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International evidence on output fluctuation and shock persistence ☆

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Abstract

We estimate output growth rate spectra for 58 countries. The spectra exhibit diverse shapes. To study the sources of this diversity, we estimate the short-run, business cycle, and long-run frequency components of the sampled series. For most OECD countries the bulk of the spectral mass is in the business cycle frequency band, and the magnitude of this cyclical component increases with income. For the developing countries, however, the spectral mass is not concentrated in the business cycle frequency band, and the income-cycle relationship is not as strong. We also estimate two frequency domain measures of shock persistence and find both measures to vary considerably across countries, with the U.S. having the lowest estimates. For the OECD countries most of the variation in the variance ratio statistic appears to be explained by the variation in the long-term growth component.

JEL classification: C32; E30; E32; O40; O57

Keywords: Business cycles; Developing countries; OECD countries; Output growth; Shock persistence; Spectral analysis

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1. Introduction

Spectral methods are used increasingly to uncover time series characteristics that are useful for economic theory and model building. For example, the power spectrum of the growth rates for macroeconomic variables provides important information about the nature of business cycles. King and Watson (1996) report that the spectra of growth rates for several U.S. macroeconomic series have similar shapes. These growth rate spectra are hump-shaped: attaining low values at low frequencies, rising to a peak at business cycle frequencies, and declining at high frequencies, with the spectral mass mostly concentrated in the business cycle frequency band.

We contribute to this literature by examining the spectra of output growth rate series for 58 countries consisting of 23 OECD, 17 high-income developing, and 18 low-income developing countries. We find that the spectral shape changes considerably across countries. To better understand this diversity and what it implies, we analyze the frequency domain properties of the output growth series. We decompose the variance of each series into short-run, business cycle, and long-run frequency components and determine their relative importance. Accordingly, we draw cross-country comparisons and note similarities and contrasts within and between groups of countries. We also estimate several regression equations to examine the relationship between a country's cyclical component of output growth and its income level. We pay attention to data quality issues and how they may affect an inference about such relationship. In particular, we use income measures that are less sensitive to data contamination and Summers and Heston's (1991) data quality rankings in our estimation of the income-cycle relationship.

Moreover, we use the estimated spectra to assess the extent of shock persistence in the international output series. There is a plethora of studies that use low power unit root tests to examine the shock persistence properties of international macroeconomic series, but similar studies using frequency domain methods are scant.[1] Meltzer (1990) argues that economic theory does not imply that shocks to growth rate are identical over time, and that these shocks are, indeed, heterogeneous. A likely reason for such heterogeneity, he argues, is that the distribution of shocks that an economy experiences is conditional on its technology, institutions, and policy, all of which are likely to vary over time. Much the same way, the distribution of shocks is likely to exhibit a cross-country variation, perhaps due to differences in technology, institutions, and policy among countries. It, therefore, merits to document similarities as well as contrasts between various countries in terms of the shock persistence properties of their output growth series.

We employ two measures of shock persistence in the frequency domain. The first is the spectral density evaluated at the zero frequency, which is equivalent to Cochrane's (1988) variance ratio statistic, and the other is the proportional variation in growth series that is due to long-run frequency components, as measured by the

[1] 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 U.K. output.

area under the spectrum in the long-run frequency band. The latter measure operationalizes the notion that the magnitude of the time series variance contained in this band can be interpreted as the degree of shock persistence (Granger, 1966). This measure includes frequency components corresponding to highly persistent, but temporary shocks. Since in many economic models such fluctuations are considered a long-run phenomenon, it is useful to have a sense of their magnitude.

Campbell and Mankiw (1989), Kormendi and Meguire (1990), and Cogley (1990) report that the U.S. has a considerably smaller shock persistence than many other countries. Here, we extend these results to a large sample of countries with different income levels. Furthermore, using Cochrane's (1988) variance ratio statistic, we examine the variation in shock persistence to assess whether it originates in the statistic's numerator, which measures the variation in cumulative long-term growth, or denominator, which measures growth variation over a one-year horizon (volatility).

While we use annual data to conduct most of our analysis, in cases where quarterly data were available, we supplemented our analysis. Most of the results that we report for the annual data seem to hold for the quarterly data as well. These include the diversity of spectral shapes, the income-cycle relationship, and the observed cross-country variation in shock persistence and from where it originates.

The paper is organized as follows. Section 2 discusses the econometric method. Section 3 presents the empirical findings on the spectral shape of the annual growth rate series. Section 4 reports the results of spectral analysis of the annual growth rate series. This analysis includes frequency domain variance decomposition, cross-country comparison of variance ratio statistics and its components, and a regression analysis of the cyclical component of output, with special attention to data quality issues. Section 5 contains analysis similar to those in Sections 3 and 4 but using quarterly data for selected OECD countries. Section 6 summarizes and concludes the paper.

2. Econometric method

It has long been recognized that spectral analysis can provide a powerful tool for studying time series and identifying their fluctuation dynamics.[2] The analysis 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 and restricts the analysis to a limited set of frequencies, the spectral analysis is conducted on a frequency-by-frequency basis, using the entire frequency range, 0 to π. In the univariate context, used here, the method identifies how much of the total variance of the series is determined by each periodic (frequency) component.

[2] See, for example, Granger and Hatanaka (1964), Priestley (1981), and Koopmans (1995). For more recent applications and surveys, see Granger and Watson (1984), Baxter and King (1995), and King and Watson (1996). See Appendix A for more details.

Each frequency component, ω, corresponds to a particular periodicity (cycle length) according to the mapping $p = 2\pi/\omega$, where "period" p measures the cycle length. 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 $0 \leqslant \omega \leqslant \pi$ into three segments: the long-run frequency band, the business cycle frequency band, and the short-run frequency band. The cut-off points that we choose are similar to those used in modern business cycle literature. Accordingly, we define the long-run (LR) frequency band as $0 \leqslant \omega \leqslant 0.785$ which corresponds to cycles of 8 years or longer, the business cycle (BC) frequency band by the interval $0.785 \leqslant \omega \leqslant 2.09$ which corresponds to cycles of 3–8 years, and the short-run (SR) band by $2.09 \leqslant \omega \leqslant \pi$ which corresponds to cycles of 2–3 years.[3]

To assess the long-run persistence characteristics of the output growth rate, we estimate two measures of persistence. The first measure is Cochrane's (1988) variance ratio statistic, $V = (1/k)\mathrm{var}[y(t) - y(t-k)]/\mathrm{var}[y(t) - y(t-1)]$, where $y(t)$ is the natural logarithm of the sampled series at time t. The numerator of V is proportional to the variance of the cumulative growth over the horizon of k years while the denominator measures the variance of the growth rate over one year. Note that $V = 0$ and 1 correspond to trend stationary and random walk cases, respectively. A value larger than one suggests that the data generating process exhibits more shock persistence than a pure random walk. The advantage of the variance ratio statistic is that it offers a continuum of possible values between zero and one and beyond one.

Cochrane (1988) demonstrates that the numerator of the variance ratio statistic can be consistently estimated by Bartlett's estimator of spectral density at the zero frequency. The denominator of the variance ratio statistic can be estimated by computing the unconditional variance of the differenced series. Therefore, Bartlett's estimator of spectral density at the zero frequency normalized by the estimated unconditional variance of the differenced series σ_y^2 is a consistent estimator of Cochrane's variance ratio statistic V; i.e., $\mathrm{plim}\{\hat{h}_y(0)\} = V$, where $\hat{h}_y(0) = \hat{f}_y(0)/\hat{\sigma}_y^2$.

The second measure of persistence is the estimate of the proportion of output growth variance due to the 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 over the long-run frequency band. This integral is $H_y^{LR} = \int_0^{0.785} h_y(\omega)\,\mathrm{d}\omega$, where $h_y(\omega) \equiv f_y(\omega)/\sigma_y^2$ is the normalized spectral density at frequency ω and $f_y(\omega)$ is its non-normalized counterpart. 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 falling below $\omega = 0.785$), and then estimating the variance of the resulting series. The measure, therefore, captures the proportion of the variance due to cycles with periodicities of 8 years or more. In addition to the zero-frequency component, this measure includes frequency components corresponding to highly persistent, but

[3] For example, Prescott (1986) defines business cycles as 3–8 year cycles. Similar cutoff points are used by Granger and Hatanaka (1964), Lucas (1980), Summers (1980), Englund et al. (1990), Hassler et al. (1992), Zarnowitz (1992), Levy and Chen (1994), Carpenter and Levy (1998), and Levy (2000).

temporary shocks. Since in many economic models such fluctuations are considered a long-run phenomenon, it is useful to have a sense of their magnitude.

Furthermore, 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 this measure. We also estimate and report the proportion of the total output growth variation due to (i) cyclical shocks, $H_y^{BC} = \int_{0.785}^{2.09} h_y(\omega)\,\mathrm{d}\omega$, and (ii) short-run frequencies, $H_y^{SR} = \int_{2.09}^{\pi} h_y(\omega)\,\mathrm{d}\omega$. Non-normalized counterparts of the above are $F_y^{LR} = \int_0^{0.785} f_y(\omega)\,\mathrm{d}\omega$, $F_y^{BC} = \int_{0.785}^{2.09} f_y(\omega)\,\mathrm{d}\omega$, and $F_y^{SR} = \int_{2.09}^{\pi} f_y(\omega)\,\mathrm{d}\omega$, respectively.

3. Evidence on spectral shape

Our annual data set covers 58 countries over the 1950–1994 period.[4] Using annual data allows us to include more countries, as long span quarterly data are not available for many countries.[5] We later supplement our analysis using quarterly data for a subset of the sampled countries where such data are available for a reasonably long span. Of the 58 sampled countries 23 are OECD members that we refer to as the developed countries. We divide the remaining countries—which we refer to as the developing countries—into 17 high-income and 18-low income countries. The latter grouping follows a rank ordering of countries based on their average income, and using the substantial income gap between Guatemala and El Salvador as a "natural" break point. Note that in all tables and figures in this paper, we list the countries based on their average income (in descending order), so various reported statistics can be compared with income ranking regardless of our grouping which, although natural, is arbitrary.

Figs. 1, 2, and 3 present the estimated output growth rate spectra and the corresponding 95 percent confidence intervals for the developed (OECD), high-income developing, and low-income developing countries, respectively.[6] The figures show that the growth rate spectra do not conform to a particular shape. Only a few countries have growth rate spectra with the distinct shape that King and Watson (1996) report for several U.S. series—low values at low frequencies, rising to a peak at business cycle frequencies, and declining at high frequencies, with the spectral mass mostly concentrated in the business cycle frequency band. These countries include USA, Australia, Luxembourg, U.K., Iceland, and Ireland, among the developed countries; Cyprus and Chile among the high-income developing countries;

[4] Our data source is TSM Global Economic Database, which is the expanded version of IMF's International Financial Statistics tape, published by Data Services Incorporated.

[5] Campbell and Mankiw (1989) also note that long span international quarterly series are too few. Using a small sample is not without cost: the small sample yields large standard errors for the estimated spectra. This, however, is quite common in the literature. For example, King and Watson's (1996) and Cochrane's (1988) estimates of spectra also have large standard errors. Campbell and Mankiw (1989) also emphasize the substantial imprecision of the persistence estimates they report.

