Long Cycles: A New Look At the Evidence

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Recent economic misfortunes have renewed interest in the possibility of long 20–50 year cycles in economic activity. Interestingly enough, the belief in long waves has itself undergone a cycle of acceptance, rejection and resurrection.[1] Supporters now include Rostow (1978) and Forrester (1978) on the 50th anniversary of the Great Depression. But do long cycles really exist or are they merely random fluctuations in economic activity? Commonsense suggests that economists have disagreed about long waves because reliable data series are too short to detect them with much confidence [Samuelson, 1979], and so any deep recession tends to resurrect the theory. However, there is evidence to support the view that disagreements are due in particular, to differences in (a) scholarly precedures for defining and isolating long cycles in data and (b) interpretations of statistical tests performed on the resulting data. When the influence of these differences is corrected a fairly consistent pattern of empirical findings tends to emerge. This pattern does not support the long-cycle hypothesis. Rather, it is consistent with a model in which the deviations of growth rates from their historical average are a random and uncorrelated sequence of shocks, i.e., what in spectral language has come to be called a "white noise" process.

Summary Survey of Long Cycle Studies

Kondratieff found evidence for 50 year periods between major peaks in the nine-year moving averages of annual prices [Garvey]. Averaging was used to suppress short-cycle disturbances. Although Kondratieff's conclusions were challenged and he was unable to provide a convincing theory for his waves, Schumpeter made them part of his famous three-cycle schema in the 1930s. At about the same time Kuznets [1930] was finding approximate 20 year periods between major peaks in the 10-year moving averages of annual growth rates of many economic time series. Later, Lewis and O'Leary found similar major-peak periods in the unaveraged deviations from a logarithmic trend of data in several nations. Because these 20-year periods appeared in a variety of data and data forms (i.e., growth rates and deviations from trend) they were thought to be induced by some common force, such as demographic waves [Kuznets, 1961; Abramovitz]. But most of these classical studies used moving averages, and all of them ignored minor ripples in the averaged data while concentrating on major peaks. Moving averages tend to lengthen any underlying cycle pattern in the unaveraged data [Howrey, 1968; Fishman; Klotz, 1973], while the practice of ignoring ripples allows

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[1]Acceptance: Kuznets (1930), Schumpeter, Lewis and O'Leary, Abrdmovitz. Rejection: Adelman, Granger, Hatanaka and Howrey, Howrey (1968). Resurrection: Harkness, Poulson and Dowling, Cargill.

one to find major peaks even in random-walk processes [Klotz, 1977].

Analysts turned to spectral methods to avoid the distortions caused by the classical methods.[2] Adelman found no statistically significant peaks in the U.S. spectra at the long-cycle frequencies. She analyzed unaveraged deviations of annual time series from their logarithmic trend. Hatanaka and Howrey refined Adelman's methods and reached the same conclusion. The typical spectral shape resulting from these and other studies indicated that cycle amplitude increased smoothly with length over the spectrum of cycles examined. Granger pointed out that this shape is consistent with a first-order Markov process in the deviations, D_t, of data, Y_t, from their logarithmic trend: $\log Y_t = a + b\,t + D_t$, where "$a$" and "$b$" are constants of the trend formula, t is time, $D_t = r\,D_{t-1} + u_t$, $r \gtrsim 1.0$ is the Markov parameter, and u_t is a random, serially uncorrelated sequence of shocks (ie., u_t is a "white noise" process). A first-order process leaves no place for cycles because their generation requires at least a second-order process in the D_t [Baumol].

However, the question remains whether the typical shape comes from a higher order process whose spectrum, in certain special cases, might resemble that of a first-order process. A growth rate transformation, essentially $\Delta \log Y_t$, is sensitive for picking up significant departures of D_t from the random walk case $D_t = r\,D_{t-1} + u_t$, $r = 1.0$. This case implies $\Delta \log Y_t = b + u_t$, so the growth rate of Y_t equals a constant b plus u_t which reflects shocks. The spectrum of the rates is a constant across all frequencies in this case [Fishman]. Significant departures of an estimated growth rate spectrum from a constant level implies that the D_t do not follow a random walk. Employing this reasoning Howrey [1968] found seemingly significant peaks in the growth rate spectra of several macroeconomic time series. But the peaks were at frequencies corresponding to 10–14 year cycles. Howrey showed that moving averages would transfer these peaks to the frequency range corresponding to 20 year waves, thus creating long cycles in the averages of growth rates examined in classical studies.

