International Evidence on Output Fluctuation and Its Persistence*

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Granger (1966) identifies, what he terms, “the typical spectral shape” for several US macroeconomic series measured in level. King and Watson (1996) report that the growth rates of many US macroeconomic series have similar spectral shapes, although markedly different than the shape Granger identifies for level series. We estimate the spectra of post war output level and growth rate series for 57 countries grouped into developed, high-income, and low-income developing economies. Our most robust finding is that output series measured in level have strikingly similar spectra which exhibit Granger’s typical shape. The output growth rate series, however, exhibit diverse patterns. To further explore the implications of such diversity, we estimate the short-run, the business cycle, and the long run frequency components of growth series and obtain two frequency domain measures of shock persistence for each series. An interesting result, which parallels King and Watson’s for the US, is the large magnitude of the business cycle component in nearly all the output series examined. We also find output growth rates for most countries to exhibit a considerably higher shock persistence than for the US, and the cross-country distribution of the shock persistence measure to be more dispersed across the high income group. Finally, we find that the predictability of the cyclical component of the output growth increases with the extent of development. Macroeconomic implications are discussed.
1. Introduction

Spectral methods are used increasingly to uncover the basic characteristics of economic variables. The shape of spectra in particular is of interest because of its implications for economic theory and economic model building. Several studies have documented striking similarities in the spectral shapes of many US macroeconomic series. For example, Granger (1966) identifies, what he terms, “the typical spectral shape” for series measured in level. He finds that the spectral mass of the series is concentrated at low frequencies, declining as the frequency increases.\(^1\) King and Watson (1995, 1996) examine the spectral properties of several US growth rate series. They find that these power spectra have similar shapes, although markedly different than those identified for level series by Granger (1966). Specifically, they find that the spectra of growth rate series attain low values at low frequencies, rise to a peak at cycle length of about 20–40 quarters and decline at very high frequencies, with most of the spectral mass concentrated in the business cycle frequency band (5–10 years).

The objectives of this paper are twofold. First, we estimate the spectra of international output series measured both in level and in growth rate for 57 countries, grouped into developed (OECD), high-income developing, and low-income developing economies. We find that for the level series the spectra exhibit the typical shape that Granger identifies, with very little cross-country variation. For the growth rate series, however, we observe considerable variation in the spectral shape. We base the rest of our analysis on growth rate because the observed homogeneity of the spectra for level series deters from their usefulness for examining cross-country differences. Second, we examine the frequency domain properties of the output growth series by decomposing each series’ variance into the short-run, the business cycle, and the long-run frequency components to determine the relative importance of each. Moreover, we assess the extent of shock persistence in the international output series using frequency domain methods. In each case we draw cross-

\(^1\)Granger also reports that the length of the available series, the size of the truncation point and the type of window used in estimation do not alter the spectral shape.
country comparisons and note similarities and contrasts within and between groups of countries.

Fluctuations in any time series can be temporary, permanent, or partly temporary and partly permanent (Cochrane, 1988). Fluctuations in a random walk series are permanent because any shock to the data generating process has a lasting effect on the series and on its long-term forecasts. Fluctuations in a trend stationary series, on the other hand, are temporary as the effect of a shock on the data generating process dies out quickly, leaving the long-term forecasts unaffected. It is possible to model series as having a random walk and a stationary component, allowing the series to exhibit, both permanent and temporary shock persistence. Cochrane (1988) proposes a variance ratio statistic to measure the relative magnitude of the temporary and permanent fluctuations in output series. He finds the random walk component of the US output series to be rather small, implying little long-term persistence in output. While there is a plethora of studies that use low power unit root tests to examine the shock persistence properties of international macroeconomic series, similar studies using frequency domain methods are scant.

It is useful to conduct such studies in order to supplement the existing evidence that relies on time domain analysis. Our shock persistence analysis provides such supplementary evidence.

Moreover, according to Meltzer (1990), the economic theory does not imply that shocks to growth rate are identical over time, in fact they are heterogeneous. A likely reason for such heterogeneity is that the distribution of shocks that an economy experiences are conditional on

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2 The distinction between a random walk and a trend stationary series is often critical both for choosing appropriate econometric method and for macroeconomic interpretation of the results. As an example, consider the issue of a bubble in price-dividend ratio discussed by Cochrane (1991). As Hamilton and Whitman (1985) and Cochrane (1989) show, if dividend growth and discount rates are stationary, then the price dividend ratio has a unit root if and only if there is a bubble.