[6] Levy and Dezhbakhsh (2002) estimate the spectra of output levels for the 58 countries in our sample and find that the level series have strikingly similar spectra that exhibit the shape that Granger (1966) calls "the typical spectral shape" for economic variables measured in level—the spectral mass is concentrated mostly at low frequencies, declining exponentially as the frequency increases.

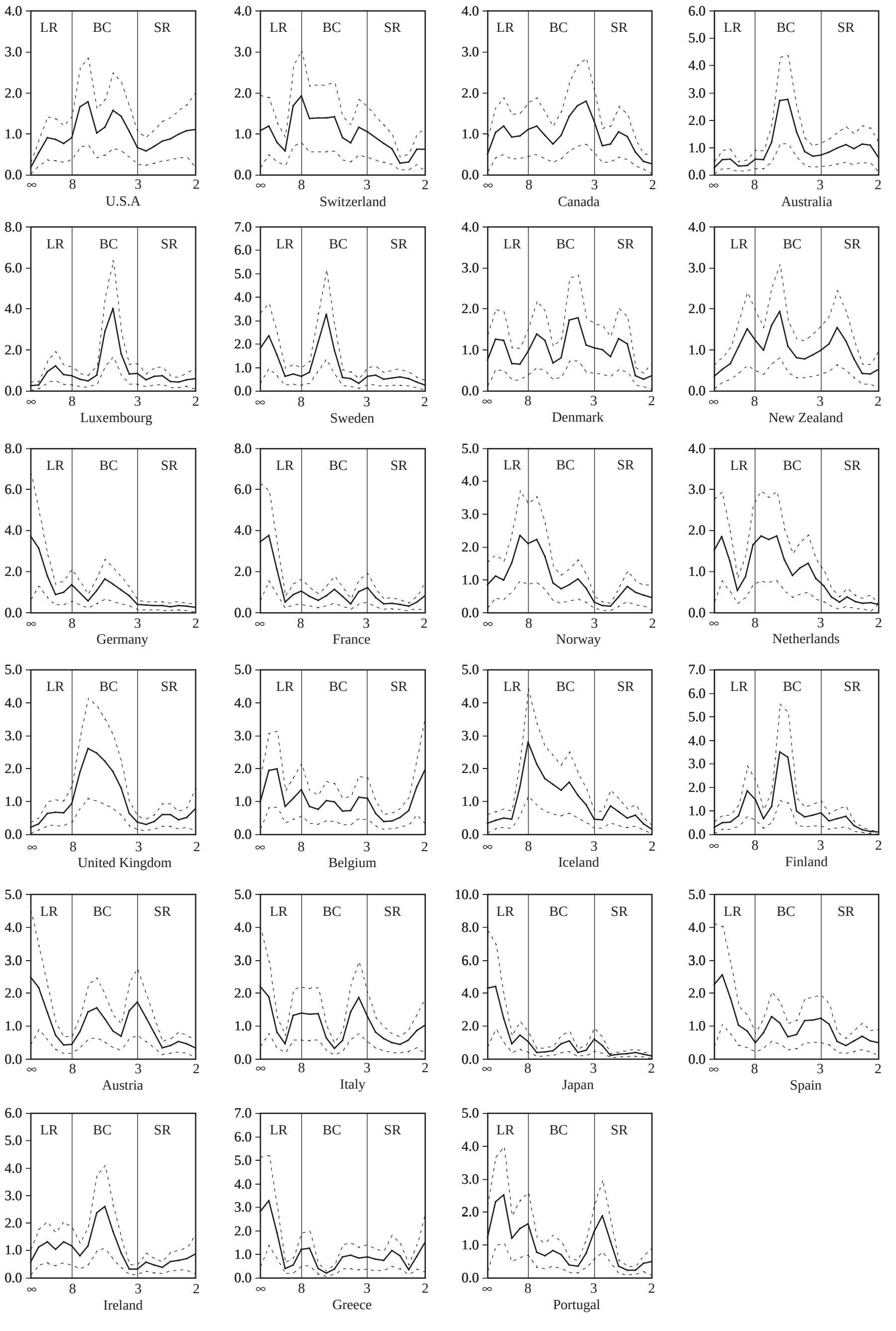

Fig. 1. Spectral densities of the growth rates of Real GDP, 23 OECD countries. The horizontal axis measures the cycle-length in years (annual data). LR = long run, BC = business cycle, and SR = short run.

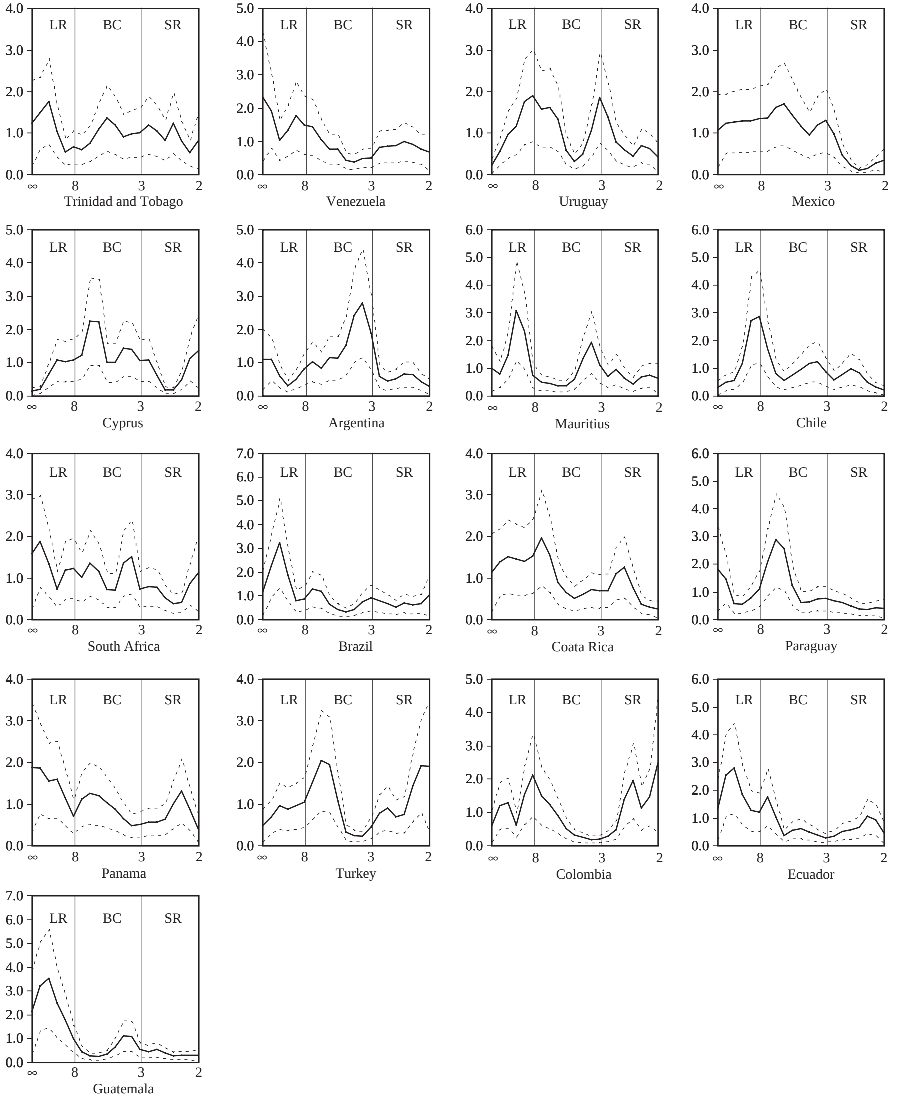

Fig. 2. Spectral densities of the growth rates of Real GDP, 17 high-income developing countries. The horizontal axis measures the cycle-length in years (annual data). LR = long run, BC = business cycle, and SR = short run.

and Uganda, among the low-income developing countries.[7] The spectra of the other countries in our sample exhibit diverse patterns.

[7] Note that for Iceland and Chile, the spectral peak is at the 8-year cycle (border line between the long-run and business cycle frequency bands). We consider these two countries to meet Stock and Watson's criteria, which categorizes 8-year cycles within the business cycle frequency band.

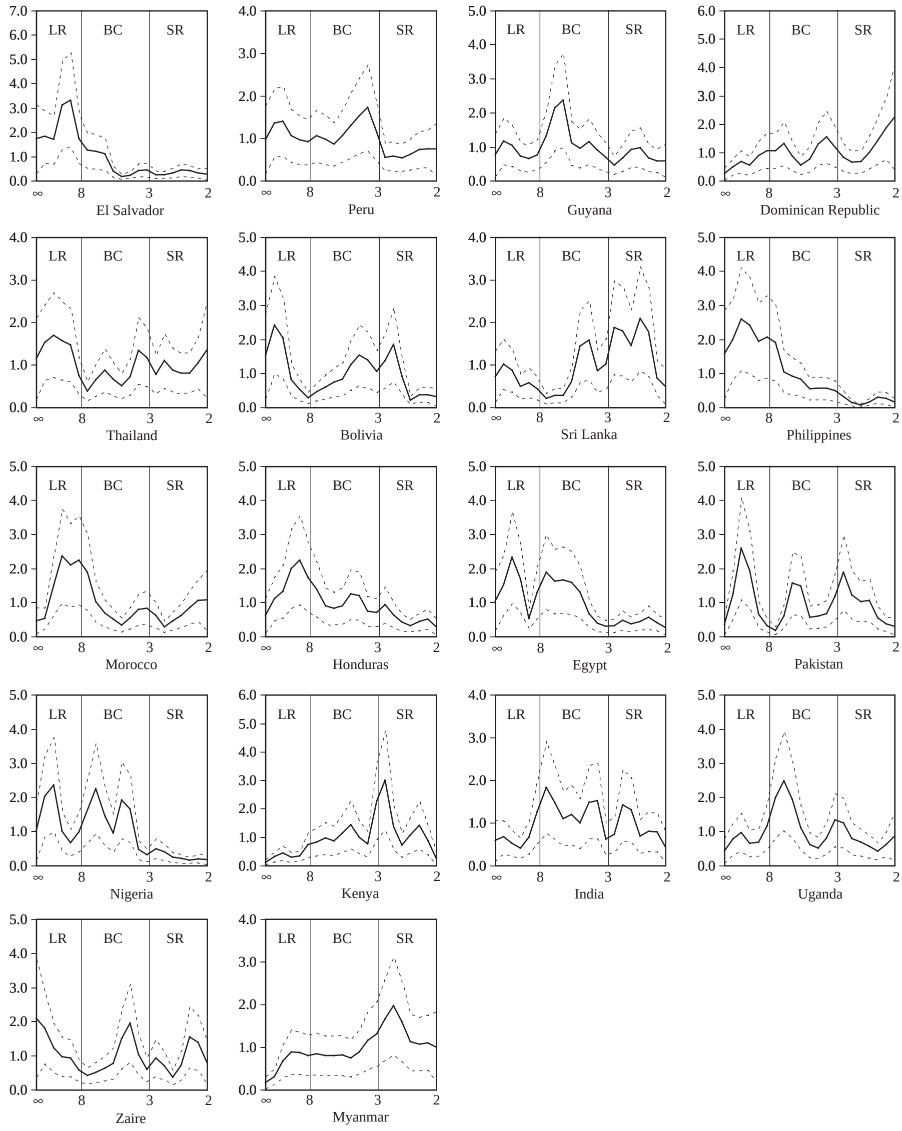

Fig. 3. Spectral densities of the growth rates of Real GDP, 18 low-income developing countries. The horizontal axis measures the cycle-length in years (annual data). LR = long run, BC = business cycle, and SR = short run.

