Part Two: ANALYSIS

CHAPTER EIGHT

Defining Long Cycles: Epistemology and Methodology

The following questions are of central importance in the long wave debate: (1) Can long waves be identified in a variety of economic time series? (2) In which time periods, countries, and types of economic variables can long waves be found? (3) Is there a connection between the ups and downs of wars and the phases of the long wave? (4) From the above, what relationships among various economic and political elements can be adduced and what causal theories of the long wave do these relationships suggest?[1] Through these questions, I have tried to address the gap between theory and empirical investigation that has plagued past work on long waves.[2]

The long wave field is weak in data, and this sharply limits what is possible. In this study I try to push out the frontiers where little research has been done and data are very limited. In a sense everything is provisional. I believe the analysis presented below shows that the long wave theory proposed can account for empirical data in a coherent manner. But I do not believe it is the last word on long waves, and I expect parts of the theory to be revised in the future as further evidence emerges. I am seeking new possibilities, not final conclusions.

The Definition of Social Cycles

The first subject of this chapter is the conceptualization of social cycles in general and long waves in particular. There has been much confusion about definitions of "cycles" or "waves." I will start with a dictionary definition: "Cycle: an interval of time during which one sequence of a regularly recurring

1. Van der Zwan (1980:185) calls the long wave "a pre-eminent methodological problem," while Ehrensaft (1980:78) calls long wave research "an intimidating process because of the very scope of the questions that must be raised."

2. Wallerstein (1984a) notes that the results of empirical research to date "have been meager." And he agrees with Gordon (1980:10), who writes that long wave scholars have failed "to elaborate a coherent (much less a unified) theoretical foundation for their interpretation of long cycles." My overall approach is: (1) Define research schools and their hypotheses; (2) Test alternative hypotheses against others' and my own evidence; (3) Synthesize surviving hypotheses into an adduced theoretical framework; (4) Identify anomalies, unanswered questions, and potentially fruitful avenues of future research; and (5) Use the adduced theoretical framework to develop new interpretive insights into history (in Part Three).

succession of events or phenomena is completed.''[3] This definition contains two elements: an interval of time and a repeating sequence. If the time interval is fixed in length, the definition corresponds to *periodicity,* but if the time interval varies, then the *repeating sequences* define the cycle.

Periodicity versus ''Cycle Time''

I distinguish two general approaches to social cycles. The first defines cycles in terms of ''periodicity'' relative to a fixed external time frame. The second approach defines cycles as repeating sequences best measure in ''cycle time.''[4]

Time itself is always relative to some referent, not absolute. Time is always measured by a *repeating* change of state in some phenomenon and is thus inherently cyclic. Physical time is measured by physical cycles—the rotations and orbits of atoms and planets. ''Social time'' may likewise be measured by such social cycles as long waves. Allan (1984; 1987) suggests the desirability of building ''social clocks'' in which the succession of social phenomena is timed against its own internal dynamic rather than against a fixed external time line.[5]

The regular periodicities of the physical world make possible a variety of measurement and statistical analysis techniques that are appropriate only to cycles defined by fixed periodicities.[6] These techniques include spectral analysis, Fourier analysis, and related approaches that use sine waves as the underlying model of cyclicity.[7]

But periodicity is not appropriate to the social world. While physical phenomena underlie social phenomena, the latter constitute a higher level of analysis, exhibit greater complexity, and contain the added elements of intention and choice. Complex social phenomena are not well described by physical laws of mechanical motion (see Alker 1981).

Kondratieff ([1928] 1984:81–82) argues that ''in social and economic phenomena, there is nothing like strict periodicity.'' Kondratieff holds that the ''regularity'' of long waves should refer not to periodicity but to ''the regularity of their repetition in time'' and to the international synchrony of different economic series. Trotsky[8] suggests that the long cycle does not resemble the fluctuations of a wire under tension

3. *Webster's 3d New International Dictionary,* S. V. ''cycle.''

4. As I will argue, the periodicity approach is conducive to the use of inferential statistics, while for the cycle time approach descriptive statistics are more appropriate.

5. Allan criticizes the social sciences for using a time referential ''directly borrowed from physics'' (1984:2). He proposes looking at the interrelationships of social processes in time in terms of the ''sequence and covariations at different phase lags, where the phases are defined as relevant theoretical parts of the dynamic process under consideration'' (p. 3). See also Ruggie (1985).

6. In the biological sciences, periodicities tend to be less regular. Although cycles still exist on many levels (biochemistry to population), the cycles can be irregular in duration and timing (e.g., menstrual cycles, life cycles).

7. Spectral analysis produces a curve showing how well the sine wave fits the data as a function of the wavelength of the sine wave (see chap. 4). Fourier analysis finds a set of sine waves (of varying wavelengths), the sum of which at a given point in time approximates the value of a time series.

8. Trotsky (1921), quoted in Day (1976:70).

(periodicity) but might better be compared with a heartbeat.[9] As Sorokin (1957:563) puts it: "History seems to be neither as monotonous and uninventive as the partisans of the strict periodicities . . . think; nor so dull and mechanical as an engine, making the same number of revolutions in a unit of time. It repeats its 'themes' but almost always with new variations." Wallerstein (1984a) suggests an analogy between social cycles and the process of breathing in animal life:

> Physiologists do not argue about whether breathing occurs. Nor do they assume that this regular, repetitive phenomenon is always absolutely identical in form or length. Neither do they assume that it is easy to account for the causes and consequences of a particular instance. . . . [Nonetheless,] all animals breathe, repetitively and reasonably regularly, or they do not survive.

