" of the autoregression of y_t (i.e., the roots of $F^p\lambda(F)$, where $F=z^{-1}$). Denote the maximum of the roots $\lambda_1, \lambda_2, \ldots, \lambda_p$ by $\Lambda \equiv \max_j|\lambda_j|$. We are interested in this maximum root because it governs how the aggregate time series responds to a "shock", i.e., to a nonzero value for ε_t. Larger values of Λ are associated with more persistence: the larger is Λ, the longer it takes shocks to die out.

Given the normality assumption made concerning ε_t, the likelihood function for the data can be written

$$(y,X|\theta) = (2\pi\sigma^2)^{-T/2}\exp[-(1/2\sigma^2)(y-X\beta)'(y-X\beta)].$$

Letting $\nu \equiv T-5$, $b \equiv (X'X)^{-1}X'y$, $s^2 \equiv \nu^{-1}(y-Xb)'(y-Xb)$, and completing the square in brackets,

$$(y,X|\theta) = (2\pi\sigma^2)^{-T/2}\exp[-(1/2\sigma^2)\{\nu s^2 + (\beta-b)'X'X(\beta-b)\}].$$

Classical inference involves viewing this function of y, X, and θ along constant-θ planes. For example, the data contain evidence against a particular value of θ if given that value of θ the observed y and X cause $(y,X|\theta)$ to be "small."

In the Bayesian approach, the parameters are the legitimate object of (subjective) probability statements. Thus summarizing prior views concerning the unknown parameters via the density $p(\theta)$ and using Bayes' rule, the posterior density for θ is

$$P(\theta|y,X) = (y,X|\theta)p(\theta)/f(y,X) \propto (\theta|y,X)p(\theta),$$

where the marginal density $f(y,X)$ is a constant from the point of view of the θ distribution. The function $P(\theta|y,X)$ is the probability density function for θ *conditioned* on the data y and X, and is the sole source of inferences concerning θ and functions of θ. Thus neglecting $p(\theta)$ for the moment, Bayesian inference involves viewing the likelihood function along constant-y and X planes.

Given the noninformative prior $p(\theta) \propto \sigma^{-1}$,

$$P(\theta|y,X) \propto (2\pi\sigma^2)^{-(T+1)/2}\exp[-(1/2\sigma^2)\{\nu s^2 + (\beta-b)'X'X(\beta-b)\}].$$

It is useful to "factor" $P(\theta|y,X)$ as[1]

$$\begin{aligned} P(\theta|y,X) &\propto \sigma^{-T-1}\exp\{-(1/2\sigma^2)\nu s^2\}\exp\{-(1/2\sigma^2)(\beta-b)'X'X(\beta-b)\} \\ &\propto \sigma^{-\nu-1}\exp\{-(1/2\sigma^2)\nu s^2\}\sigma^{-5}\exp\{-(1/2\sigma^2)(\beta-b)'X'X(\beta-b)\} \\ &\propto P(\sigma|y,X)P(\beta|\sigma,y,X), \end{aligned}$$

where

$$P(\sigma|y,X) \propto \sigma^{-\nu-1}\exp\{-\nu s^2/2\sigma^2\},$$

and

$$P(\beta|\sigma,y,X) \propto |\sigma^2(X'X)^{-1}|^{-1/2}\exp\{-0.5(\beta-b)'[X'X/\sigma^2](\beta-b)\}.$$

Conditioned on σ, the posterior distribution for β is normal with mean b and covariance matrix $\sigma^2(X'X)^{-1}$. The marginal density for σ, $P(\sigma|y,X)$ is of the inverted gamma type. In particular, let $u = \nu s^2/\sigma^2$ and note that $du = -2\nu s^2\sigma^{-3}d\sigma$. Then the density of u is

$$P(u|y,X) \propto P(\sigma|y,X)|d\sigma/du| \propto \sigma^{-\nu+2}e^{-u/2} \propto u^{-1+\nu/2}e^{-u/2},$$

i.e., u is distributed as χ^2 with ν degrees of freedom.