3 Since Beveridge and Nelson (1981) and Nelson and Plosser (1982), many studies have examined the time series dynamics and the shock persistence properties of the US output series, focusing on zero-frequency behavior and using unit root tests. The results of these studies are mixed. Nelson and Plosser (1982) and Campbell and Mankiw (1987) report findings consistent with a substantial persistence in the US output series. Cochrane (1988), Cogley (1990), and Kormendi and Meguire (1990), on the other hand, report findings that suggest a much lower shock persistence in output.

4 The only exceptions, as far as we know, are Cogley (1990), who studies the shock persistence properties of 9 countries, and Leung (1992), who studies shock persistence properties of the UK output.
technology, institutions, and policy, and all such factors are likely to vary over time. Much the same
way, the distribution of shocks is likely to exhibit a cross-country heterogeneity. It, therefore,
merits to document similarities as well as contrasts between various countries in terms of the shock
persistence properties of the output series. To examine such variations, we employ two measures of
persistence using frequency domain methods: the first is Cochrane’s (1988) variance ratio statistic,
which is equivalent to the value of the spectral density of the growth rate at zero frequency, and the
other is the estimated variation in the proportion of the growth rate that is due to long run frequency
components. The latter estimates the area below the spectrum in the long run frequency band.5 As
Granger (1966, footnote 7, p. 155) indicates, the magnitude of the time series variance contained in
the long run frequency band can be interpreted as the degree of shock persistence.6

The paper is organized as follows. In section 2, we briefly discuss the econometric method
we use. In section 3, we present the empirical findings regarding the spectral shape of the level and
growth rate series. In section 4 we report the results of spectral analysis of the growth rate series,
focusing on the variance decomposition of the series and their shock persistence properties.
Macroeconomic implications are also discussed in sections 3 and 4. Section 5 contains some
concluding remarks.

2. Econometric Method

It has long been recognized that spectral analysis can provide a powerful tool for studying the
behavior of time series and identifying the dynamics of the series’ fluctuations.7 The analysis

5Leung (1992) uses a variant of this measure to document time varying behavior of the UK output during the
1856-1990 period.

6King and Watson (1996) show that if one considers a frequency domain interpretation of the trend-cycle
decomposition of Beveridge and Nelson (1981), then the zero-frequency value of the spectral density of the output
growth rate is equivalent to the variance of the change of output trend component at that frequency. Furthermore,
Watson (1986) and King and Watson (1996) demonstrate that under the Beveridge-Nelson decomposition, the
frequency domain interpretation of the variation of output growth rate in terms of shock persistence at non-zero
frequencies requires that the covariance between the changes of the trend and the cyclical components be zero.
Following Watson (1986) and King and Watson (1996), we assume that this condition holds; this is further
discussed in Section 2.
involves decomposing a series into a sum of sine and cosine waves of different frequencies and amplitudes. Unlike the standard time domain analysis, which implicitly assigns all frequencies equal weight, spectral analysis is conducted on a frequency-by-frequency basis, using the entire frequency range, from 0 to $\pi$. In the univariate context, which we use here, the method reveals how much of the total variance of the series is determined by each periodic (or frequency) component. Most existing time series studies of output dynamics, however, use time domain framework which restricts the analysis to a limited set of frequencies.

It is useful to briefly review the key measures we use in the frequency domain analysis that follows. Recall that the autocovariance function of a covariance stationary univariate process $y_t$, is $\gamma(\tau) = E[(y_{t+\tau} - \mu)(y_t - \mu)]$, where $\mu$ is the mean of the process, and both $\gamma(\tau)$ and $\mu$ are time independent. The spectrum of the series $y_t$ is defined as the Fourier transform of its autocovariance function, and is given by $f_y(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \gamma(\tau) e^{-i\omega \tau} d\tau$, with $-\pi \leq \omega \leq \pi$, where $\omega$ is the frequency and is measured in cycles per period (in radians). Since $f_y(\omega)$ is symmetric about $\omega = 0$, it is customary to limit the analysis to the frequency interval $0 \leq \omega \leq \pi$. To interpret the spectrum, note that the autocovariance function is the inverse Fourier transform of the spectrum. That is, $\gamma(\tau) = \int_{\pi}^{0} f_y(\omega) e^{i\omega \tau} d\omega$, which, after setting $\tau = 0$, implies that $\gamma(0) = \sigma_y^2 = \int_{\pi}^{0} f_y(\omega) d\omega$. Thus, the integral of the spectrum equals the total unconditional variance of the series and therefore, the spectrum at each frequency $\omega$ measures the contribution of that particular frequency component to the total variance of the series. The normalized spectral density function is defined as $h_y(\omega) = f_y(\omega)/\sigma_y^2$. By definition, frequency is reciprocal of periodicity where the latter measures the length of time required for a cycle to complete. Therefore, the spectrum of a series decomposes the total variation in the time series by the cycle length of various periodic components. An additional feature usually emphasized in spectral analysis is the presence of peaks in the spectrum which indicates that periodicities are present in the time series.