In identifying these countries we had to decide whether an estimated spectrum attains low values at low frequencies, rises to a peak at business cycle frequency band, and most of its mass is concentrated in the business cycle frequency band. Obviously, any statistical inference about similarity of two geometric shapes must be made with caution, particularly when the maintained (null) shape is verbally rather than mathematically defined. The fuzziness inherent in verbal descriptions makes any rigorous statistical inference impossible in such cases. One then has to confine to qualitative inference as the second best option.

To classify spectral shapes while taking into account the statistical imprecision associated with the spectral estimates, we have adopted the following criteria: (a) Is the spectral peak located in the business cycle frequency band? (b) Does the upper bound of the spectral density estimate at zero frequency fall at the same level or below the lower bound of the estimated density at peak frequency?[8] and (c) Is most of the spectral mass concentrated in the business-cycle frequency band? If the answer to all three questions is yes, then we classify the country as having output growth rate with King and Watson's typical spectral shape. Note that condition (a) requires some degree of qualitative assessment. Condition (b) is more rigorous as it predicates the inference on confidence bands around the estimated spectrum at zero frequency and at peak frequency. Condition (c) is checked using confidence intervals for the estimated mass in the three frequency bands; these confidence intervals are reported in Tables 1–3.[9]

For several countries, including Germany, France, Japan, Spain, Greece (Fig. 1), and Venezuela (Fig. 2), the estimated growth rate spectrum starts with a peak value at or near the zero frequency and declines smoothly as the frequency increases. This is the shape that Granger (1966) calls "the typical shape" for economic series measured in level. For the Dominican Republic and Myanmar (Fig. 3), the spectrum has an unusual shape: it is low in the vicinity of the zero frequency and then increases with frequency. For the remaining countries, the spectral shapes do not fall into any of these categories. In sum, the international data exhibit substantial variation in the shape of the output growth spectrum.

The presence of a peak in the spectrum is an indication of a predictable component in the corresponding series, because peaks imply strong periodicity in the data. A peak in the business cycle frequency band, for example, suggests that business cycle fluctuations have a predictable component. We find that for ten of the developed (OECD) countries, the peak appears to fall in the business cycle frequency band. Iceland and Switzerland have peaks which are located between the long-run and business cycle frequency bands. For Germany, France, Norway, Austria, Japan, Spain, and Greece the peak appears to fall in the long-run frequency band. For the remaining countries the location of the peak is not clear. Note that the above inference is qualitative, as explained earlier. There are few clear cases, however, including Australia, Luxembourg and the U.K.

For seven of the high-income developing countries, the peak falls in the business cycle frequency band; two of these countries (Chile and Uruguay) have peaks that fall between the business cycle and another frequency band. For Venezuela, Brazil,

[8] That is, we try to determine whether the confidence intervals of the estimated spectrum at the zero and peak frequencies overlap, or whether the latter lies strictly above the former.

[9] A more rigorous assessment of the spectral mass distribution across the three bands is presented in Section 4.

Panama, Ecuador, and Guatemala, the peak appears to be in the long-run frequency band. The location of the spectral peak is less clear for the remaining countries in this group. Finally, for the low-income developing countries, the peak falls in the business cycle frequency band for four of the eighteen countries, in the long-run frequency band for ten countries, and in the short-run frequency band for the remaining four countries.

Overall, it appears that the developed and high-income developing countries are more likely to have a spectrum that peaks in the business cycle frequency band than the low-income countries. This implies a relationship between the predictability of the cyclical component of output growth and the a country's stage of development: the cyclical component of output growth is more likely to be predictable for the more developed countries.

Two issues related to the observed diversity of the spectral shapes are worth noting. First, spectral shapes become more diverse as we move from the developed to high- and low-income developing countries. The inverse relationship between the diversity of the spectral shapes and the income level may partially be an artifact of measurement errors in the income data reported by poorer countries. Errors may add noise to the data, therefore, inflating the short-term component of the spectrum leading to divergence of spectral shapes among countries with otherwise similar growth patterns. Institutional inadequacies as well as data overstating are among the major causes of measurement error; see, e.g., Summers and Heston (1991) and Romer (1989, 1994). We examine this issue further in our regression analysis of the cyclical component in Section 4.3.

Second, since a given spectral shape has certain implications about the stochastic properties of the underlying data generating process,[10] the observed diversity of the spectra must be taken into consideration in the empirical studies that examine business cycles. For example, consider the spectral shape that we report here for several countries' including the U.S. and the U.K. and that King and Watson (1996) report for several U.S. growth rate series. Here the spectra is hump-shaped with most of its spectral mass and its peak falling in the business cycle frequency band. As discussed by King and Watson (1996), the implication of this shape can be seen by considering the frequency domain interpretation of Beveridge and Nelson (1981) trend-cycle decomposition. Accordingly, output is represented as the sum of trend and cyclical components; i.e., $y_t = y_t^\tau + y_t^c$, where y_t^τ is the trend component that follows a random walk and y_t^c is the stationary cyclical component. The assumption—made by, e.g., Watson's (1986)—that $\mathrm{cov}[\Delta y^\tau(\omega), \Delta y^c(\omega)] = 0$ for all ω implies that trend has only a small contribution to growth and the remaining variability is due to highly persistent, but ultimately temporary, variations in Δy^c.

[10] These implications relate to the underlying probability distribution or its moments, in general, and characteristics such as trend-cycle decomposition, in particular. A flat spectra, for example, implies a white noise series, while an ARIMA model implies a spectra with a maximum at the zero frequency (see, e.g., Watson, 1986).

4. Spectral analysis of output growth

4.1. Variance decomposition in the frequency domain

Tables 1–3 report the results of variance decomposition of the normalized spectra of output growth rates for the developed, high-income developing, and low-income developing countries, respectively. The first column of each table contains the proportion of the variance due to long-run components (our second measure of shock persistence).[11] In the next two columns, we report the proportion of the output growth variance due to business and short-run cycles, respectively. Along with the estimates of these frequency components, we also report their asymptotic standard errors. The method for computing these standard errors is discussed in Section A.4 of Appendix A.

The estimated distribution of the output growth variance across long-run, business cycle, and short-run frequencies (columns 1–3, respectively) suggests that for 29 out of the 58 countries in our sample, the business cycle frequency component explains most of the output growth rate variance. Statistically speaking, for these countries the 90 percent confidence interval for the estimated business cycle component does not overlap with similar intervals for the long- and short-run components, implying that the business cycle component is larger than the other two components.[12]

When grouped according to stage of development, we find that business cycle frequency band contains the bulk of the variance for sixteen out of the 23 developed (OECD) countries—an inference supported by a large estimated business cycle component with a confidence interval that does not overlap with the confidence interval of the other two estimated components. For five out of these sixteen countries (Luxembourg, Netherlands, the U.K., Iceland, and Finland), the business cycle component is statistically larger than 50 percent. For Japan, on the other hand, it is the long-run component that is statistically larger than 50 percent. For Germany, France, Belgium, Spain, Greece and Portugal, none of the three components can statistically be deemed the largest.

Among the G-7 countries, the U.K. output growth exhibits the highest proportional cyclical variation (over 70 percent). Next are the U.S. and Canada with about 55 percent each, followed by Italy, Germany, and France. Japan's output exhibits the highest cyclical stability in this group with about 29 percent of the total variance accounted for by cyclical fluctuations. The observed stability in Japan's cyclical fluctuations is not surprising in light of the country's institutional arrangements aimed at alleviating output cycles.

[11] The first measure of shock persistence which is the value of the growth rate spectrum at the zero-frequency, or the frequency domain equivalent of Cochrane's (1988) variance ratio statistic, is reported in Table 4.

[12] Note that if confidence intervals for two independent estimates do not overlap, then the confidence interval for the difference between the two estimates lies above zero (the lower bound is larger than zero). Statistically, this implies that the parameters corresponding to these two estimates are not equal—the first parameter exceeds the second.

Table 1
Variance decomposition of the post-war GDP growth rates by frequency component, normalized, 23 developed (OECD member) countries, annual data

Country	Long-run component	Business-cycle component	Short-run component
United States	0.1573 (0.0215)	0.5447 (0.0344)	0.2980 (0.0314)
Switzerland	0.2555 (0.0325)	0.5448 (0.0354)	0.1997 (0.0240)
Canada	0.2255 (0.0280)	0.5482 (0.0339)	0.2263 (0.0257)
Australia	0.1018 (0.0153)	0.5682 (0.0366)	0.3299 (0.0338)
Luxembourg	0.1711 (0.0259)	0.6322 (0.0406)	0.1967 (0.0338)
Sweden	0.3346 (0.0421)	0.5010 (0.0423)	0.1644 (0.0209)
Denmark	0.2219 (0.0285)	0.5213 (0.0347)	0.2568 (0.0287)
New Zealand	0.2015 (0.0270)	0.5028 (0.0349)	0.2957 (0.0313)
Germany	0.4774 (0.0503)	0.4227 (0.0448)	0.0999 (0.0141)
France	0.4837 (0.0494)	0.3519 (0.0392)	0.1643 (0.0238)
Norway	0.3304 (0.0378)	0.5112 (0.0384)	0.1583 (0.0208)
Netherlands	0.2895 (0.0340)	0.5969 (0.0343)	0.1137 (0.0123)
United Kingdom	0.1204 (0.0178)	0.7041 (0.0302)	0.1754 (0.0234)
Belgium	0.3176 (0.0369)	0.4004 (0.0354)	0.2820 (0.0370)
Iceland	0.1552 (0.0238)	0.6702 (0.0319)	0.1746 (0.0216)
Finland	0.1950 (0.0297)	0.6693 (0.0356)	0.1356 (0.0193)
Austria	0.3352 (0.0441)	0.4750 (0.0404)	0.1897 (0.0246)
Italy	0.3081 (0.0412)	0.4707 (0.0391)	0.2212 (0.0279)
Japan	0.6052 (0.0464)	0.2872 (0.0376)	0.1075 (0.0172)
Spain	0.3982 (0.0427)	0.4040 (0.0366)	0.1979 (0.0243)
Ireland	0.2558 (0.0314)	0.5438 (0.0370)	0.2004 (0.0250)
Greece	0.4032 (0.0483)	0.3113 (0.0346)	0.2855 (0.0362)
Portugal	0.4176 (0.0410)	0.3576 (0.0350)	0.2248 (0.0306)
Median	0.2895	0.5112	0.1979
Interquartile range	0.2015–0.3352	0.4227–0.5482	0.1644–0.2263

Notes: The figures reported in this table are based on $\hat{h}_y^B(\omega)$, which is Bartlett's estimate of the normalized spectral density. Asymptotic standard errors are in parentheses. The countries are listed according to their sample average incomes in descending order.