In what follows, we will be interested in making posterior probability statements concerning θ and functions of θ; e.g., $g(\theta) = (\delta,\Lambda)$. We may be interested in the quantiles of the distribution of Λ, or in some other function of θ. Generally, we shall be interested in a subset A of the parameter space Θ. In any case, if $g(\theta)$ is any function of interest, we will

[1] We follow the convention of using the same letter (here P) to denote joint, conditional, and marginal densities, relying on context and indicted arguments to distinguish the various functions.

find it necessary to compute integrals of the form

$$E[g(\theta)|A,y,X] = \int_{\Theta\cap A} g(\theta)\ (\theta|y,X)p(\theta)d\theta / \int_{\Theta\cap A}\ (\theta|y,X)p(\theta)d\theta .$$

In general, integrals like this cannot be evaluated analytically. However, integration by Monte Carlo (Kloeck and van Dijk, 1978; Geweke, 1986, 1987, 1988) is relatively straightforward. Take $\{\theta_i\}^n_{i=1}$ to be a sequence of independent drawings from the posterior distribution $P(\theta|y,X)$, let $\iota_{\Theta\cap A}(\theta_i)$ denote the indicator function for $\theta_i \in A$, and define

$$g_n = n^{-1}\Sigma^n_{i=1} g(\theta_i)\iota_{\Theta\cap A}(\theta_i)/\Sigma^n_{i=1}\iota_{\Theta\cap A}(\theta_i).$$

Employing a standard Central Limit Theorem, Geweke (1987) shows that $g_n \rightarrow E[g(\theta)|y,X]$ and $p_n \rightarrow pr[\theta \in A|y,X] \equiv q$ in probability (provided the indicated expectations exist). Thus summation can be used in place of integration, provided that it is possible to obtain a sufficiently large number of independent drawings from the probability distributions in question.

To obtain a drawing from the joint distribution of (β,σ), one proceeds as follows. First, draw $\underline{x}^2$ from a $\chi^2(\nu)$ and compute $\underline{\sigma} = (\underline{x}^2/\nu s^2)^{-1/2}$. Now draw $\underline{\beta}$ from $N(b,\underline{\sigma}^2(X'X)^{-1})$. Alternatively, an algebraically equivalent procedure, used in Geweke (1986) is: draw $\underline{x}^2$ from $\chi^2(\nu)$, draw $\underline{w}$ from $N(0,s^2(X'X)^{-1})$, and compute $\underline{\beta} = b + \underline{w}(\underline{x}^2/\nu)^{-1/2}$. The drawing $b - \underline{w}(\underline{x}^2/\nu)^{-1/2}$ is an *antithetic* replication; the two drawings are said to constitute an antithetic pair.

In the next section, we investigate the international data by conducting posterior inference on δ, Λ, and other functions of the parameter θ. The inferences are based on 20,000 replications (10,000 antithetic pairs) of the drawing of $\underline{\beta}$ discussed above.

4. WORLD AGGREGATES

4.1 The Data

We construct eleven world aggregates: three slightly different measures of real gross world product in constant I$ (RGWP1, RGWP2, and RGWP3, which correspond to the three similar measures in PWT4); one of real gross world product in current I$ (CGWP); world aggregate population, consumption, investment, and government spending (WPOP, WC, WI and WG); and world net exports, total exports and imports (NX, EXP, and IMP).[2]