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To interpret the spectrum in terms of the extent of shock persistence of a series, we follow Watson (1986) and King and Watson (1996) by adopting the Beveridge and Nelson’s (1981) trend-cycle decomposition. Accordingly, output is represented as a sum of trend and cyclical components, where the trend component follows a random walk while the cyclical component is stationary. That is, \( y_t = y^T_t + y^c_t \), where \( y^T_t \) is the trend component and \( y^c_t \) is the cyclical component. Following King and Watson (1996), assume that \( \text{cov} [\Delta y^T(\omega), \Delta y^c(\omega)] = 0 \) for all \( \omega \). Then the frequency domain variance decomposition of \( \Delta y_t \) at frequency \( \omega \) is given by \( f_{\Delta y}(\omega) = f_{\Delta y^T}(\omega) + f_{\Delta y^c}(\omega) \). This allows us to interpret the output growth variation in terms of the persistence properties of the underlying shocks. The empirical work presented in this paper is predicated on this decomposition.

Each frequency component corresponds to a particular periodicity (or a cycle length) according to the mapping, \( p = 2\pi / \omega \), where \( p \), which denotes “period,” measures the length of a cycle. For example, the frequency \( \omega = 2.09 \) corresponds to a 3-year cycle when annual data are used. Following a common practice in macroeconomic applications of spectral analysis, we divide the frequency interval \( 0 \leq \omega \leq \pi \) into three segments: long-run frequency band, business cycle frequency band, and short-run frequency band. The cut-off points of the frequency bands we adopt are similar to those used in modern business cycle literature. For example, Prescott (1986) defines business cycles as 3–8 year cycles. Therefore, we define the frequency interval \( 0.785 \leq \omega \leq 2.09 \) as business cycle frequency band. The frequencies below the business cycle frequency band (\( \omega \leq 0.785 \)) correspond to long-run, while the frequencies above the business cycle frequency band (\( \omega \geq 2.09 \)) correspond to short-run.

The spectral estimates are obtained from smoothed estimates of periodograms of the series. The smoothing is done to get consistent estimates of the spectra. Here we smooth the periodograms

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8 Similar cutoff points are used by Granger and Hatanaka (1964), Lucas (1980), Summers (1983), Englund et al. (1990), Hassler et al. (1992), Zarnowitz (1992), and Carpenter and Levy (1998). Using 5–10 cycles as the definition of the business cycle frequency band, which is the definition King and Watson (1995, 1996) employ, does not alter our conclusions.
using three different lag windows: Bartlett’s, Tukey’s, and Parzen’s. However, since the three windows yield very similar results, we only report the estimates using Bartlett’s window which assigns linearly decreasing weights to the autocovariances in the neighborhood of the frequencies considered and zero weight thereafter. The number of ordinates, \(m\), which is the number of frequency points for which the spectrum is estimated, is set using the rule \(m = 2\sqrt{n}\) as suggested by Chatfield (1989, p. 115), where \(n\) is the number of observations. Thus, we estimate \(f(\omega)\), where \(\omega = \frac{j}{m}\), and \(j = 0, 1, 2, \ldots, m\). The estimated spectral density function is denoted by \(f(\omega)\).

To compare the long run persistence characteristics of the output growth rate, we use two measures of persistence. The first measure is Cochrane’s (1988) variance ratio statistic, 
\[
V = \frac{(1/k) \text{var}[\{y(t) - y(t-k)\}]}{\text{var}[y(t) - y(t-1)]},
\]
where the numerator measures the variance of the cumulative growth of the sampled series over a horizon of \(k\) years while the denominator measures the variance of the sampled series’ one-year growth. Cochrane (1988) demonstrates that the numerator of the variance ratio statistic is asymptotically equivalent to the Bartlett’s estimator of spectral density at the zero frequency. That is, \(f_y B(0) = \lim_{k \to \infty} \frac{1}{k} \text{var}[\{y(t) - y(t-k)\}]\), where \(f_y B(0)\) denotes the Bartlett’s estimate of spectral density. The denominator of the variance ratio statistic can be estimated by computing the unconditional variance of the differenced series. Therefore, the Bartlett’s estimator of spectral density at the zero frequency normalized by the unconditional variance of the differenced series is asymptotically equivalent to Cochrane’s variance ratio statistic computed in frequency domain. That is, we can use the result that \(\hat{V} = \hat{f}_y B(0) = f_y B(0)/\sigma_y^2\). The cases \(V = 0\) and \(V = 1\) correspond to a trend stationary and a pure random walk data generating process, respectively. The advantage of the variance ratio statistic is that it offers a continuum of possible values between zero and one and beyond one. A value larger than one suggests that the data generating process exhibits more shock persistence than a pure random walk process.