Finally, the output series of the U.K., the U.S., and Canada tend to have the smallest long-run frequency components. Germany, France, and Japan, have the largest long-run frequency components. For the developed economies, the median values of the proportion of the output growth variation due to the 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 cycle frequency band accounts for most of the variance for seven of the 17 countries (Uruguay, Mexico, Cyprus, Argentina, Chile, South Africa and Paraguay). For these countries, the estimated business cycle component exceeds the other two component estimates and has a 90 percent confidence interval that does not overlap with the confidence interval for the other two estimated components. The business cycle component is statistically larger than 50 percent for four of these countries (Mexico, Cyprus, Argentina, and

Table 2
Variance decomposition of the post-war GDP growth rates by frequency component, normalized, 17 high-income developing countries, annual data

Country	Long-run component	Business-cycle component	Short-run component
Trinidad & Tobago	0.2872 (0.0346)	0.4059 (0.0335)	0.3068 (0.0313)
Venezuela	0.3887 (0.0420)	0.3389 (0.0337)	0.2724 (0.0301)
Uruguay	0.2293 (0.0304)	0.5272 (0.0362)	0.2435 (0.0279)
Mexico	0.2962 (0.0342)	0.5816 (0.0356)	0.1222 (0.0176)
Cyprus	0.1492 (0.0225)	0.6097 (0.0360)	0.2411 (0.0321)
Argentina	0.1749 (0.0274)	0.6548 (0.0334)	0.1703 (0.0209)
Mauritius	0.4152 (0.0416)	0.3540 (0.0357)	0.2308 (0.0272)
Chile	0.2575 (0.0370)	0.5378 (0.0389)	0.2047 (0.0249)
South Africa	0.3152 (0.0374)	0.4571 (0.0362)	0.2277 (0.0283)
Brazil	0.4415 (0.0417)	0.3213 (0.0328)	0.2372 (0.0290)
Costa Rica	0.3324 (0.0360)	0.4392 (0.0357)	0.2283 (0.0267)
Paraguay	0.2449 (0.0371)	0.5966 (0.0392)	0.1585 (0.0204)
Panama	0.3795 (0.0398)	0.3691 (0.0337)	0.2514 (0.0285)
Turkey	0.1865 (0.0252)	0.4182 (0.0383)	0.3953 (0.0396)
Colombia	0.2422 (0.0319)	0.3327 (0.0367)	0.4251 (0.0430)
Ecuador	0.4663 (0.0412)	0.3177 (0.0337)	0.2160 (0.0263)
Guatemala	0.6175 (0.0393)	0.2650 (0.0320)	0.1174 (0.0166)
Median	0.2962	0.4182	0.2308
Interquartile range	0.2422–0.3887	0.3389–0.5378	0.2047–0.2514

Notes: The figures reported in this table are based on $\hat{h}_y^B(\omega)$, which is Bartlett's estimate of the normalized spectral density. Asymptotic standard errors are in parentheses. The countries are listed according to their sample average incomes in descending order.

Paraguay). Ecuador and Guatemala, on the other hand, have the largest mass in the long-run frequency band; for Guatemala this component is statistically larger than 50 percent. The remaining countries in this group do not have a component ranking that can be statistically supported. For the sampled high-income developing countries, the median values of the proportion of the output growth variation explained by the 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 cycle frequency band contains most of the variance for six of the 18 low-income developing countries (Peru, Guyana, Egypt, Pakistan, India, and Uganda), exceeding the other two component estimates with a 90 percent confidence interval which does not overlap with the confidence interval for the other two estimated components. Only for Uganda, however, does the estimated business cycle component statistically exceed 50 percent. For El Salvador the long-run component is the largest (0.55) and for Sri Lanka the short-run component is the largest (0.49). The remaining countries in this group do not have a component ranking that can be statistically supported. For this group, the median values of the proportion of the output growth variation, explained by the long-run, business cycle, and short-run

Table 3
Variance decomposition of the post-war GDP growth rates by frequency component, normalized, 18 low-income developing countries, annual data

Country	Long-run component	Business-cycle component	Short-run component
El Salvador	0.5566 (0.0422)	0.3336 (0.0375)	0.1098 (0.0151)
Peru	0.2758 (0.0323)	0.5067 (0.0346)	0.2174 (0.0249)
Guyana	0.2106 (0.0274)	0.5516 (0.0348)	0.2378 (0.0268)
Dominican Republic	0.1348 (0.0195)	0.4551 (0.0376)	0.4100 (0.0402)
Thailand	0.3486 (0.0366)	0.3328 (0.0311)	0.3186 (0.0334)
Bolivia	0.3498 (0.0407)	0.3904 (0.0362)	0.2598 (0.0323)
Sri Lanka	0.1796 (0.0249)	0.3265 (0.0331)	0.4939 (0.0376)
Philippines	0.5042 (0.0427)	0.4278 (0.0409)	0.0680 (0.0099)
Morocco	0.3352 (0.0389)	0.4258 (0.0379)	0.2390 (0.0297)
Honduras	0.3559 (0.0377)	0.4719 (0.0363)	0.1722 (0.0212)
Egypt	0.3441 (0.0388)	0.5181 (0.0385)	0.1377 (0.0173)
Pakistan	0.3320 (0.0391)	0.3531 (0.0346)	0.3149 (0.0344)
Nigeria	0.3448 (0.0402)	0.5641 (0.0401)	0.0911 (0.0125)
Kenya	0.0731 (0.0112)	0.4941 (0.0389)	0.4328 (0.0397)
India	0.1388 (0.0196)	0.5601 (0.0339)	0.3011 (0.0310)
Uganda	0.1707 (0.0230)	0.5780 (0.0349)	0.2513 (0.0290)
Zaire	0.3284 (0.0401)	0.3711 (0.0355)	0.3005 (0.0330)
Myanmar	0.1409 (0.0203)	0.3963 (0.0333)	0.4628 (0.0360)
Median	0.3284	0.4278	0.2513
Interquartile range	0.1707–0.3486	0.3711–0.5181	0.1722–0.3186

Notes: The figures reported in this table are based on $\hat{h}_y^B(\omega)$, which is Bartlett's estimate of the normalized spectral density. Asymptotic standard errors are in parentheses. The countries are listed according to their sample average incomes in descending order.

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.

Overall, these results suggests that the bulk of the spectral mass is concentrated in the business cycle frequency band for the majority of the developed countries. This pattern accords with King and Watson's (1996) report for the U.S. growth rate series. However, we do not observe a similar pattern for developing countries. We also note that the short-run frequency components seem to contribute the least to the output growth rate variation.[13]

4.2. *Cross-country variation in variance ratio statistic*

Table 4 reports Cochrane's variance ratio statistic computed in the frequency domain.[14] Following Cogley (1990), we set the parameter k equal to 20. His results

[13] The robustness of our finding is further underscored by King and Watson's (1996) observation that the business cycle character of the growth rate spectra is insensitive to the choice of the spectral estimator used.

[14] Results for the second measure of shock persistence are discussed in Section A.5 of Appendix A.

Table 4
Variance of growth components and variance ratio statistic estimates, annual data

Developed countries		High-income developing countries		Low-income developing countries	
Country	Variance ratio	Country	Variance ratio	Country	Variance ratio
United States	0.014/0.076 = 0.18 (0.07)	Trinidad & Tobago	0.671/0.541 = 1.24 (0.51)	El Salvador	0.255/0.148 = 1.72 (0.71)
Switzerland	0.106/0.099 = 1.07 (0.45)	Venezuela	0.546/0.233 = 2.34 (0.97)	Peru	0.246/0.256 = 0.96 (0.40)
Canada	0.039/0.078 = 0.50 (0.21)	Uruguay	0.075/0.355 = 0.21 (0.09)	Guyana	0.606/0.798 = 0.76 (0.31)
Australia	0.032/0.118 = 0.27 (0.12)	Mexico	0.174/0.163 = 1.06 (0.44)	Domin. Rep.	0.092/0.356 = 0.26 (0.11)
Luxembourg	0.055/0.214 = 0.26 (0.11)	Cyprus	0.095/0.679 = 0.14 (0.06)	Thailand	0.273/0.237 = 1.15 (0.48)
Sweden	0.054/0.030 = 1.81 (0.75)	Argentina	0.266/0.242 = 1.10 (0.45)	Bolivia	0.323/0.214 = 1.51 (0.62)
Denmark	0.073/0.097 = 0.75 (0.31)	Mauritius	0.553/0.558 = 0.99 (0.41)	Sri Lanka	0.157/0.216 = 0.73 (0.30)
New Zealand	0.054/0.155 = 0.35 (0.15)	Chile	0.138/0.459 = 0.30 (0.12)	Philippines	0.208/0.132 = 1.57 (0.65)
Germany	0.325/0.087 = 3.73 (1.54)	South Africa	0.184/0.116 = 1.59 (0.66)	Morocco	0.125/0.272 = 0.46 (0.19)
France	0.138/0.040 = 3.45 (1.43)	Brazil	0.195/0.171 = 1.14 (0.47)	Honduras	0.085/0.137 = 0.62 (0.26)
Norway	0.030/0.035 = 0.84 (0.35)	Costa Rica	0.196/0.174 = 1.13 (0.46)	Egypt	0.118/0.113 = 1.04 (0.43)
Netherlands	0.130/0.085 = 1.52 (0.55)	Paraguay	0.630/0.344 = 1.83 (0.76)	Pakistan	0.063/0.179 = 0.35 (0.14)
UK	0.013/0.063 = 0.20 (0.08)	Panama	0.545/0.290 = 1.88 (0.78)	Nigeria	0.866/0.841 = 1.03 (0.48)
Belgium	0.054/0.055 = 0.97 (0.40)	Turkey	0.144/0.300 = 0.48 (0.20)	Kenya	0.063/0.574 = 0.11 (0.04)
Iceland	0.081/0.246 = 0.33 (0.14)	Colombia	0.043/0.072 = 0.59 (0.24)	India	0.099/0.168 = 0.59 (0.24)
Finland	0.035/0.122 = 0.29 (0.12)	Ecuador	0.242/0.183 = 1.32 (0.54)	Uganda	0.465/1.082 = 0.43 (0.18)
Austria	0.183/0.074 = 2.48 (1.02)	Guatemala	0.177/0.084 = 2.11 (0.87)	Zaire	0.922/0.441 = 2.09 (0.86)
Italy	0.157/0.071 = 2.20 (0.90)			Myanmar	0.091/0.571 = 0.16 (0.07)
Japan	0.506/0.118 = 4.29 (1.78)				
Spain	0.398/0.176 = 2.26 (0.94)				
Ireland	0.053/0.095 = 0.56 (0.23)				
Greece	0.365/0.130 = 2.81 (1.16)				
Portugal	0.171/0.141 = 1.21 (0.50)				
Median	0.97		1.13		0.73
Interquartile range	0.35–2.20		0.59–1.59		0.43–1.15

Notes: The numerator and the denominator entries are $100 \times \hat{\sigma}_k^2$ and $100 \times \hat{\sigma}_y^2$, respectively, where $\hat{\sigma}_k^2$ denotes the estimated long-horizon cumulative growth variance and $\hat{\sigma}_y^2$ denotes the estimated one-year growth variance. Asymptotic standard errors for the variance ratio statistics are in parentheses. The countries are listed according to their sample average incomes in descending order.

show that the estimated variance ratio statistic is not sensitive to the choice of k. We also use Cogley's approach to compute asymptotic standard errors which are reported in parentheses.[15] We ignore for now the numerator and the denominator values, focusing on the variance ratio statistic itself. The figures in Table 4 suggest that there is a substantial cross-country variation in the size of the random-walk component of output growth. The variance ratio statistic varies from 0.11 for Kenya to 4.29 for Japan.[16] Note the positive relationship between the variance ratio statistic and its standard error, a result predicted by Priestley's (1981) asymptotic analysis of the statistic. Campbell and Mankiw (1989) report a similar relationship.