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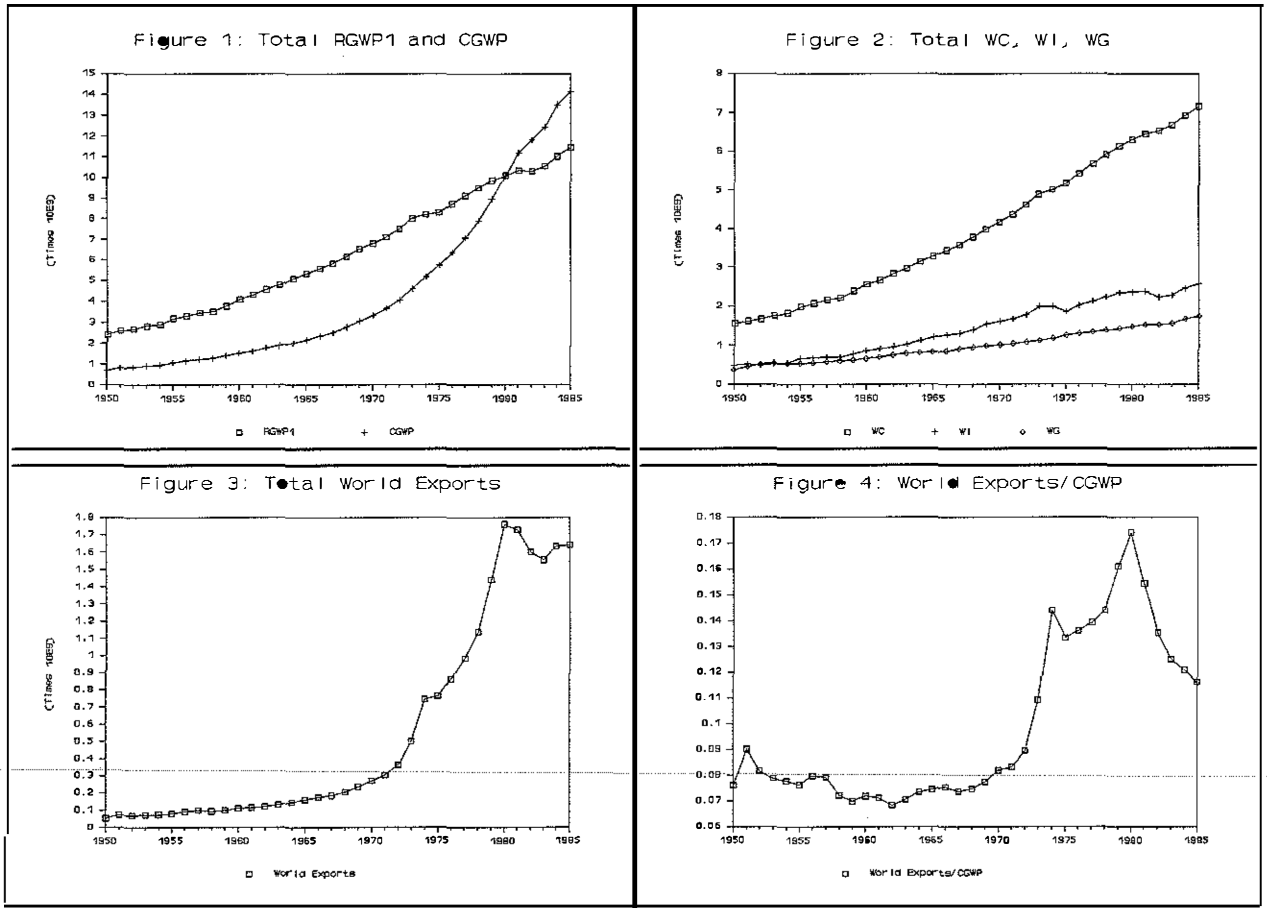
[2] Net exports are constructed from PWT4 and are in constant I$. The exports and imports series are from the IMF Financial Statistics and are in current $.



We begin by looking at the data. Figure 1 displays RGWP1 and CGWP and Figure 2 has WC and WI. These data look as one would expect, with both GDP measures and consumption being quite smooth relative to investment.

Total world exports are in Figure 3. These data have a very interesting pattern: slow but steady growth through the 1950's and 1960's is followed by spectacular growth in the 1970's. An abrupt halt and reversal of the growth in the volume of world trade occurs in the 1980's. This is even more dramatic when one looks at exports as a fraction of GDP in Figure 4. For the 1950's and 1960's the volume of international trade divided by gross product is about 8%. Starting in the late 1960's this grows to more than 17% by 1980. The most startling fact, however, is the sharp drop in trade volume to slightly under 12% by 1985. This could be due to increased protection, the "new protectionism", or other factors such as increased international investment. In a sequel we explore explanations for this sharp reduction in trade volume.

The data are obviously trended. In order to better understand the *cyclical* properties of the data, we would like to remove the trend. But to do so, it is necessary to understand *how* the data are trended. The time series will contain a *deterministic exponential trend* if $\delta \neq 0$ in (1). If $\delta = 0$ but $\Lambda = 1$ and $\beta_0 \neq 0$, the time series has a *unit root* and will behave like a random walk with drift.[3] Thus there are two general ways to detrend: exponential detrending removes the effects of δ; differencing the series removes the effects of $\Lambda = 1$. Past work (Chan, Hayya, and Ord, 1977; Nelson and Kang, 1981) indicates that mistaken inferences about cyclical variations may result if the wrong detrending method is used. We now turn to a discussion of which type of trend (random walk with drift, deterministic exponential trend) looks most plausible for each series; to do this, we employ the Bayesian Monte Carlo procedures introduced above.

4.2 Persistence Investigations

The results of our search for unit roots in the eleven aggregate series are reported in Table 1: Dickey-Fuller (1981) test statistics are given in column 1; the remainder of the table characterizes the posterior distributions of δ and Λ. For none of the eleven variables would one reject the existence of a unit root using the Dickey-Fuller test. The Bayesian approach suggests that for at least one of the variables the existence of a unit root looks doubtful.