The second measure of the extent of persistence is the estimate of the proportion of the output

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Footnote: Smoothing is usually done by taking weighted integral of the periodogram ordinates considered. Several weight structures, also called lag windows, have been proposed in the literature. The main difference between the various lag windows is in the way they generate the weights.
growth variance that is due to long run frequency components. We obtain this measure by estimating the spectral density, normalizing it by the series variance, and then computing a discrete approximation of its integral in the business cycle frequency band. This integral is
\[ H_y^B(\omega) = \int_0^{\omega_0} h_y^B(\theta) d\theta, \]
where \( \omega_0 = 0.785 \) is the cutoff point between the long run and the business cycle frequency bands. Estimating this measure is equivalent to passing the output growth series through a low pass filter (i.e., a filter which isolates the frequency components of the series that fall below \( \omega_0 \)) and then estimating the variance of the resulting series. The measure, therefore, gives an estimate of the proportion of the variance of the output growth that is due to cycles with periodicities of 8 years or more. Assessing the magnitude of this proportion is useful because, in addition to the zero frequency component, it also covers frequency components corresponding to highly persistent, although ultimately temporary, components. Since in many economic models such fluctuations are considered a long run phenomenon, it is useful to have a sense of their magnitude. Further, by comparing the values of this shock persistence measure across countries, we can assess the importance of macroeconomic fluctuations corresponding to the frequencies captured by the measure.

3. Evidence on Spectral Shape

The data source is the International Financial Statistics tape of the IMF. The data set covers the 1950–94 period with an annual frequency. We have chosen to work with annual data because there are insufficient quarterly data for many countries in our sample and we want to cover the same time period to allow an easier cross-country comparison of our results.\(^{10}\)

3.1. Level Series

Figures 1–3 display estimates of the spectra for output series measured in level. Spectral plots for developed (OECD) countries are shown in Figure 1 and similar plots for high-income and low-

\(^{10}\)But this choice is not without cost: because of the small sample size the standard errors of the estimated spectra are large, ranging between 20–40 percent of the point estimate of the spectrum. This, however, is quite common in the literature. For example, King and Watson (1996, footnote 2) also report large standard errors, about 35 percent of the value of the spectrum. Cochrane’s (1988) estimates also have large standard errors.
income developing countries are presented in Figures 2 and 3, respectively. With few exceptions, these plots are remarkably similar to the typical spectral shape that Granger (1966) identifies. Specifically, the spectral mass of the series is concentrated at low frequencies, declining as the frequency increases. This implies that much of the series variation is due to the long run component.

The similarity of the spectral plots for the OECD countries (Figure 1) makes it difficult to distinguish visually among them. There is less conformity among the developing countries. Specifically, we find that among the high income developing countries (Figure 2) there are four countries with a spectral density that differs slightly from the typical shape. These are Venezuela, Uruguay, Mauritius, and Chile. Among the low-income developing countries (Figure 3) there are three exceptions: Guyana, Uganda, and Zaire. In all seven cases, however, most of the spectral mass is still concentrated around the zero-frequency band, declining as the frequency increases. However, the spectral mass here is spread on a wider frequency range, and the zero-frequency peak of the spectrum is substantially lower in comparison to the rest of the countries in these groups. Overall, we note a striking similarity between the spectra of most countries’ output level and the typical spectral shape that Granger identifies.

3.2. Growth Rate Series

Figures 4–6 provide the plots of the spectra of the output growth rate for the 58 countries in our sample, the developed (OECD) countries (Figure 4), high-income developing countries (Figure 5), and low-income developing countries (Figure 6). These figures illustrate that the estimated spectrum for some countries resemble the spectra that King and Watson (1995, 1996) find for several US growth series. These include Australia, Luxemburg, UK, Iceland, Finland, and Ireland among the developed countries, Cyprus, Argentina, and Chile, among the high-income developing countries, and Guyana, Morocco, Honduras, and Uganda, among the low-income developing countries. For some countries, such as Germany, France, Austria, Japan, Spain, Greece (Figure 4), Venezuela, South Africa, Panama, Ecuador, Guatemala (Figure 5), and Zaire (Figure 6), the
estimated spectrum actually exhibits a shape that is closer to the Granger’s (1966) typical shape for a level series: it starts with a peak value at the zero frequency and declines smoothly as the frequency increases. For few countries, such as Dominican Republic, Kenya, and Myanmar (Figure 6) the spectrum has an unusual shape: it is low in the neighborhood of the zero frequency and then increases with frequency. Finally, for other countries, such as Netherlands, Italy, Belgium (Figure 4), Uruguay, Mexico, Colombia (Figure 5), Peru, Sri Lanka, Nigeria, and Zaire (Figure 6), for example, the spectrum has shapes that do not fall in any of these categories. In sum, these plots suggest that the international data exhibits substantial variation in the shape of the output growth spectrum.