Among the developed (OECD) countries, twelve (almost half) have a statistic less than one; a value of one implies a random walk process. Only nine of these twelve (United States, Canada, Australia, Luxembourg, New Zealand, the United Kingdom, Iceland, Finland, and Ireland), however, have a statistic that is significantly smaller than one at the 10 percent level. Among these, the United States has the smallest estimate, 0.18. Among the European countries, the U.K. has the smallest point estimate of 0.20.[17] For the developed countries, the variance ratio 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 less than one. The statistic, however, is significantly smaller than one for only five countries (Uruguay, Cyprus, Chile, Turkey, and Columbia). Cyprus has the smallest and Venezuela the largest random walk component with 0.14 and 2.34, respectively. Here the median value for the variance ratio statistic is 1.13 and the interquartile range is 0.59–1.59.

Finally, among the low-income developing countries, eleven have a statistic smaller than one but only eight of these (the Dominican Republic, Morocco, Honduras, Pakistan, Kenya, India, Uganda, and Myanmar) are significantly so. In this group, Kenya has the smallest and Zaire has the largest random walk component (0.11 and 2.09, respectively). The median value of the variance ratio statistic in this group is 0.73 with the interquartile range of 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. The statistic, moreover, 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, and relatively the largest number of cases with a statistic that is significantly less than one. 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. Also note that an overall cross-country ranking cannot be statistically supported given the relatively large standard errors. Japan's variance ratio statistic, nonetheless, is statistically larger than that of the U.S.

[15] See Section A.4 of Appendix A for details.

[16] Campbell and Mankiw (1989) also find that Japan's output has the highest measure of persistence.

[17] Campbell and Mankiw (1989) and Stockman (1987) also report that the U.K. output exhibits less shock persistence than the output of other European countries.

Comparing our results with other studies, we note that Cogley (1990) uses an extended Maddison's (1982) data set and finds that the United States and Canada have a smaller random walk component than other sampled countries. Kormendi and Meguire's (1990) findings based on the postwar data are also similar to those reported here. In particular, they also find that the U.S. has the smallest random walk component in the output growth. In addition, for common countries the variance ratio statistics we report are of the same order of magnitude as those found by Kormendi and Meguire. This similarity is in spite of the differences between our study and theirs in terms of output measure (they use growth rate of per capita output while we use growth rate of output), and econometric method (they use time-domain while we use frequency-domain methods).

As stated earlier, the numerator of the variance ratio statistic measures the variation in a country's cumulative long-term growth while the denominator measures growth variation over a 1-year horizon. A country with a high variance ratio statistic either has a large numerator (a high cumulative long-term growth variance), a small denominator (a low 1-year growth variance), or both. To explore the source of the cross-country variation in Cochrane's measure, we estimate the variation in the numerator and the denominator of the variance ratio statistic for each country, and compare these estimates with those reported for the country with the smallest variance ratio statistic in that group.[18] Table 4 also presents the estimate of the cumulative long-term growth variance $\hat{\sigma}_k^2$ and the corresponding 1-year growth variance estimate $\hat{\sigma}_y^2$ for each country.

Consider first the developed countries. Out of the 22 countries with a larger variance ratio statistic than the U.S., all but one (the U.K.) have a larger estimated long-term growth variance (numerator) than the U.S. The proportional difference varies from about two-fold for Norway, to over 30-fold times for Japan. Comparing the estimated 1-year growth variance (denominator), we find that of the 22 countries, only seven (Sweden, France, Norway, the United Kingdom, Belgium, Austria, and Italy) have an estimated variance smaller than the U.S. Note also that the proportional differences between the U.S. and other countries in the group are substantially smaller, ranging from about 0.4-fold for Sweden to about 0.97-fold for Austria. Therefore, it seems that most developed countries with a higher variance ratio statistic than the U.S. have a more variable long-term growth component than the U.S., but a short-term variation of a magnitude similar to that of the U.S. Thus, overall, the long-term growth variation may explain a substantial portion of the cross-country variation in the variance ratio statistic for the developed countries.

Among the seventeen high-income developing countries, Cyprus has the smallest variance ratio statistic (0.14). Of the sixteen countries with variance ratio statistic larger than Cyprus, all but two (Uruguay and Colombia) have a larger estimated long-term growth variance. The proportional difference between these countries and Cyprus varies from about one-and-a-half-fold for Chile, to over seven-fold for

[18] Here we follow Cogley (1990), who makes similar comparisons between each of the sampled countries and the one with the smallest variance ratio statistic, the U.S.

Trinidad and Tobago. In terms of the estimated 1-year growth variance, however, all sixteen countries have an estimated variance smaller than that of Cyprus. But the differences are close in magnitude, ranging from about 0.1-fold for Colombia to about 0.8-fold for Mauritius. Overall, it appears that most countries with a variance ratio statistic larger than Cyprus have a larger long-term variation and a smaller short-term variation than Cyprus. Therefore, for the high-income developing countries, unlike the developed countries, both short- and long-term growth variations may contribute to the cross-country variation in the variance ratio statistic.

Finally, among the low-income developing countries, Kenya has the lowest variance ratio statistic (0.11). Of the 17 countries with a higher variance ratio statistic than Kenya, all but one (Pakistan) have an estimated long-term growth variance that exceeds Kenya's. The proportional difference varies from about 1.35-fold for Honduras, to over fourteen-fold for Zaire. Comparing the estimated 1-year growth variance, we find that all but three out of the seventeen countries (Guyana, Nigeria, and Uganda) have an estimated variance smaller than Kenya's. The proportional difference ranges from about 0.2-fold for Egypt, to about 0.71-fold, for Zaire. Therefore, it appears that for the low-income developing countries, both short-term and long-term growth variations contribute to the cross-country differences in variance ratio statistics.

Our analysis, therefore, suggests an important difference between developed and developing countries in terms of the source of variation in variance ratio statistic: among the developed countries most of the variation can be explained by the variation in the countries' long-term growth component, while among the developing countries, both long-term and short-term growth components contribute to the cross-country variation in the variance ratio statistic. Also, note that the denominator of the variance ratio statistic for the developed countries appears to be much smaller than those for the developing countries in Table 4. This suggests that output growth is less volatile in the former than in the latter group. Given that our country grouping is income based, this finding accords well with Kraay and Ventura's (2001, p. 1) who report "... fluctuations in per capita income growth are smaller in rich countries than in poor ones."

4.3. Cross-country variation in the cyclical component

To further examine the variation in the cyclical component[19] of income, we run several cross-country regressions relating this component to various measures of income. In these regressions, the business cycle component $\hat{H}_y^{BC}$, which denotes the estimated normalized share of output growth variance, is the dependent variable and various income measures serve as regressors. More specifically,

$$(\hat{H}_y^{BC})_i = \beta_o + \beta_1 y_i + u_i, \tag{1}$$

[19] We are thankful to the Associate Editor, David Backus, and an anonymous referee for their suggestions that helped shape this section.

where i denotes a country, u's are heteroskedastic regression errors, and y is income.[20]

Income data, however, may be subject to measurement error, particularly for the developing countries where data quality, in general, is questionable. Summers and Heston (1991) provide data quality scores for various countries. These scores for the developed countries in our sample are A or A− except for Switzerland and Iceland that have a B+ score. For the high-income developing countries in our sample, the scores are C and C−, except for Mauritius that scores D+. For the low-income developing countries, the scores show more dispersion. In this group Guyana, Egypt, Nigeria, Uganda, Zaire, and Myanmar score D or D+, while the remaining countries score C or C−.

We use these scores to sort out countries into two groups for regression estimation and also to identify dummy variables in a pooled regression of all countries. We first estimate equation (1) using two samples, one consisting of countries with A or A− scores and the other for countries with C or C− scores. The first group includes all of the developed countries in our sample except for Switzerland and Iceland, and the second group includes all of the developing countries in our sample except for the seven countries with a D or D+ scores. We do not estimate separate equations for the B+ or D+/D countries, because these two categories include very few countries which would result in too few degrees of freedom for estimation.

We also estimate pooled regression equations of the form

$$(\hat{H}_y^{BC})_i = \theta_o + \theta_1 y_i + \theta_2 \mathrm{C}_i + \theta_3 \mathrm{D}_i + v_i, \tag{2}$$

where i denotes a country, v's are heteroskedastic regression errors, and C, and D are binary dummy variables where C equals 1 if a country has a data quality score of C or C−, and zero otherwise, and D equals 1 if a country has a data quality score of D+ or D, and zero otherwise.[21] The intercept term in the pooled equation (2) is then serves as the reference point capturing the coefficient of a similar dummy for countries with a data quality score of A or A−. The B countries are not included since there are only two of them in our sample.

To deal with the potential measurement error problem, we take other steps besides using the data quality scores.[22] If present, measurement error may affect the dependent variables as well as the regressors. The effect on the dependent variable, however, is not statistically serious, because measurement error is more likely to corrupt the estimates of the short-term income fluctuations than the estimates of the

[20] We also run similar regressions with non-normalized business cycle component, as the dependent variable. The results are very similar to those for the normalized component in terms of the estimated coefficients' signs and significance.

[21] Note that we do not estimate a separate equation for countries with D+ or D scores, but we do include them in the pooled regression where they are identified by a dummy variable, because introducing a dummy variable requires estimating only one additional parameter, while introducing a new regression equation requires estimating several parameters (intercept, slopes, and error variance) and thus more data points.

[22] The evidence reported in Dezhbakhsh (2002) suggests that very few studies that use data for developing countries take any steps to deal with the potential measurement error problem.

business cycles or long-term trends (Carpenter and Levy, 1998). Moreover, any resulting contamination of the measures of the business cycle component, which we use as the dependent variable, will be absorbed into the regression errors, causing heteroskedasticity of an unknown form. Our estimation method corrects for the resulting heteroskedasticity by using White's (1980) heteroskedasticity-consistent covariance estimator. Additionally, by estimating separate equations for different groups with different data quality scores, we prevent the spread of error beyond the source group. The group-specific dummy variables in the pooled regressions, on the other hand, is intended to absorb unmodeled group characteristics which may be measurement-related.