Posterior distributions of Λ are also summarized in Figure 5. Other than the three measures of real GDP and consumption, all variables have posterior means less than unity. The last column of Table 1 uses a normal approximation to the posteriors[4] to compute the upper deciles. (These are also illustrated in Figure 6.) That is, 90% of the posterior distribution lies below the number in the last column of Table 1. Thus, for government spending 90% of the posterior probability lies below 0.86256 which means that much more than 90% is below 1. It seems reasonable to conclude from this evidence that it is unlikely that there is a unit root in aggregate government spending. The same

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[3] If both trends are present and positive ($\delta > 0$, $\beta_0 > 0$), the series grows at an increasing rate. Such quadratic trends do not seem to be common in real macroeconomic data.

[4] Sims (1988), Sims and Uhlig (1988), and DeJong and Whiteman (1989a,b) provide some indication that the normal approximation is useful for the posteriors being studied here.

Figure 5: Mean Dominant Root

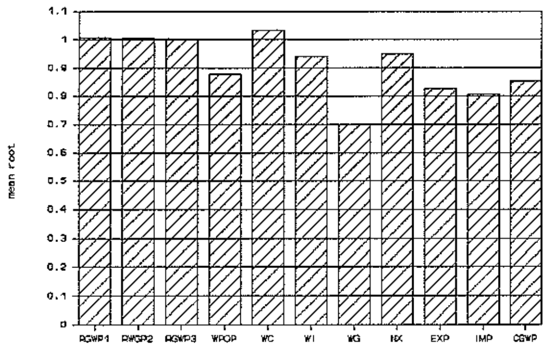
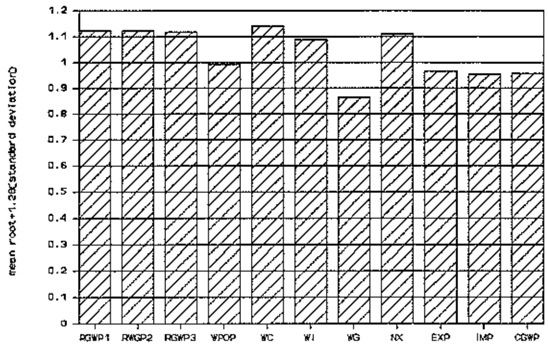


Figure 6: Upper Decile, Dominant Root



conclusion might be drawn regarding imports, exports, and GWP in current international dollars, though the posterior probability of a unit root is close to 10%. Further investigation for these nominal series suggested that relaxing the prior to allow for a *quadratic* trend made the unit root look much more plausible.

The general conclusion to be drawn from these results is that with the exception of aggregate government spending, aggregate real series appear to contain unit roots. Thus, for example, in studying the cyclical properties of world output, it is appropriate to remove trends via differencing.

4.3 Implications for World Business Cycles

Figure 7 displays the first difference of GWP1. Roughly, the 1960's were "good times", the late 1970's and 1980's were "bad times", and the 1950's were mixed. Excepting the 1960's, there appear to be business "cycles" of roughly four to five years. For a more formal investigation of the existence of cycles in world output, the *spectrum* of differenced RGWP1 is useful.

The spectrum of the first difference of y_t in (1) is given by

$$g_{\Delta y \Delta y}(\omega) = \sigma^2 |1 - e^{-i\omega}|^2 / |1 - \beta(e^{-i\omega})|^2. \tag{3}$$

When $\Lambda = 1$, the unit roots on the right cancel, and $g_{\Delta y \Delta y}(\omega)$ is well-defined at $\omega = 0$. Since $2\int_0^{\pi} g_{\Delta y \Delta y}(\omega) d\omega = \mathrm{var}(\Delta y_t)$, the standard intuition about a spectrum applies here: just as white light is the composition of colored light of various frequencies, a time series can be thought of as comprising numerous underlying uncorrelated sine waves of various frequencies. The spectrum at frequency ω^*, $g_{\Delta y \Delta y}(\omega^*)$, indicates the contribution to the variance