Considering the location of the peak of the spectral density, we find that for the group of developed (OECD) countries the peak falls in the business cycle frequency band for 13 of the 23 countries, and in the long run frequency band for the remaining 10 countries. For the high-income developing countries, the peak falls in the business cycle frequency band for 8 of the 17 countries, in the long run frequency band for 8 countries, and in the short run frequency band for just one country, Colombia. Finally, for the low-income developing countries, the peak falls in the business cycle frequency band for four of the 18 countries, in the long run frequency band for 10 countries, and in the short run frequency band for the remaining four countries. Thus, for most developing and in about half of the high-income developing countries the spectra attain peak in the business cycle frequency band. This is similar to what King and Watson (1995, 1996) report for the US growth series. Overall, these findings suggest that countries that are more developed are also more likely to have an output growth spectrum which peaks at business cycle frequency band.

The presence of a peak in a spectrum is an indicator of a predictable component in the series because peaks imply the presence of a strong periodicity in the data. Considering the location of the peaks of spectral densities, we find that for most developed countries and about half of the high-income developing countries the peak is in the business cycle frequency band, similar to what King and Watson (1995, 1996) report for the US growth series. This suggests that the cyclical fluctuations of the output growth in these countries contain a substantial predictable component. In
contrast, the findings for the low income developing countries suggest that in these countries it is
the long run component that exhibits particularly strong predictability. The implication is that there
seems to be a tradeoff between the predictability of the cyclical component of the output growth
and the stage of development: the cyclical component of output growth is more likely to be
predictable the more developed the country is. These stylized facts accentuate the need for business
cycle models with highly persistent, but ultimately temporary, components.

4. Spectral Analysis of Output Growth Rates

4.1. Variance Decomposition in Frequency Domain

Tables 1–3 report the results of variance decomposition for the output growth rates of
developed countries, high-income developing countries, and low-income developing countries,
respectively. In the first column of each table we report Cochrane’s (1988) variance ratio statistic
computed in frequency domain—the value of the spectrum at the zero-frequency. In the second
column we report the second measure of shock persistence which is the proportion of the variance
that is due to long run components. In the next two columns, we report the proportion of the
variance due to business cycles and short run cycles.

The estimated distribution of the output growth variance across long run, business cycle, and
short run frequencies (columns 2–4, respectively) suggests that for most countries in our sample, 41
of the 58 countries, the business cycle frequency components explain most of the output growth rate
variance. This accords well with King and Watson’s (1995, 1996) findings for the US growth series.

When grouped according to stage of development, we find that business cycle frequency
band contains the bulk of the variance for 18 of the 23 developed (OECD) countries. The
exceptions are Germany, France, Japan, Greece, and Portugal where the long run frequency
component seem to explain the largest proportion of the variance. Japan stands out alone with the
long run frequency components accounting for about 60 percent of its output growth rate variance.
Among the G-7 countries, the UK output growth exhibits the highest proportional cyclical
variation, over 70 percent. Next are the US and Canada with about 55 percent each, followed by Italy, Germany, and France. Japan’s output exhibits highest cyclical stability in this group with about 29 percent. The observed stability in Japan’s cyclical fluctuations is not surprising in light of the country’s institutional arrangements aimed at alleviating output cycles. Finally, we find that the output series of UK, the US, and Canada tend to have the smallest long run frequency components. In contrast, Japan, and to a lesser degree Germany and France, have the largest long run frequency components. For the group of developed economies in our sample, the median values of the proportion of the output growth variation that is explained by long run, business cycle, and short run frequencies are 0.29, 0.51, and 0.20, and the corresponding interquartile ranges are 0.20–0.33, 0.42–0.55, and 0.16–0.23, respectively.