The presence of measurement error in regressors, on the other hand, has a more serious repercussion, estimation inconsistency. The textbook remedy for this problem is to use instruments unaffected by the error but correlated with contaminated variables. The availability of such instruments, especially in the case of developing countries, is doubtful, because all other aggregate variables, such as GDP or its components, are equally suspect. As a second best remedy, we use the cross-country rank of income instead of income itself. The ranks associated with a sample of observations are highly correlated with the observations but also more resilient to observation errors. For example, two vectors of ranks, one pertaining to error free observations and the other pertaining to contaminated observations, may be similar in terms of values as well as stochastic properties, provided that the measurement error does not dominate the error-free variable.[23]

We, therefore, use four measures of income: (i) average income over the sample period, (ii) cross-country rank of average income, (iii) median income over the sample period, and (iv) cross-country rank of median income. The benchmark regressions include income measures as regressors, but we also use ranks as explanatory variables in some equations.[24] A comparison of rank-based results with benchmark results would be suggestive of the extent of data contamination. So, we run four regressions using the four measures of income for each of the two groups of countries (with data quality scores of A/A− or C/C−). We, also run four regressions using the pooled sample of all countries (except the two with a B+ score). The regressors in the pooled regressions include the dummy variables identifying the data quality of each sampled country.

The coefficient estimates for Eqs. (1) and (2) are reported in Tables 5 and 6, respectively. The results reported in the top panel of Table 5 suggest that, for the developed countries with high quality data, there is a statistically significant positive relationship between income level and the size of the business-cycle component: countries with higher income tend to have a larger business-cycle component. All coefficient estimates are significant at least at the one percent level, except for one that is significant at the five percent level. The finding is robust to the choice of

[23] The resilience of rank-based measures to data contamination render methods based on such measures quite useful in robust inference; see, for example, Huber (1981) and Hettmansperger (1984).

[24] We also used ranks as instruments, in the context of the instrumental variable estimation method, but the results did not change appreciably.

Table 5
Regression analysis of the cross-country variation in the size of the business cycle component

	Income measure	Constant	Income	R^2
Developed countries (Sample size = 21)	Average income	0.29	0.25[a]	0.24
		(4.46)***	(3.49)***	
	Median income	0.32	0.21[a]	0.18
		(4.68)***	(2.91)***	
	Average income rank	0.40	83.3[a]	0.21
		(8.77)***	(3.00)***	
	Median income rank	0.41	71.5[a]	0.15
		(8.67)***	(2.38)**	
Developing countries (Sample size = 28)	Average income	0.40	0.11[a]	0.03
		(12.7)***	(0.84)	
	Median income	0.40	0.13[a]	0.04
		(12.3)***	(0.88)	
	Average income rank	0.38	36.5[a]	0.09
		(12.1)***	(1.61)*	
	Median income rank	0.37	39.5[a]	0.10
		(11.4)***	(1.68)*	

Notes: The dependent variable is the normalized business cycles component. The numbers in parentheses are absolute values of the *t*-statistics, computed using White's (1980) heteroskedasticity consistent covariance matrix estimator. Developed countries include only those obtaining Summers and Heston's (1991) data quality score of A or A – . Developing countries include only those obtaining Summers and Heston's (1991) data quality score of C or C – . *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

[a] Indicates that the actual estimate is multiplied by 10^4.

Table 6
Regression analysis of the cross-country variation in the size of the business cycle component: all countries pooled together (Sample size = 56)

Income measure	Constant	Income	C	D	R^2
Average income	0.35	0.18[a]	0.04	0.11	0.15
	(5.04)***	(2.31)**	(0.71)	(1.43)	
Median income	0.36	0.16[a]	0.04	0.10	0.14
	(5.18)***	(2.16)**	(0.60)	(1.33)	
Average income rank	0.35	31.4[a]	0.02	0.10	0.13
	(4.06)***	(1.82)*	(0.34)	(1.11)	
Median income rank	0.35	32.0[a]	0.02	0.10	0.14
	(4.22)***	(1.93)*	(0.37)	(1.17)	

Note: The dependent variable is the normalized business cycles component. The numbers in parentheses are absolute values of the *t*-statistic, computed using White's (1980) heteroskedasticity consistent covariance matrix estimator. C is a dummy variable with a value of one if a country has a Summers and Heston's (1991) data quality score of C or C–, and zero otherwise. Similarly, D is a dummy variable with a value of one if a country has a Summers and Heston's (1991) data quality score of D+ or D, and zero otherwise. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

[a] Indicates that the actual estimate is multiplied by 10^4.

income measure, suggesting that measurement error is not an issue for this group of countries.

For the developing countries, however, the statistical significance of the income-cycle relationship seems to be less pronounced as suggested by the estimates in the lower panel of Table 5. If the regressors are ranks of average or median income, we observe a statistically significant positive relationship between the magnitude of the cyclical fluctuations of output growth and the income level. If we use the average or the median income measures as regressors, however, the coefficient estimates are still positive but statistically insignificant. Since the data quality scores for this group range from C− to C, measurement error may be present and, therefore, the rank based measure of income may result in a more reliable inference.

The pooled regression results reported in Table 6 also support the income-cycle relationship. In all cases, the estimated coefficient of income are significant at either the five or 10 percent levels, suggesting that higher income countries have a larger business-cycle component. The estimated coefficients for the dummy variables are positive but insignificant, suggesting that, ceteris paribus, other group-specific factors related to data quality do not seem to affect the income-cycle relationship. Note that inclusion of these dummy variables in the pooled regressions is similar to estimating a fixed effect model where the fixed effects (estimated by group specific dummy variables) are supposed to control for unobserved heterogeneity across groups. Here the grouping is based on data quality rankings, and the effects captured by the dummy variables relate to data quality.

Overall, the regression results suggest that, for many countries, the magnitude of the cyclical fluctuations of output growth depends positively on the level of income. The strength of this relationship, however, varies across countries. For the developed countries with high quality data, the relationship is quite strong. For the developing countries, the relationship is still positive but its statistical significance depends on the income measure used. Measures that are more robust to measurement error reveal a stronger relationship.

5. Analysis of quarterly data

We use quarterly data to supplement our analysis of the annual data and to ascertain which of the observed characteristics hold regardless of the data frequency. We were able to obtain quarterly output growth series for fourteen of the OECD countries.[25] For the remaining countries, the available series were too short to conduct the frequency domain analysis. Campbell and Mankiw (1989) also note that quarterly national incomes series that are long enough to be useful for time series analysis are available for only few countries—seven in their study.

[25] The data for all of the sampled countries, except for Germany, are from the International Financial Statistics tape of the IMF. We obtained the German data from the Bundesbank with the help of Robert Chirinko. We use all of the quarterly observations available for each country, except for Germany where we truncate the sample at the German unification date.

Using quarterly data has some notable implications. The available quarterly series have more observations but cover a shorter time span. We, therefore, loose some information about the long-run (i.e., the zero-frequency) behavior of the series. On the other hand, quarterly data provide additional information about the short-run (i.e., high-frequency) behavior of the series. This trade off has two consequences. First, with quarterly data, the short-term variation will constitute a greater proportion of the total variance than with annual data. We, therefore, expect the variance decomposition in frequency domain to exhibit a greater proportional short-run variation than we report based on the annual series. The proportion of the series variance due to the business cycle and long-run frequency components will then necessarily decline. Second, the variance ratio statistic estimated with quarterly data utilizes less information on the zero-frequency behavior of the series, and may, therefore, exhibit different shock persistence properties than those documented using the annual data.

Fig. 4 displays the estimated income growth spectra and the corresponding 95 percent confidence intervals for the fourteen sampled countries. Note that the frequency bands corresponding to the long-run, business cycle, and short-run components are different here, because data are observed at higher frequency. With quarterly data, the frequencies corresponding to the long-run, business cycle, and short-run components are $0 \leqslant \omega \leqslant 0.196$, $0.196 \leqslant \omega \leqslant 0.520$, and $0.520 \leqslant \omega \leqslant \pi$, respectively. Moreover, with quarterly data, the shortest identifiable cycle, which corresponds to $\omega = \pi$, is a two-quarter long cycle. This means that a greater proportion of the variance of the quarterly series is due to the short run frequency components—a fact this is clearly displayed in Fig. 4. For the U.S. the spectral shape has the hump shape that King and Watson (1996) document. For most other countries the spectrum does not follow this particular shape.

We note that the spectral shape we obtain using the U.S. quarterly data is not identical to the shape reported by King and Watson (1996). There are three reasons for the noted difference. First, our quarterly sample covers 1946–2000, while theirs covers 1946–1990. Second, as discussed in Appendix A, we obtain the spectrum by estimating the periodograms and then smoothing them for consistency, while King and Watson calculate their spectra from an estimated VAR (see, King and Watson (1996), footnote 2 on p. 36). Third, we define business cycles as 12–32 quarter cycles, as is common in the literature, while King and Watson define business cycle as 6–32 quarter cycles. If we use King and Watson's definition, then the spectral peak for U.S. in our Fig. 4 also falls in the business cycle frequency band.[26]

Table 7 reports the results of variance decomposition in the frequency domain. As expected, these results reflect a greater importance of the short-term variation for all countries. For example, comparing with the annual results in Table 1, we notice that the median of the short-run frequency components is 76 percent of the total output

[26] In general, it is hard to ascertain whether two geometric shapes are identical or not. Only when the maintained (null) shape is mathematically specified, a statistical inference can be made using a distance measure such as Kolmogorov–Smirnov, which is commonly used to examine statistically the similarity between an empirical distribution function and a maintained (null) theoretical distribution.

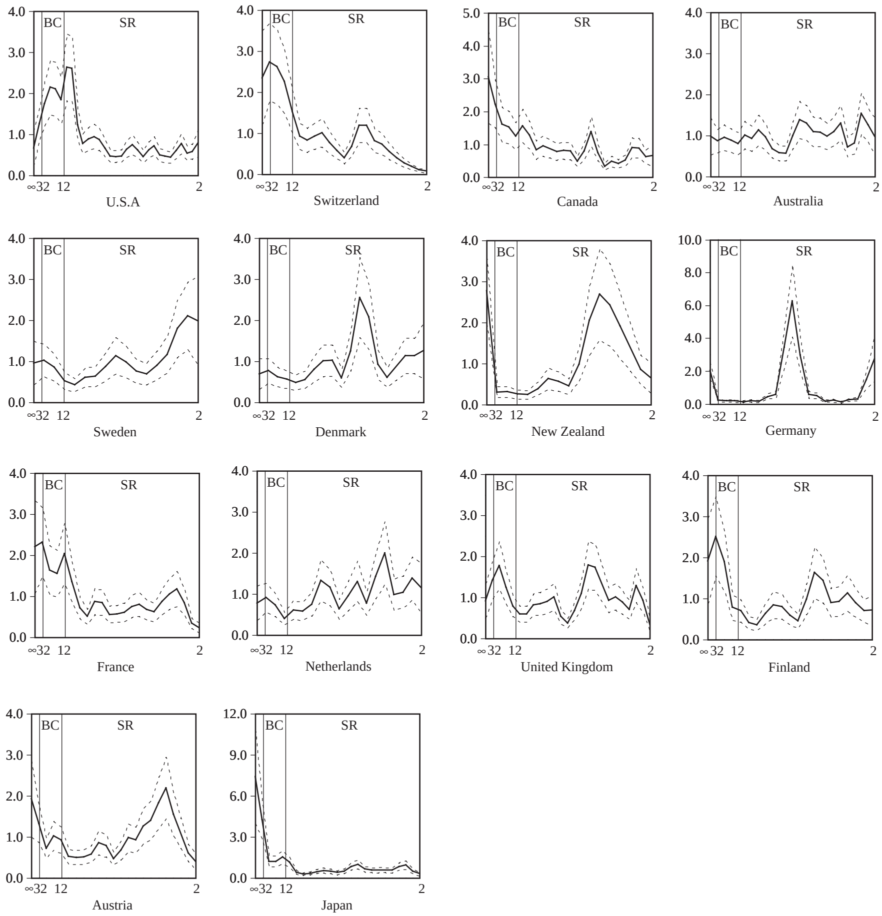

Fig. 4. Spectral densities of the growth rates of Real GDP, 14 OECD countries. The horizontal axis measures the cycle-length in quarters (quarterly data). BC = business cycle, SR = short run (LR = narrow stripe on the LHS).

growth variance of the quarterly series in contrast to about 19 percent when annual data are used. Consequently, there is a decline in the median of business cycle and the long-run frequency components from 51 percent to 11 percent and from 28 percent to 12 percent, respectively. We note a similar pattern for individual countries. For example, in the case of the U.S. the proportion of output growth variance due to short-run components is more than doubled (from 29 percent for the annual data to 67 percent for the quarterly data), and consequently, the contribution of the cyclical and long-run components are halved from 54 percent to 25 percent and from 15 percent to six percent, respectively.