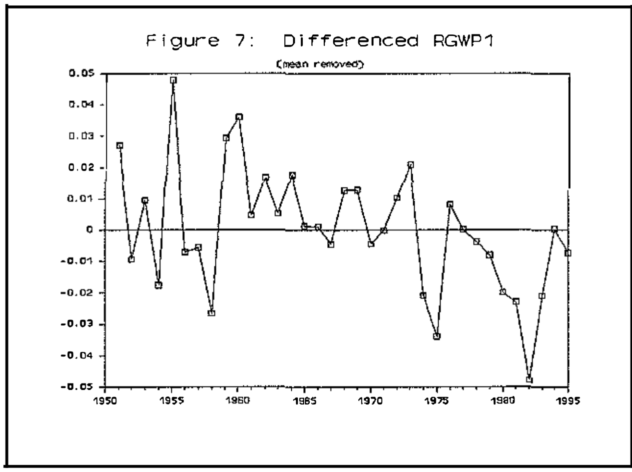


Figure 7: Differenced RGWP1

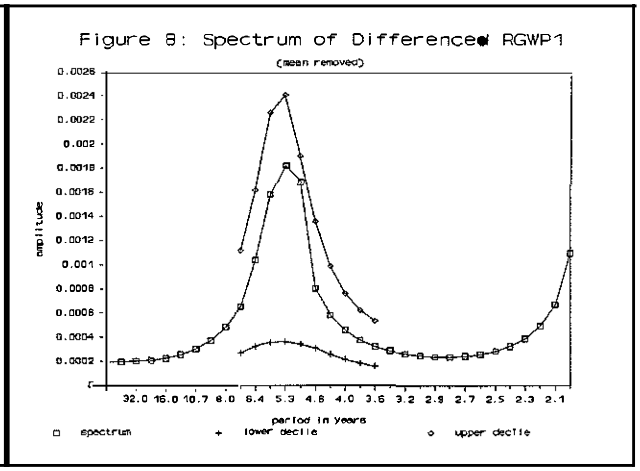


Figure 8: Spectrum of Differenced RGWP1

of the series made by the sine wave component possessing angular frequency ω^*.

Our estimate of the spectrum of Δy_t was obtained by using the Monte Carlo integration procedure described above to compute the posterior means of 32 functions of interest: $g_{\Delta y \Delta y}(\omega_j)$ for $\omega_j = 2\pi j/64$, j = 0, ..., 31. These means are aligned and presented as the spectrum in Figure 8.

The interesting feature of the estimated spectrum is the hump between 4 and 5.8 years. This indicates that there is much spectral power at frequencies typically associated with business cycles. There is also somewhat smaller spectral power at a two-year cycle; this seems to be a product of fluctuations in the early 1950's and the early 1960's.

While Figure 8 is quite suggestive of a business cycle in aggregate world output, there is a reason to be circumspect about such a conclusion. In particular, the benchmark years in the PWT4 data are 1975 and 1980, and the data end in 1985. In a short data set, three such events at five-year intervals could be enough to provide spectral power at a periodicity of five years. In any event, further study is required to determine how much, if any, of the spectral power at the business cycle frequencies is statistical artifact.

5. INDIVIDUAL COUNTRIES

Dickey-Fuller tests and summaries of posterior distributions for RGDP1 for each of the 121 countries are presented in Table 2. Unlike the aggregates of the previous section, the individual country results are for *per-capita* real

Figure 9: Dominant Root Distribution

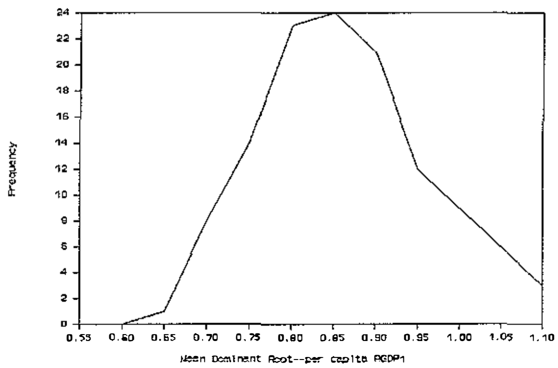
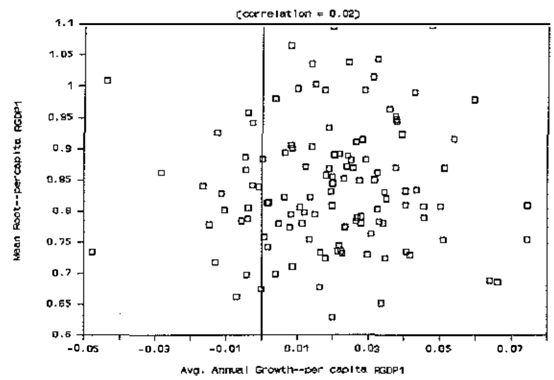


Figure 10: Persistence and Growth



gross domestic product; the per capita series seemed of greater relevance for growth issues, the total series having been more relevant for business cycle issues.

With the possible exception of Thailand, the Dickey-Fuller tests are consistent with the existence of a unit root in every country. The posterior calculations, however, indicate that the mean root is less than unity in all but 9 countries.

The upper deciles of the dominant root distributions indicate that 67 countries have less than a 10% chance of a unit root: for a large number of countries, per capita GDP is apparently trend-stationary.

While the issue of whether or not per capita GDP series possess unit roots is important, another interesting result is implied by our findings. The range of mean dominant roots across countries is quite large, ranging from 0.63 in Algeria to 1.10 for Yemen. The distribution is graphed in Figure 9.