In the high-income developing group, the business cycles frequency band contains most of the variance for 11 of the 17 countries. The exceptions are Venezuela, Mauritius, Brazil, Panama, Ecuador, and Guatemala where the long run frequency components explain the largest proportion of the variance, and Columbia, where the short run frequency components contribute the most to the output growth variance. Among these countries Guatemala stands out with the long run component accounting for over 61 percent of the output growth variance. For the group of high income developing countries in our sample, the median values of the proportion of the output growth variation that is explained by long run, business cycle, and short run frequency components are 0.30, 0.42, and 0.23, with interquartile ranges 0.24–0.39, 0.34–0.54, and 0.20–0.25, respectively.

Finally, the business cycles frequency band contains most of the variance for 13 of the 16 low-income developing countries. Here the exceptions are El Salvador and Philippines where the long run frequency components explain the largest proportion of the variance, and Myanmar where the short run frequency components contribute most to the output growth variance. For the group of low income developing countries in our sample, the median values of the proportion of the output growth variation that is explained by the long run, business cycle, and the short run
frequencies are 0.33, 0.43, and 0.25, with interquartile ranges of 0.17–0.35, 0.37–0.52, and 0.17–0.32, respectively.

Comparing the short run and the long run frequency components, we find that for the group of developed countries, the long run components dominate the short run components in 17 of the 23 countries. For the group of high-income developing countries, the long run frequency components dominate the short run in 12 of the 17 countries, and in the group of low-income countries—in 11 of the 18 countries.

Overall, these results suggest that for most countries in our sample, the bulk of the spectral mass is indeed concentrated in the business cycle frequency band. The robustness of this finding is further underscored by King and Watson’s (1996, footnote 3) observation that the business cycle character of the growth rate spectra is insensitive to the choice of the spectral estimator used. The short run frequency components seem to contribute the least to the output growth rate variation. This finding is similar to King and Watson’s (1995, 1996) findings for the US growth rate.

Blanchard and Quah (1989) attribute the fluctuations in output to shocks that have a permanent effect on output, supply shocks, and shocks that have a transitory effect on output, demand shocks. Typically, demand shocks affect the fluctuations at the business cycle frequencies while supply shocks affect the fluctuations at the long run frequencies. Following this interpretation, our result that the bulk of variation in output growth is at the business cycle frequency, implies that for the majority of countries most of the variation in output growth is due to demand shocks. This is particularly true for the developed countries. Moreover, the relatively large interquartile range of the variance ratio statistic for the developed countries and the small interquartile range for the low income developing countries suggest that the former countries’ output growth is affected by a more diverse mix of supply and demand shocks. Also, the output growth series of the low income developing countries appear to be affected primarily by demand shocks without much cross-country variation.

Blanchard and Quah (1989) offer this interpretation subject to the caveat that demand shocks may also have a long lasting effect on output, but they believe that these long run effects are small compared to those of supply shocks.
4.2. Evidence on Shock Persistence

The first column in Tables 1–3 reports Cochrane’s variance ratio statistic computed in frequency domain. These estimates suggest that there are substantial cross-country variations in the size of the random walk component of output growth. The estimates vary from 0.11 for Kenya (Table 3) to 4.29 for Japan (Table 1). Among the developed (OECD) countries, about half have a variance ratio statistic of less than one. The United States, Canada, Australia, and United Kingdom are among the countries with a low statistic, with the United States having the smallest estimate, 0.18. For the developed countries, the statistic attains a median value of 0.97 with an interquartile range of 0.35–2.20.

Among the high income developing countries, six have a statistic smaller than one. Cyprus has the smallest and Venezuela has the largest random walk component with 0.14 and 2.34, respectively. Here the median value is 1.13 and the interquartile range is 0.59–1.59. Finally, among the low-income developing countries, Kenya has the smallest and Zaire has the largest random walk component (0.11 and 2.09, respectively). The median value of the statistic in this group is 0.73 and the interquartile range is 0.43–1.15. Comparing the median and the interquartile range of the variance ratio statistic for the three groups, we note that the median values are slightly different across groups but the statistic shows more dispersion in the case of the developed countries, as this group has the largest interquartile range. For the low income group, the variance ratio statistic has the most concentrated cross-country distribution—the smallest interquartile range. Thus, overall, the most developed countries seem to be the least similar in terms of their output shock persistence, while the low income countries are the most similar.