In Section 4.3, we report a positive and statistically significant relationship between the size of the business cycle component and the level of income for the sampled OECD countries. It is of interest to see whether this relationship can also be

Table 7
Variance decomposition of the post-war GDP growth rates by frequency component, normalized, 14 developed countries, quarterly data (OECD member countries)

Country	Long-run component	Business-cycle component	Short-run component
United States	0.0634 (0.0287)	0.2580 (0.0610)	0.6785 (0.0781)
Switzerland	0.2192 (0.0744)	0.2102 (0.0598)	0.5702 (0.0599)
Canada	0.2043 (0.0788)	0.1702 (0.0408)	0.6259 (0.0637)
Australia	0.0745 (0.0268)	0.1061 (0.0250)	0.8195 (0.0784)
Sweden	0.1144 (0.0332)	0.0789 (0.0195)	0.8061 (0.0926)
Denmark	0.0774 (0.0238)	0.0627 (0.0161)	0.8599 (0.0928)
New Zealand	0.1629 (0.0324)	0.0300 (0.0091)	0.8069 (0.0898)
Germany	0.0974 (0.0227)	0.0167 (0.0078)	0.8858 (0.1166)
France	0.1951 (0.0703)	0.1378 (0.0409)	0.6671 (0.0714)
Netherlands	0.0891 (0.0272)	0.0601 (0.0159)	0.8507 (0.0866)
UK	0.0946 (0.0312)	0.1551 (0.0375)	0.7503 (0.0727)
Finland	0.2083 (0.0709)	0.1271 (0.0396)	0.6623 (0.0720)
Austria	0.1411 (0.0517)	0.0755 (0.0213)	0.7833 (0.0796)
Japan	0.4184 (0.1842)	0.1421 (0.0374)	0.4395 (0.0479)
Median	0.1277	0.1166	0.7668
Interquartile range	0.0918–0.1997	0.0691–0.1486	0.6647–0.8132

Notes: The figures reported in this table are based on $\hat{h}_y^B(\omega)$, which is Bartlett's of the normalized spectral density. Asymptotic standard errors are in parentheses. The countries are listed according to their sample average incomes in descending order.

supported by the quarterly data. We, therefore, run cross-country regressions similar to those reported in Section 4.3, Eq. (1). The results suggest that a positive and significant relationship exists between the cyclical component and various measures of income. For example, the estimated coefficient of income (using the mean measure) is 0.0000236 with a t-statistic of 2.33 (p-value of 0.037). For the median measure, the estimated coefficient is 0.0000192 with a t-statistic of 2.00 (p-value of 0.067). Thus, we conclude that there is a positive and significant relationship between the cyclical component of output growth and income for the sampled OECD countries regardless of the frequency of the time series used.

In Table 8 we report the estimates of the variance ratio statistic for the sampled OECD countries obtained using quarterly data.[27] As expected, these results are not identical to those reported for annual data (Table 4). Nevertheless, there are several similarities. First, there seems to be a substantial cross-country variation in the reported ratios which measure the size of the random walk component of output growth. Second, with few exceptions, the variance ratio statistics estimated using annual and quarterly data are of the same order of magnitude. In fact, an inspection of the standard errors (reported in parentheses) shows that for most countries the 95

[27] The size of the quarterly samples varies from country to country. Accordingly, and following Cogley (1990), we use various k values that range from 16 to 24 when computing the variance ratio statistics.

Table 8
Variance of growth components and variance ratio statistic estimates: 14 developed (OECD member) countries, quarterly data

Country	Variance ratio
United States	$0.007/0.011 = 0.66$ (0.21)
Switzerland	$0.025/0.011 = 2.35$ (0.57)
Canada	$0.032/0.010 = 3.05$ (0.70)
Australia	$0.017/0.017 = 0.99$ (0.23)
Sweden	$0.014/0.015 = 0.96$ (0.26)
Denmark	$0.010/0.014 = 0.70$ (0.19)
New Zealand	$0.023/0.008 = 2.78$ (0.81)
Germany	$0.039/0.019 = 2.03$ (0.51)
France	$0.010/0.004 = 2.20$ (0.56)
Netherlands	$0.008/0.011 = 0.78$ (0.21)
UK	$0.010/0.011 = 0.91$ (0.21)
Finland	$0.044/0.023 = 1.92$ (0.52)
Austria	$0.022/0.011 = 1.93$ (0.46)
Japan	$0.108/0.015 = 7.42$ (1.71)
Median	1.92
Interquartile range	0.93–2.27

Notes: The numerator and the denominator entries are $100 \times \hat{\sigma}_k^2$ and $100 \times \hat{\sigma}_y^2$, respectively, where $\hat{\sigma}_k^2$ denotes the estimated long-horizon cumulative growth variance and $\hat{\sigma}_y^2$ denotes the estimated one-quarter growth variance. Asymptotic standard errors for the variance ratio statistics are in parentheses. The countries are listed according to their sample average incomes in descending order.

percent confidence interval for the variance ratio statistic using the annual data overlaps with a similar confidence interval based on the quarterly data.[28] This suggests that the variance ratio statistics based on annual and quarterly data are statistically similar. Third, the U.S. still obtains the lowest variance ratio statistic, while Japan still obtains the highest statistic. Fourth, the U.S. data still exhibit the smallest long-horizon cumulative growth variance, $\hat{\sigma}_k^2$, as measured by the numerator of the ratio, while Japan maintains the largest value. Moreover, this variance (the numerator) explains most of the variation in the variance ratio statistic. For example, excluding the two extreme values (0.004 and 0.023), the denominator values range from 0.008 to 0.019. But for the numerator such range is 0.008 to 0.044, or more than three times larger.

One question of interest is whether, output volatility falls with income—a result that we (and also Kraay and Ventura, 2001) report for annual data. The denominator of the variance ratio statistics reported in Table 8 are estimates of the one period variance of the output growth rate (output volatility). These estimates do not seem to vary with income in a clear way. In fact, a regression of these variance estimates against various measures of income produces negative but insignificant coefficient estimates. For example, for the mean measure of income we obtain a

[28] Exceptions are Canada, Australia, New Zealand, U.K., and Finland.

t-statistic of -1.12 (p-value of 0.28). Similar results are obtained using other measures of income. Thus, the negative relationship between income level and volatility that holds for annual data does not seem to be significant for quarterly data.

6. Conclusion

King and Watson (1996) report that the spectral shapes of many U.S. macroeconomic growth rate series are similar: the spectra attain low values at low frequencies, rise to a peak at business cycle frequencies, and decline at high frequencies, with the spectral mass mostly concentrated in the business cycle frequency band. We use annual data to examine the frequency domain properties of output growth series for 58 countries, separated into developed (OECD), and high- and low-income developing groups. To supplement our analysis of annual data, we also use quarterly data for a sample of OECD countries where such data are available for a reasonably long time period. We find diverse spectral shapes using both annual and quarterly data. We also find that the growth rate spectrum for the developed (OECD) and high-income developing countries is more likely to peak in the business cycle frequency band, suggesting that the cyclical component of output growth rate is more predictable for these countries.

We further explore the implications of the observed diversity. Accordingly, we estimate the proportion of the variance due to the short-run, business cycle, and long-run frequency components of growth rate series to measure the relative importance of these components in the total variation of each series. The output growth variance decomposition reveals that, similar to what King and Watson (1996) report for the U.S., the bulk of the spectral mass of output growth rate for the developed countries is concentrated in the business cycle frequency band. We do not find, however, a similar result for the developing countries.

We also estimate several regression equations relating the size of the business cycle component to a country's income level. In this estimation, we use Summers and Heston's (1991) data quality rankings and income measures that are less affected by measurement error, to deal with the potential contamination in the developing countries data. The results suggest the presence of an overall positive income-cycle relationship. The strength of this relationship, however, varies across groups of countries: the relationship is strongly significant for OECD member countries for all income measures used. The relationship is weaker for developing countries; here statistical significance is observed only when income measures that are less sensitive to data contamination are used. The regressions we estimate using quarterly data also suggest the presence of a statistically significant positive income-cycle relationship for the sampled OECD countries.

Furthermore, we estimate the extent of shock persistence in the output growth series, using two frequency domain-based measures. Both annual and quarterly results suggest a substantial variation in shock persistence of output for the sampled countries. The U.S. has the smallest variance ratio statistic. This finding accords well with results reported by Campbell and Mankiw (1989), Cogley (1990), and Kormendi and Meguire (1990). The median values of the statistic estimated using the annual data are slightly different across groups. Furthermore, the distribution of the statistic appears more dispersed for the developed (OECD) countries and more condensed for low-income countries. This implies that the extent of shock persistence varies more across the high income countries than it does across low-income countries.

To examine the source of cross-country variation in the variance ratio statistic, we examine the numerator and the denominator of the statistic. The results suggest that for the developed (OECD) countries, most of the variation in the variance ratio statistic can be explained by the variation in the long-term growth component. This finding is supported by both annual and quarterly data. For the developing countries, however, both the long-term and the one-year growth variation contribute to the cross-country variation in the variance ratio statistic.

Meltzer (1990, p. 2) remarks: ‘‘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 the distribution of shocks are not stable across countries either. Indeed, the countries appear to be experiencing a variety of shocks with varying degrees of persistence. The frequency domain behavior of the output growth rate we document here is a reflection of these variations. These findings may be viewed as additional stylized facts that modern macroeconomic theory should confront and explain.

Appendix A

A.1. Spectral density

The autocovariance function of a covariance stationary process y_t, is $\gamma(\tau) = \mathrm{E}[(y_{t+\tau} - \mu)(y_t - \mu)]$, where μ is the mean of the process, and both $\gamma(\tau)$ and μ are time independent. The spectrum of the series y_t is defined as the Fourier transform of its autocovariance function, and is given by $f_y(\omega) = (1/2\pi)\int_{-\infty}^{\infty} \gamma(\tau)\mathrm{e}^{-\mathrm{i}\tau\omega}\,\mathrm{d}\tau$, with $-\pi \leqslant \omega \leqslant \pi$, where the frequency ω 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 $0 \leqslant \omega \leqslant \pi$.