From the point of view of existing endogenous growth models based on Romer (1986) and Lucas (1988), dispersion in dominant roots is puzzling. Such models take as given that different economies possess the same dynamic structure, and thus the same dominant roots. Further, as noted by Tamura (1989), in such models, economies grow at the same rate κ. This is at odds with the data.

For a new generation of *multiple equilibrium* endogenous growth models (Aghion and Howitt, 1989; Azariadis and Drazen, 1988; Tamura, 1989) dispersion in dominant characteristic roots is the cornerstone of the explanation of dispersion in growth rates. Thus it is of interest to determine whether dominant roots and growth rates are related across economies. They are not. Figure 10 displays (Λ,κ) pairs for the 121 market economies; the puzzle for the new generation models is that there is virtually no correlation.

The standard interpretation would then be that countries are different not because they process shocks differently, but because they are hit by different shocks. An alternative, perhaps more palatable view is that economies *do* process shocks differently, but in a way which does not impinge on persistence. The lattice economies of Durlauf (1989), with disparate success across economies in solving coordination problems, provides one class of models consistent with this view.

CONCLUSION

We have used Bayesian procedures which *condition* on the data to study the persistence and cyclical properties of time series drawn from the Penn World Tabes, a data set constructed to facilitate cross-country comparisons. Though the data set is short, our methods enable us to extract what information the data contain. Our analysis suggests that there is some evidence of a world business cycle, that there is much dispersion across countries in the persistence of shocks, but that persistence is *not* related to economic growth.

Appendix

The PWT4 data set comprises:

1. Population - in 1000's

2. RGDP1 - Real Gross Domestic Product per Capita in 1980 International Dollars (I$). Purchasing Power indices (in local currency units) are constructed for each product category using domestic data. These are divided into expenditure data to obtain quantities. To get real GDP in I$ these quantities are multiplied by international prices for each product category. The product category prices are obtained by taking a quantity-weighted average of each country's price for a given category.

   $RGDP1 = C + I + G + X - M$

3. $c = C/RGDP1$ % consumption in real terms

4. $i = I/RGDP1$ % investment in real terms

5. $g + G/RGDP1$ % government expenditure in real terms

   $$(X-M)/RGDP1 = 1 - (c+i+g)$$

6. RGDP2 - Modification of RGDP1 which uses a Chain index.

7. RGDP3 - Modification of RGDP1 which takes into account changes in the terms of trade.

8. y - RGDP per capita relative to the US (in current I$): $y = CGDP/CGDP(US)$.

9. CGDP- per capita RGDP in current I$.

10-12. Like 3-5 except in current I$.

13-16. Prices for GDP, C, I, G

   $$P = (PPP \times 100)/XR.$$

   The PPPs are constructed from the purchasing power indices, and the XR comes from standard sources. Thus 1/P measures the extent to which the exchange rate undervalues GDP. P is constructed for GDP, C, I, and G. Also, PPP = Domestic Expenditures in local currency/Corresponding expenditures in 1980 I$. PPPs are constructed for GDP, C, I, and G.

17. XR - The exchange rate (foreign currency per $). These are official exchange rates.

18. Exports - The value of exports in current US$, converted using official exchange rates.

19. Imports - The value of imports in current US$, converted using official exchange rates.

Table 1: Posterior Calculations; Aggregate Data

Series	Dickey-Fuller "t"	Mean Dominant Root	Standard Deviation of Root	Mean Trend	Standard Deviation of Trend
RGWP1	0.29	1.01	0.09	−0.00	0.00
RGWP2	0.25	1.01	0.09	−0.00	0.01
RGWP3	0.22	1.00	0.09	−0.00	0.00
WPOP	−1.65	0.88	0.09	0.00	0.00
WC	0.61	1.03	0.08	−0.00	0.00
WI	−0.49	0.94	0.11	0.00	0.01
WG	−2.16	0.70	0.13	0.01	0.01
NX	−2.89	0.95	0.13	−0.22	0.08
EXP	−1.72	0.83	0.11	0.01	0.01
IMP	−1.83	0.81	0.11	0.02	0.01
CGWP	−2.20	0.85	0.08	0.01	0.00

Table 2: Posterior Calculations, Country Data
Sorted by Upper Decile of Dominant Root