For the purpose of comparison to other studies, it is worth noting that Cogley (1990) uses an extended Maddison’s (1982) data set and also finds that the United States and Canada have a smaller random walk component in comparison to other countries. Kormendi and Meguire’s (1990) general findings for the postwar data are also similar to what we report here. In particular,
they also find that the United States has the smallest random walk component in the output growth. In addition, with the exception of six countries, the estimates of the variance ratio statistic we report here have the same order of magnitude as the statistics they report. This similarity is in spite of the differences between our study and Kormendi and Meguire’s in terms of the sample size (their sample size is larger than ours), data frequency (they use quarterly data while we use annual), the output measure (they use growth rate of per capita output while we use the growth rate of output), and the econometric method (they use time domain methods while we use the frequency domain methods).

We find a substantial variation across countries in terms of the second measure of shock persistence—the proportion of the output growth variance that is due to long run components. First consider the developed countries. Here we find that the estimated contribution to variance in this group varies from about 10 percent for Australia to over 60 percent for Japan. Other countries with low estimates include the UK with 12 percent, the US and Iceland with 15 percent each, Luxemburg with 17 percent, and Finland with 19 percent. France with 48 percent, Germany with 47 percent, Portugal with 41 percent, and Greece with 40 percent are at the other end. Among the G-7 countries the UK and the US attain the lowest estimates of the long run component contribution, while Japan, France, and Germany attain the highest values. The contrast between the extreme values within the G-7 countries is startling: the proportion of output growth variance explained by shocks that generate long term fluctuations is five times larger for Japan than it is for the UK and four times larger than for the US. This contrast is also reflected in the relative magnitude of the business cycle components of these countries’ output. As discussed earlier, over 70 percent of the output growth fluctuation in the UK and over 54 percent in the US is cyclical, in contrast to only 28 percent in Japan. This implies that most of the shocks the Japanese economy is experiencing are more permanent in the sense that they lead to cycles that are long lasting. In the UK and the US, in contrast, most of the shocks have a more temporary effect leading to primarily cyclical and shorter horizon fluctuations.\footnote{Note that countries with higher variance ratio statistic also tend to have a larger proportion of their income}
Next consider high income developing countries. For this group, the contribution of the long run components to the output growth variance varies from about 15 percent for Cyprus to over 61 percent for Guatemala. Other countries with low estimates include Argentina and Turkey with about 18 percent each while countries with particularly high estimates include Ecuador with 46 percent, and Brazil with 44 percent. The contrast between the extreme values within the high income developing countries is also substantial: the proportion of output growth variance explained by shocks that generate long term fluctuations is about four times higher for Guatemala than it is for Cyprus and Argentina. Here also, this contrast reflects the relative magnitude of the business cycle components of these countries output growth.

Finally, for low income developing countries, the contribution of the long run components to the output growth variance varies from about 7 percent for Kenya to over 55 percent for El Salvador and over 50 percent for Philippines. The contrast between the extreme values within this group is even more startling: the proportion of output growth variance explained by shocks that generate long term fluctuations is about eight times higher for El Salvador than it is for Kenya. Overall, these results suggest that there are substantial variations in shock persistence between groups of countries as well as between countries in the same group.

Issues related to the practical feasibility and the macroeconomic efficiency of establishing a single currency area among the countries of the European Monetary Union (EMU) have recently received a substantial interest. As Caporale and Pittis (1998) demonstrate, a necessary condition for the desirability of EMU membership for national economies is a similarity in the degree of persistence of shocks affecting them. Results of the spectral analysis reported here may be useful for assessing the degree of conformity of the EMU countries in terms of the size and the persistence of their output shocks. The figures reported in Table 1 suggest that the majority of the eleven EMU countries (marked with an asterisk) exhibit relatively similar behavior in terms of the proportion of the total variance accounted for by long-run, business, cycle, and short run components. For most of these countries the variance ratio statistic is about one or higher with the exception of Ireland with growth variance explained by long run frequency components.
0.56 and United Kingdom with 0.20. The cyclical variation figures for the United Kingdom and Greece stand out particularly with the business cycle frequency component contributions of 70 percent and 60 percent, respectively. Thus, overall, the EMU countries, with the exception of United Kingdom and Greece, exhibit substantial conformity in terms of their output growth rate behavior over the short run, business cycle, and long run frequency bands. Similar interpretations can be drawn to assess the feasibility of other regional alliances.

5. Conclusion

We examine the frequency domain properties of the output series (both in level and growth rate) for 57 countries, grouped into developed (OECD), high-income developing, and low-income developing economies. For level series we find that the spectra closely follow the typical shape identified by Granger (1966): the spectral mass is concentrated at low frequency, and it declines as frequency increases. For growth rate series we find more diverse spectral shapes, although many exhibit the hump-shape that King and Watson (1995, 1996) report for several US growth series. We also find that the estimated value of the output growth rate spectrum at the zero frequency is substantially variable across countries. Moreover, the spectra do not always attain peak at the business cycle frequency band. Rather, the peaks often occur in the long run frequency band suggesting a predictability of the long run component.