Although this "first round" of spectral studies tended to reject long cycles as a statistical artifact, a second round quickly followed which seemed to resurrect the idea. Harkness found peaks in 40 of 44 growth rate spectra at long-cycle frequencies. But the peaks were not tested for significance versus the corresponding spectrum average, and their abundance is not convincing evidence for long waves: one would expect to find almost 40 peaks even if all 44 data series were independent "white noise" processes. Harkness used Parzen weights to smooth each spectrum. This would cause the spectrum of even a white noise process to average six frequency bands between peaks, implying that each frequency band estimate has a .167 chance of being a peak.[3] Because Harkness estimated five frequencies in the long-cycle range for each of 44 spectra we would expect $.167 \times 5 \times 44 = 37$ peaks even if the spectra were of 44 independent white noise processes. Thus,

[2]Spectral analysis decomposes the total variance of a time series into a spectrum of cycles of differing wavelengths (the inverse of their frequency). Long and short waves can then be examined separately without recourse to moving-average or ripple-suppression methods. Also, spectral analysis can detect periodic, but irregular, fluctuations: they would cause peaks in the spectrum at the frequency of the period in question and at its harmonic frequencies.

[3]With Parzen weights and $i = 1, 2, \ldots, M$ lags, adjacent point estimates of the spectrum, denoted by f_i and f_{i-1}, have correlation $R_1 = 0.8$. Once removed points have correlation $R_2 = 0.4$ [Fishman, p. 100]. Supposing these two correlations imply that a second-order process such as $f_i + a\,f_{i-1} + b\,f_{i-2} = u_i$ describes the spectrum estimates, then the observed spectrum will exhibit an average peak-to-peak distance of $P = 2\pi/\cos^{-1}B$, where $B = [b^2 - (1 + a)^2]/\,2(1 + a + b)$. (See Howrey (1968) for a discussion of peak-to-peak periods.) With R_1 and R_2 as above, regression formulas [Kendall] imply $a = -1.33$ and $b = .67$. So $B = 0.5$ and $P = 6.0$ in this Parzen case.

Harkness' finding of 40 peaks is weak evidence in favor of long cycles.

Although Harkness did not compute the statistical significance of his peaks relative to their respective spectrum average, Poulson and Dowling [1974] followed with a study that did.[4] They estimated spectra at 30 frequencies, five in the long cycle range of 10+ years, for 25 annual time series. They discovered that eight peaks in the long cycle range exceeded the 90 percent confidence bound placed about their respective spectral averages, and 10 peaks exceeded the 80% bound. Poulson and Dowling interpreted this as convincing evidence for long cycles. However, they did not mention that these numbers of significant peaks could also have occurred due to sampling fluctuations, even if their series had been a set of 25 independent white noise processes. With white noise the spectrum estimate at each frequency has about a .05 (.10) probability of exceeding the 90% (80%) confidence interval.[5] Thus, with five point estimates in the long cycle range for 25 data series we would expect roughly $.05 \times 5 \times 25 = 6.25$ points to exceed the 90% confidence band and $.10 \times 5 \times 25 = 12.5$ to exceed the 80% bound. This is similar to the Poulson and Dowling finding.

But an even more fundamental objection applies to the claim that long cycles are evidenced by counting peaks exceeding some X% confidence bound about the average spectral height. Had growth rates followed a simple, non-cyclical first-order process $\Delta\log Y_t = c\Delta\log Y_{t-1} + u_t$, with $0 \leqslant c \leqslant 1$, then the growth rate spectrum would have had more power at the lower frequencies corresponding to the long cycle wavelengths [Fishman]. Then sampling variation in the estimated spectrum about its true value could cause some peaks in the low frequency range, and these peaks could exceed the, say, 90% confidence bound placed about the spectrum average. The bounds test assumes that $\Delta \log Y_t$ is a white noise process with a flat spectrum, but this assumption should itself be tested before applying the bounds test. Unfortunately, neither Harkness nor Poulson and Dowling report their spectral estimates at all frequencies so we cannot test their spectra for flatness.[6]

Clearer evidence on the true shape of the growth rate spectra appears in Howrey's 1968 study. He graphs spectral power for all frequencies, displaying 13 spectra based on 1969–1955 annual data. Apart from the inevitable fluctuations, three spectra tend to slope mildly upward as frequency increases (Net National Product, pig iron, and consumers semi-durables), three slope mildly downward (consumer durables, gross capital formation, and gross nonfarm residential construction), and seven appear to be basically flat.[7] Interestingly enough, the series with downward sloping spectra (ie., more power at lower

[4]Their earlier 1971 study contained similar results.