To interpret the spectrum, note that the autocovariance function is the inverse Fourier transform of the spectrum. That is, $\gamma(\tau) = \int_{-\pi}^{\pi} f_y(\omega)\mathrm{e}^{\mathrm{i}\tau\omega}\,\mathrm{d}\omega$, which, after setting $\tau = 0$, implies that $\gamma(0) = \sigma_y^2 = \int_{-\pi}^{\pi} f_y(\omega)\,\mathrm{d}\omega$. Thus, the integral of the spectrum equals the total unconditional variance of the series and therefore, the spectrum at each frequency ω measures the contribution of that particular frequency component to the series' total variance. By definition, frequency is reciprocal of periodicity where the latter measures the time required for a completion of a cycle. Therefore, the spectrum of a series decomposes its total variation 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 indicate that periodicities are present in the time series.

A.2. Normalized spectral density

The normalized spectral density function which is defined as $h_y(\omega) = f_y(\omega)/\sigma_y^2$, measures the proportion (percentage) of total variation that is due to frequency component ω. By definition, $\int_{-\pi}^{\pi} h_y(\omega)\,\mathrm{d}\omega = 1$.

A.3. Consistent spectral estimation

The spectral estimates are obtained from smoothed estimates of the periodograms of time series. The smoothing, intended to make the spectral estimates consistent, is accomplished by taking weighted integral of the periodogram ordinates. Several weight structures, also called lag windows, have been proposed in the literature. We smoothed the periodograms using three lag windows (Bartlett's, Turkey's, and Parzen's). All yielded very similar results; we, therefore, 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. Thus, we estimate $f(\omega_j)$ and $h(\omega_j)$, where $\omega_j = j\pi/m$, and $j = 0, 1, 2, \ldots, m$. The number of ordinates, m, is set using the rule $m = 2\sqrt{n}$, as suggested by Chatfield (1989, p. 115), where n is the number of observations.

A.4. Variance of normalized spectra

To obtain the standard error for each of the three normalized frequency components, H_y^{LR}, H_y^{BC}, and H_y^{SR}, we apply Taylor expansion to variance of each normalized ratio. For example, the proportion of output growth variation that is due to long-run frequency components is given by

$$H_y^{LR} = \frac{F_y^{LR}}{F_y^{LR} + F_y^{BC} + F_y^{SR}},$$

where the F's are the normalized components of the spectrum. The asymptotic approximation of the variance of this ratio is given by

$$Var(H_y^{LR}) = \frac{(F_y^{BC} + F_y^{SR})^2\,Var(F_y^{LR}) + (F_y^{LR})^2[Var(F_y^{BC}) + Var(F_y^{SR})]}{(F_y^{LR} + F_y^{BC} + F_y^{SR})}$$

where $Var(F_y^{LR})$, $Var(F_y^{BC})$, and $Var(F_y^{SR})$, are the variances of various components of the non-normalized spectra. The covariance terms in the above expansion are all set to zero because the covariance between spectral estimates at different frequencies are asymptotically zero.

To estimate $Var(H_y^{LR})$, we replace F_y^{LR}, F_y^{BC}, and F_y^{SR} by their sample estimates, $\hat{F}_y^{LR}$, $\hat{F}_y^{BC}$, and $\hat{F}_y^{SR}$. To obtain the variances of $\hat{F}_y^{LR}$, $\hat{F}_y^{BC}$, and $\hat{F}_y^{SR}$, we use the fact that the estimate of the spectrum at frequency ω, $\hat{f}_y(\omega)$, is approximately distributed as a

χ_v^2/v variate, where $v = 3n/m$ (Fuller, 1976, p. 296). The distributions of the three components are also chi-square given the asymptotic independence of the spectral estimates at adjacent frequencies, and the fact that each component is a sum of independent chi-square variates (Priestley, 1981, p. 466). The degrees of freedom of each distribution depends on the number of observations and the number of ordinates, where the latter varies across the frequency bands. Variances are then computed using the fact that the variance of a chi-square variable is twice the degrees of freedom.

The estimates for $Var(H_y^{BC})$ and $Var(H_y^{SR})$ are obtained in a similar fashion.

A.5. Second measure of shock persistence

Results reported in the first column of Tables 1–3 suggest a substantial cross-country variation in the second measure of shock persistence—the proportion of output growth variance that is due to long-run components. For the developed countries the estimated contribution to variance varies from about 10 percent for Australia to over 60 percent for Japan. Other countries with low estimates include the U.K. with 12 percent, the U.S. and Iceland with 15 percent each, Luxembourg 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 U.K. and the U.S. attain the lowest estimates of the contribution of long-term fluctuations to output growth variance, while Japan, France, and Germany attain the highest estimates. The contrast between the extreme estimates within the G-7 countries is remarkable: the estimate for Japan is five times larger than for the U.K. and four times larger than for the U.S. This contrast is also reflected in the relative magnitude of the business cycle components of these countries' outputs. As discussed earlier, over 70 percent of the output growth fluctuation in the U.K. and over 54 percent in the U.S. 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 long-lasting cycles. On the contrary, most of the shocks in the U.K. and the U.S. have a more temporary effect leading to primarily cyclical and short-term fluctuations. Using quarterly data (Table 7), we find that the U.S., the U.K., and Australia still maintain the lowest estimates of shock persistence, while Japan maintain the largest estimate. The diverse range observed for the annual data is also noted here.

Next consider high-income developing countries (Table 2, first column). For this group, the contribution of 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 are Argentina and Turkey with about 18 percent each. Countries with particularly high estimates are Ecuador with 46 percent and Brazil with 44 percent. The contrast between the extreme values within this group is also substantial. Finally, for low-income developing countries (Table 3, first column), the contribution of long-run frequency components to the output growth variance varies from about seven percent for Kenya to over 55 percent for El Salvador. The contrast between the extreme values within this group is even more pronounced as evidenced by a large interquartile range.

Overall, these results suggest that there are substantial variations in shock persistence between groups of countries as well as between countries within the same group.

References

Baxter, M., King, R.G., 1995. Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series, NBER, Working Paper No. 5022.

Beveridge, S., Nelson, C., 1981. A new approach to decomposition of time series into permanent and transitory components with particular attention to the measurement of the 'Business Cycle'. Journal of Monetary Economics 7, 151–177.

Campbell, J.Y., Mankiw, N.G., 1989. International evidence on the persistence of economic fluctuations. Journal of Monetary Economics 23, 319–333.

Carpenter, R., Levy, D., 1998. Seasonal cycles, business cycles, and the comovement of inventory investment and output. Journal of Money, Credit, and Banking 30, 331–346.

Chatfield, C., 1989. The Analysis of Time Series. Chapman and Hall, London.

Cochrane, J., 1988. How big is the random walk in GNP? Journal of Political Economy 96, 893–920.

Cogley, T., 1990. International evidence on the size of the random walk in output. Journal of Political Economy 98, 501–518.

Dezhbakhsh, H., 2002. The political economy of statistical evidence: economic data problems in developing countries and their impact on empirical research. Conference on Development Issues in the New Economy. Cape Town, South Africa.

Englund, P., Persson, T., Svensson, L.E.O., 1990. Swedish Business Cycles: 1861–1988. Seminar Paper No. 473, Institute for International Economic Studies.

Fuller, W.A., 1976. Introduction to Statistical Time Series. Wiley, New York.

Granger, C.W.J., 1966. The typical spectral shape of an economic variable. Econometrica 34, 150–161.

Granger, C.W.J., Hatanaka, M., 1964. Spectral Analysis of Economic Time Series. Princeton University Press, Princeton.

Granger, C.W.J., Watson, M.W., 1984. Time series and spectral methods in econometrics. In: Griliches, Z., Intriligator, M.D. (Eds.), The Handbook of Econometrics, Vol. II. North Holland and Elsevier Science, New York, pp. 980–1022.

Hassler, J., Lundvik, P., Persson, T., Söderlind, P., 1992. The swedish business cycle: stylized facts over 130 years. Discussion Paper 63, Institute for Empirical Macroeconomics, Federal Reserve Bank of Minneapolis.

Hettmansperger, T.P., 1984. Statistical Inference Based on Ranks. Wiley, New York.

Huber, P.J., 1981. Robust Statistics. Wiley, New York.

King, R.G., Watson, M.W., 1996. Money, prices, interest rates, and the business cycle. Review of Economics and Statistics 78, 35–53.

Koopmans, L.H., 1995. The Spectral Analysis of Time Series. Academic Press, San Diego.

Kormendi, R.C., Meguire, P., 1990. A multicountry characterization of the nonstationarity of aggregate output. Journal of Money, Credit, and Banking 22, 77–93.

Kraay, A., Ventura, J., 2001. Comparative advantage and the cross-section of business cycles. National Bureau of Economic Research, Working Paper No. 8104, Cambridge.

Leung, S.K., 1992. Changes in the behavior of output in the United Kingdom, 1856–1990. Economics Letters 40, 435–444.

Levy, D., 2000. Investment-saving comovement and capital mobility: evidence from century long US time series. Review of Economic Dynamics 3, 100–136.

Levy, D., Chen, H., 1994. Estimates of quarterly capital stock series for the post-war US economy. Review of Income and Wealth 40, 317–349.

Levy, D., Dezhbakhsh, H., 2002. On the typical spectral shape of an economic variable. Working Paper No. 02-03, Emory University.

Lucas, R.E., 1980. Two illustrations of the quantity theory of money. American Economic Review 70, 1005–1014.

Maddison, A., 1982. Phases of Capitalist Development. Oxford University Press, New York.

Meltzer, A.H., 1990. Unit roots, investment measures, and other essays. Carnegie-Rochester Conference Series on Public Policy 32, 1–6.

Prescott, E.C., 1986. Theory ahead of business cycle measurement. Quarterly Review, Federal Reserve Bank of Minneapolis, 9–22.

Priestley, M.B., 1981. Spectral Analysis and Time Series. Academic Press, San Diego.

Romer, C.D., 1989. The prewar business cycle reconsidered: new estimates of gross national product, 1869–1908. Journal of Political Economy 97, 1–37.

Romer, C.D., 1994. Remeasuring business cycles. Journal of Economic History 54, 573–609.

Stockman, A., 1987. Sectoral and National Aggregate Disturbances to Industrial Output in Seven European Countries. Manuscript, University of Rochester.

Summers, L.H., 1980. The non-adjustment of nominal interest rates: a study of the fisher effect. In: Tobin, J. (Ed.), Macroeconomics, Prices, and Quantities. The Brookings Institution, Washington, DC, pp. 201–244.

Summers, R., Heston, A., 1991. The penn world table (Mark 5): an expanded set of international comparisons, 1950–1988. Quarterly Journal of Economics 106, 327–368.

Watson, M.W., 1986. Univariate detrending with stochastic trends. Journal of Monetary Economics 18, 49–75.

White, H., 1980. A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. Econometrica 48, 817–838.

Zarnowitz, V., 1992. Business Cycles. University of Chicago Press, Chicago.