Given the diversity observed in the spectra of growth rate series, we base much of our analysis on growth rate to further explore the implications of such diversity. We estimate the proportion of the variance due to the short run, the business cycle, and the long run frequency components of growth series to measure the relative importance of these components in the total variation of each series. Furthermore, we estimate the extent of shock persistence in the international output series, using two frequency domain based measures. The results suggest that for most of the sampled countries, the bulk of the spectral mass is concentrated in the business cycle frequency band. This is similar to the pattern that King and Watson (1996) observe for US economies.

\[^{13}\text{Caporale and Pittis (1998) reach a similar conclusion using a different methodology.}\]
growth rate. The short run frequency components seem to contribute the least. Our findings also suggest that there is a substantial variation in the size of the random walk component of output of the countries considered. The point estimate of the variance ratio statistic varies from 0.11 for Kenya to 4.29 for Japan. We compute the median value of the statistic and its interquartile range for each group of countries. The median values are slightly different across groups and the distribution of the statistic seems to be more disperse for developed countries and more condense for low income countries. This implies that the extent of shock persistence varies more across developed countries than does across low income countries. Our findings also suggest that the countries with higher income tend to have a smaller short run fluctuation and a larger cyclical fluctuation in output.

We note several macroeconomic implications of these results. First, for the majority of the countries, and especially for the developed countries, we find that most of the variation in output growth is due to demand shocks. The developed countries' output growth seems to be affected by a more diverse mix of supply and demand shocks than those of the low income countries. Second, we find that for most developed countries and about half of the high-income developing countries, the cyclical fluctuations of the output growth contain a large predictable component. Third, we find that the predictability of the cyclical component of output growth increases with the extent of development. For the low income developing countries, however, the long run component appears to be predictable. Finally, we find that the European Monetary Union countries, with the exception of United Kingdom and Greece, seem to exhibit substantial conformity in terms of their output growth behavior over the short run, business cycle, and long run frequency band. This suggests that these countries are perhaps good candidates to form a monetary union.

Meltzer (1990, p. 2) recently remarked: “Is there reason to believe that the distributions of shocks between real and nominal, permanent and transitory, shocks to level and growth rate, remain fixed over time? Economic theory has no implication that leads us to expect stability and constancy of these distributions.” Our findings suggest that such stability is not observed across
countries either. Indeed, the results we report indicate that the countries are experiencing a variety of shocks with varying degree of persistence. The frequency domain behavior of the output growth rate we document here is likely to be a reflection of these variations. Future studies may view these findings as additional stylized facts that modern macroeconomic theory needs to confront and explain.
References


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<tr>
<th>Country</th>
<th>Variance Ratio</th>
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<th>Short-Run Component</th>
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<td>0.5682</td>
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<tr>
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Notes: An asterisk indicates European Monetary Union membership. See the text for details.
Table 2. Variance Decomposition of Post War GDP Growth Rates by Frequency Component, 17 High-Income Developing Countries

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<tr>
<th>Country</th>
<th>Variance Ratio</th>
<th>Long-Run Component</th>
<th>Business-Cycle Component</th>
<th>Short-Run Component</th>
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<td>Interquartile Range</td>
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<td>0.1707–0.3486</td>
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Figure 1. Spectral Densities of the log of real GDP, 23 OECD Countries.
The horizontal axis measures the cycle-length in years.
LR = Long Run, BC = Business Cycle, and SR = Short Run.
Figure 2. Spectral Densities of the log of real GDP, 17 High-Income Developing Countries. The horizontal axis measures the cycle-length in years. LR = Long Run, BC = Business Cycle, and SR = Short Run.
Figure 3. Spectral Densities of the log of real GDP, 18 Low-Income Developing Countries. The horizontal axis measures the cycle-length in years. LR = Long Run, BC = Business Cycle, and SR = Short Run.
Figure 4. Spectral Densities of the growth rate of Real GDP, 23 OECD Countries. The horizontal axis measures the cycle-length in years. LR = Long Run, BC = Business Cycle, and SR = Short Run.
Figure 5. Spectral Densities of the growth rate of Real GDP, 17 High-Income Developing Countries. The horizontal axis measures the cycle-length in years. LR = Long Run, BC = Business Cycle, and SR = Short Run.
Figure 6. Spectral Densities of the growth rate of Real GDP, 18 Low-Income Developing Countries. The horizontal axis measures the cycle-length in years. LR = Long Run, BC = Business Cycle, and SR = Short Run.