[5]More than five percent of the points tend to lie above the 90% interval because asymptotic, rather than small-sample, confidence formulas are used, the random process investigated may not be normally distributed, and the spectrum estimates are only approximately chi-square [Fishman, pp. 102–06]. But, countering these factors, Parzen smoothing causes two adjacent outliers to appear as one. Adjacent outliers are more frequent the greater is M and the lower the confidence bounds.

[6]The recent studies of Rostow and Forrester cannot settle this question either because neither uses spectral methods. Instead, both employ the questionable method of implicitly eliminating ripples and focussing on the remaining major peaks in their data series. Rostow uses historical data from real economies. Forrester analyses simulated time series data from an a priori model which seems to contain a hierarchy of lagged (or weighted moving-average) relationships linking consumer spending to desired capital in the capital goods industry. Such hierarchies tend to create long waves [Howrey, 1968, 1971].

[7]This even distribution of spectrum slopes about the zero-slope (white noise) case is perhaps why, over 13 spectra estimated at 30 frequencies, only 10 peaks exceeded the 95% confidence bound about their respective spectrum average (we would expect $13 \times 30 \times (1.00 - .95)/2 = 9.75$ peaks to occur by chance even if all 13 series were independent white noise processes) and why the 10 peaks did not bunch in any particular frequency range.

frequencies) have long been thought to contain long cycles.[8]

Cycles or Random Fluctuations?

Are seemingly significant spectral peaks in the long cycle frequencies due to sampling fluctuations of mildly downward sloping spectra (associated with mildly correlated growth rates)? To answer this question we computed spectra for annual Gross National Product, Employment, Gross Capital Formation, and Residential Construction (all in real terms).[9] GNP and Employment were chosen because they are important summary measures of economic activity; GCF and RC were picked because they are widely believed to contain cycles, if not long waves.[10]

The four spectra are evident in Table 1. To test peaks versus a flat (white noise) spectrum we compare peaks to the spectral average. Only RC has a 90% (and 95%) significant peak in the "long" cycle range (at 12 years). Two other 90% significant peaks appear: in GNP (7-year waves) and GCF (5-year waves). These three peaks are less than we would expect to appear by chance if we were viewing the spectra of four independent white noise processes estimated at 24 frequencies (four of them in the long cycle range): the expected number of 90% peaks would be 4 × 24 × (1.00 − .90)/2 = 4.8. But the GNP, GCF and RC spectra in Table 1 do not appear to be flat. In fact, the estimated spectra seem to rise, and then fall, as cycle length decreases. To some extent, however, this undulation may be due to the Parzen weights which were used to smooth the spectrum prior to estimation. These weights impart correlations between spectrum estimates at adjacent frequencies in such a way that the random sampling fluctuations of even a white noise process will be transformed into a second-order process across the set of frequencies estimated, from lowest to highest.[11] Thus, the spectrum estimates of Table 1 should be transformed by this process prior to testing the spectrum for flatness.

Denoting the transformed spectral estimates at frequency band i by f'_i, we regress them on band i using the linear model $f'_i = b'_0 + b'_1 i + v_i$, where b'_0 and b'_1 are constants and v_i is assumed to be a random component representing sampling fluctuations. Estimates of b'_0 and b'_1 can be re-transformed to obtain efficient estimates of b_0 and b_1 in the original model $f_i = b_0 + b_1 i$, and thus used to compute a f_i value at band i for comparison with any peak value at that band revealed by Table 1. For example, if b'_1 is negative then so is b_1 and the spectrum $f_i = b_0 + b_1 i$ slopes downward (decreases as frequency increases).