Country	Dickey Fuller "t"	Mean Dom. Root	Std. Dev.	Trend	Std. Dev.	Upper Decile Root
Thailand	-4.37	0.65	0.13	0.02	0.01	0.82
Algeria	-3.18	0.63	0.15	0.03	0.01	0.83
Burundi	-2.91	0.66	0.13	0.01	0.00	0.83
India	-2.57	0.68	0.14	0.01	0.00	0.86
Taiwan	-2.39	0.69	0.14	0.03	0.01	0.87
Egypt	-2.87	0.73	0.11	0.01	0.00	0.87
Mali	-2.55	0.70	0.14	0.00	0.00	0.88
U.S.	-2.61	0.72	0.13	0.01	0.00	0.88
Norway	-2.87	0.72	0.13	0.02	0.01	0.89
Hong Kong	-2.46	0.69	0.16	0.05	0.02	0.89
Cyprus	-3.43	0.73	0.13	0.02	0.01	0.89
Senegal	-2.54	0.67	0.17	-0.00	0.00	0.89
Chile	-2.73	0.71	0.15	0.00	0.00	0.90
Nepal	-2.52	0.70	0.16	0.00	0.00	0.90
Somalia	-2.26	0.72	0.15	-0.00	0.00	0.90
Dominica	-2.21	0.74	0.13	0.01	0.01	0.91
Malaysia	-2.18	0.74	0.14	0.02	0.01	0.91
Tanzania	-2.34	0.74	0.14	0.01	0.00	0.91
Pakistan	-2.23	0.78	0.11	0.01	0.00	0.91
Turkey	-2.83	0.78	0.11	0.01	0.01	0.92
Uganda	-2.08	0.76	0.13	-0.00	0.00	0.92
Kuwait	-2.89	0.73	0.15	-0.04	0.02	0.92
Korea	-2.62	0.81	0.09	0.01	0.00	0.92
Luxembourg	-1.84	0.73	0.15	0.01	0.00	0.92
Haiti	-2.27	0.74	0.14	0.00	0.00	0.92
Jordan	-2.21	0.80	0.09	0.00	0.00	0.92
Ireland	-2.46	0.78	0.11	0.01	0.00	0.93
Niger	-2.55	0.73	0.16	0.01	0.00	0.94
Rwanda	-2.07	0.75	0.14	0.02	0.01	0.94
Canada	-1.95	0.77	0.13	0.01	0.00	0.94
Mauritius	-2.04	0.80	0.11	0.01	0.00	0.94
W. Germany	-2.77	0.87	0.06	0.00	0.00	0.94
Angola	-2.01	0.78	0.13	-0.01	0.00	0.94
U.K.	-1.74	0.74	0.16	0.01	0.00	0.94
Nigeria	-1.90	0.78	0.13	0.00	0.00	0.94
Iceland	-3.11	0.79	0.12	0.02	0.01	0.95
Botswana	-2.29	0.75	0.15	0.03	0.01	0.95
Uruguay	-2.46	0.81	0.11	0.00	0.00	0.95
Cameroon	-2.60	0.76	0.15	0.02	0.01	0.95
Syrian	-2.14	0.78	0.14	0.02	0.01	0.96
Afghanistan	-2.07	0.79	0.14	-0.00	0.00	0.96
Columbia	-2.06	0.85	0.09	0.00	0.00	0.96
Oman	-2.07	0.76	0.16	-0.00	0.01	0.96
Burma	-1.71	0.79	0.14	0.01	0.00	0.96
Iran	-1.78	0.81	0.12	0.01	0.01	0.97
Finland	-1.56	0.78	0.14	0.01	0.01	0.97
Ecuador	-2.31	0.85	0.09	0.01	0.00	0.97
Indonesia	-2.73	0.83	0.11	0.02	0.01	0.97
Malta	-3.00	0.87	0.08	0.01	0.00	0.97
Guyana	-1.55	0.78	0.15	0.00	0.00	0.97
Congo	-1.98	0.83	0.11	0.01	0.00	0.98
Lesotho	-2.17	0.79	0.15	0.02	0.01	0.98
Panama	-2.24	0.85	0.10	0.01	0.00	0.98
Honduras	-2.06	0.82	0.12	0.00	0.00	0.98
Zimbabwe	-1.53	0.81	0.13	0.00	0.00	0.98
Brazil	-1.86	0.81	0.14	0.02	0.01	0.98
New Zealand	-1.54	0.83	0.12	0.00	0.00	0.98
Paraguay	-1.75	0.85	0.10	0.00	0.00	0.98
Ethiopia	-1.46	0.81	0.13	0.00	0.00	0.98
Mozambique	-1.78	0.84	0.11	-0.01	0.00	0.99
Mauritania	-1.53	0.78	0.16	0.00	0.00	0.99