Panel 1 of Table 2 shows that b'_1 is significantly negative for GNP and RC. The spectral peak in GNP (in Table 1) is not significant when compared to the computed spectrum ($b_0 + b_1$ i) at the same frequency, but the peaks in the RC and GCF spectra retain their significance.[12] However, only the RC peak is in the long-wave region, and then just barely because it indicates a 12-year construction cycle.

In summary, our results for the U.S. show that (a) whatever the behavior of their components, the major macroeconomic time series GNP, GCF and Employment exhibit no long waves, (b) GNP does not exhibit significant short waves, when a correlated growth rate model is posed as the alternative hypoth-

[8]Cargill found 14 peaks that were 95% significant, in the 10–20 year cycle range, in 43 construction series. However, the confidence formulas are questionable when the ratio of observations to lags is less than 3.0 [Fishman], and this was the case with 33 of the 43 series examined. Furthermore, only 17 of the 43 series are reasonably independent (not major subcomponents or merely price-deflated versions of others). Only three 95% peaks appear in these 17 spectra, while two would be expected even if all 17 series had been independent white noise processes.

[9]The 80-year time period examined, 1889–1969, is a compromise. Earlier less reliable data are omitted. Although they are alleged to exhibit long waves it is unlikely any such waves would be obliterated completely during 1889–1969. We stop at 1969 because later data were not used in the studies we review in this paper.

[10]In fact, Forrester believes in long waves because he found 50-year intervals between major peaks in the capital goods output of his simulated model.

[11]See footnote three of this paper.

[12]The peaks also remain significantly above the computed spectrum when the latter is estimated by the flexible form $\log f_i = b_0 + b_1 \cos(b_2 i)$ which is a linear approximation to $f_i = k/(1 + c^2 - 2c \cos(b_2 i))$, the spectrum of a first-order process in the growth rates.

TABLE 1: United States Growth Rate Spectra, 1889–1969

Cycle Length	*Frequency (in π/24)*	*GNP*	*GCF*	*EMPLMT*	*RC*
—	0	.33 (10^{-3})	.04 (10^{-1})	.21 (10^{-3})	.03 (10^{-1})
48.0	1	.42	.05	.23	.05
24.0	2	.66	.09	.30	.14
16.0	3	.84	.17	.34	.29
12.0	4	.83	.24	.28	.35[a,b]
9.6	5	.87	.23	.19	.27
8.0	6	1.03	.16	.22	.17
6.9	7	1.10[a]	.20	.33	.14
6.0	8	.96	.38	.35	.13
5.3	9	.61	.50[a,b]	.27	.12
4.8	10	.35	.39	.17	.10
4.4	11	.32	.18	.12	.08
4.0	12	.40	.09	.13	.06
3.7	13	.56	.13	.23	.08
3.4	14	.68	.20	.32	.10
3.2	15	.62	.24	.27	.11
3.0	16	.52	.22	.16	.10
2.8	17	.48	.16	.12	.07
2.7	18	.37	.10	.10	.07
2.5	19	.27	.11	.08	.09
2.4	20	.36	.18	.10	.10
2.3	21	.50	.23	.16	.10
2.2	22	.57	.20	.21	.09
2.1	23	.55	.13	.23	.09
2.0	24	.52	.09	.22	.10

a: 90 percent significant.
b: 95 percent significant.
Source: U.S. Department of Commerce, *Long Term Economic Growth, 1860–1965,* 1966; updates from *Survey of Current Business.*

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Table 2: Tests for White Noise Spectra

Model	*Gross National Product*	*Gross Capital Formation*	*Residential Construction*	*Employment*
$f'_i = b'_0 + b'_1 i$				
b'_1	−0.68	−0.21	−0.22	−0.14
Stand. Error (b'_1)	0.30	0.21	0.10	0.16
Durbin-Watson	1.53	1.29	1.30	1.51
$f_i = b_0 + b_1 i$				
b_0	57	19	20	12
b_1	−2.0	−0.6	−0.4	−0.65

esis (rather than a white noise model),[13] (c) the short 5-year wave in GCF could be real but could also be due to chance, (d) the 12-year wave in RC might also be due to chance, but it may well be the exception that tests the simple rule that long waves are merely sampling fluctuations of uncorrelated, or mildly correlated, growth rate processes.

[13]McCulloch found no second-order process in annual U.S. growth rates, based on regressions of the rates on their lagged values. However, his procedure did not bar the possibility of lower (or higher) order processes.

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