Morocco	-3.88	0.88	0.08	0.01	0.00	0.99
Benin	-3.34	0.81	0.14	-0.01	0.00	0.99
Iraq	-1.43	0.81	0.14	0.00	0.00	0.99
Sudan	-1.62	0.84	0.12	-0.00	0.00	0.99
Papua	-1.70	0.87	0.10	-0.00	0.00	0.99
Tunisia	-1.54	0.82	0.14	0.01	0.01	0.99
Gambia	-1.50	0.77	0.18	0.00	0.01	1.00
Bangladesh	-1.52	0.80	0.16	0.00	0.00	1.00
Kenya	-1.32	0.80	0.16	0.00	0.00	1.00
Zaire	-1.35	0.89	0.09	-0.00	0.00	1.00
Singapore	-2.58	0.81	0.15	0.04	0.02	1.01
Trinidad	-1.41	0.87	0.11	0.00	0.00	1.01
Burkina Faso	-2.49	0.82	0.15	0.01	0.00	1.01
Belgium	-1.37	0.88	0.10	0.00	0.00	1.01
Switzerland	-1.37	0.89	0.10	0.00	0.00	1.02
Barbados	-1.84	0.83	0.15	0.01	0.01	1.02
Malawi	-1.22	0.84	0.14	0.00	0.00	1.02
Madagascar	-1.32	0.83	0.15	-0.00	0.00	1.02
Guinea	-1.19	0.84	0.15	0.00	0.00	1.03
Bolivia	-1.18	0.88	0.11	0.00	0.00	1.03
Venezuel	-0.86	0.96	0.06	-0.00	0.00	1.03
Sierra Leone	-1.15	0.86	0.14	-0.00	0.00	1.03
Jamaica	-0.93	0.93	0.08	-0.00	0.00	1.04
El Salvador	-1.37	0.91	0.10	0.00	0.00	1.04
Nicaragua	-1.02	0.90	0.11	-0.00	0.00	1.04
Liberia	-0.42	0.98	0.05	-0.01	0.00	1.04
Sweden	-0.88	0.91	0.11	0.00	0.00	1.05
Costa Rica	-0.98	0.87	0.14	0.00	0.00	1.05
Togo	-1.01	0.89	0.12	-0.01	0.00	1.05
Australia	-0.94	0.89	0.12	0.00	0.00	1.05
Chad	-1.06	0.86	0.15	-0.01	0.00	1.05
Austria	-0.68	0.94	0.08	0.00	0.00	1.05
Denmark	-0.86	0.91	0.11	0.00	0.00	1.05
Bahrain	-1.97	0.80	0.20	-0.02	0.01	1.06
C.A.R.	-1.11	0.87	0.15	-0.00	0.00	1.06
Surinam	-1.22	0.86	0.16	0.01	0.01	1.07
Mexico	-1.56	0.89	0.14	0.01	0.01	1.07
Ghana	-0.64	0.93	0.12	-0.00	0.00	1.08
Fiji	-0.88	0.87	0.17	0.00	0.01	1.09
Ivory Coast	-0.65	0.90	0.15	-0.00	0.00	1.09
Swaziland	-0.59	0.92	0.14	0.00	0.01	1.10
Japan	-0.13	0.98	0.09	-0.00	0.00	1.10
Gabon	-0.61	0.92	0.14	-0.00	0.01	1.10
Italy	-0.32	0.95	0.12	0.00	0.00	1.10
Spain	-0.19	0.96	0.12	-0.00	0.01	1.12
Portugal	-0.30	0.95	0.14	0.00	0.01	1.12
Israel	0.28	1.01	0.09	-0.00	0.00	1.13
Guatemala	-0.75	1.00	0.11	0.00	0.00	1.13
Greece	0.07	0.99	0.11	-0.00	0.01	1.14
Netherlands	0.09	0.99	0.11	-0.00	0.00	1.14
Zambia	-0.33	0.94	0.16	-0.00	0.00	1.14
Peru	0.60	1.04	0.09	-0.00	0.00	1.15
France	0.46	1.04	0.11	-0.00	0.00	1.18
Sri Lanka	0.07	0.99	0.15	0.00	0.00	1.18
Argentina	0.81	1.06	0.09	-0.01	0.00	1.18
South Africa	0.12	1.00	0.15	-0.00	0.00	1.19
Saudi Arabia	1.01	1.09	0.11	-0.01	0.01	1.23
Philippines	-0.34	1.04	0.17	0.00	0.00	1.26
Yemen	0.90	1.10	0.14	-0.02	0.02	1.27
U.A.R.	-1.54	1.01	0.30	-0.03	0.02	1.40
	mean	0.84				
	std	0.10				

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