Critics will say that what I call a cycle is not a cycle but just a series of ups and downs, a "random walk." Only periodicity would satisfy them that a cycle exists. But periodicity is only the superficial aspect of a cycle—the essence of the cycle is a (sometimes unknown) inner dynamic that gives rise to repetition. In a single time series variable, there is no way (other than periodicity) to distinguish superficial ups and downs from a deeper cyclic dynamic. But when ups and downs correlate throughout a worldwide political-economic system, it is safe to conclude that there is a deeper systemic dynamic at work, not just a scatter of random ups and downs.

Past studies of social cycles have had little success when using a mechanistic definition of cycles as fixed periodicities and the statistical techniques appropriate to such a definition. In the long wave field, Bieshaar and Kleinknecht (1984:281) note that "research experience has shown that spectral analysis is not a very promising method for the analysis of long waves."[10] And as I noted in chapter 5, the search for war cycles based on periodicity was a self-proclaimed dead end.

An example of the problems inherent in periodicity approaches is the work of E. R. Dewey and his Foundation for the Study of Cycles[11] (Dewey and Mandino 1971). This foundation subjects all manner of time series—on social, economic and natural processes—to Fourier analysis. Each series is broken down as the sum of, say, 4.8-year, 11.2-year, 51.9-year, and 211.4-year cycles, and these numbers vary for every series.[12] Dewey's journal lists so many alleged cycles that they are indexed in the

9. For once Kondratieff and Trotsky agree (that periodicity is the wrong definition). Rose (1941:107) agrees that "we may speak of long waves . . . without being concerned with . . . the periodicity of those two-phase wave movements." Morineau (1984) likewise prefers sequences to "rigid cycles" as a basis of defining long waves. By contrast, some long wave studies rely heavily on the concept of periodicity. Kuczynski (1978:81), for example, argues that "generally, Kondratieff's hypothesis can be described as a set of trigonometric functions."

10. Both because time series are too short compared with the wave length and because the results are too sensitive to the method used to eliminate long-term trends (to make the series "stationary," which is necessary for spectral analysis).

11. Which puts out the journal *Cycles*.

12. Dewey (1970), for example, claims to find a cycle of close to 50 years in an index of international battles over the past 2,500 years. However, he also claims to find cycles of several other lengths in the same series (it is the sum of these cycles that approximates the series).

back of each volume according to the length of the cycle. Mechanistic work of this kind may be largely responsible for the skepticism many social scientists express toward cycles.

In contrast to the periodicity approaches, my analysis defines long waves in terms of a simple repeating sequence, that of two alternating phases. Each long wave phase is one unit of cycle time, although the lengths of the phases vary in terms of calendar time. The unit of analysis is thus the phase period rather than the year, and the methodology I develop seeks to identify patterns of regular alternation between successive phase periods. Eventually the analysis moves beyond a simple two-phase analysis, as I look for lagged correlations among variables *within* cycle time. This opens up a fuller theory of timing and causality among variables (see chapter 12).

Several other methodologies relevant to the reconceptualization of social cycles in terms of sequences deserve mention here, although I do not pursue them. Kruskal (1983) summarizes recent research on "sequence comparison" in fields as diverse as macromolecular genetics, speech recognition, and bird-song analysis. These approaches embody techniques for identifying isomorphic sequences even when particular elements have been inserted or deleted from one sequence or when the time axis has been compressed or expanded. Such techniques could someday form the starting point for the statistical analysis of *repeating* sequences of political, economic, and social processes. Mefford (1984) uses "artificial intelligence" techniques to develop a sequence-matching algorithm for political events, finding common patterns in similar (but not identical) case histories.[13] Similar techniques could prove useful in identifying political cycles defined by repeating sequences in political events.

World History: The N=1 Problem

The move away from periodicity to cycle time means defining the long wave as a unique, historically defined set of alternating phases. The level of analysis is thus world history. History is a unique process, and the past five centuries of the core of the world system present only one such history to be studied. It is not a sample of a larger population but the "universe" of cases, and the number of cases in a real sense is one.[14]

This raises methodological problems because the statistical tools useful in testing hypotheses in randomly drawn samples are not appropriate to testing hypotheses in a single historical sequence.[15] Because there is only one history, the underlying thrust

13. His application is the analysis of historical precedents in decision-making—specifically the response of the Soviet leadership to the Czech situation in 1968, based on outcomes of previous Soviet actions in Eastern Europe.

14. And at best, in comparing the repeating pattern over time we can find only ten cases of a long wave in the past five centuries.

15. As Freeman and Job (1979:125, 134) point out, problems with inference increase as one moves to higher levels of analysis and as the number of cases decreases: "our ability to understand contextual novelty decreases rapidly because we have less and less information about the contingencies and effects of structural transformations."

of this study will be toward the statistical *description* of that history rather than toward the inferential statistics appropriate to the analysis of statistical samples within "confidence intervals." I will draw on such simple inferential techniques as bivariate regressions and t-tests, but mainly as tools toward building the most consistent and compelling *description* of long waves. The emphasis, furthermore, is on testing alternative contradictory hypotheses against each other rather than testing a general long cycle hypothesis against the null hypothesis.

Adduction

The logic of inquiry in this approach is adductive. Fischer (1970:xv) calls adduction the most appropriate "logic of historical thought."[16] The study of history

> consists neither in inductive reasoning from the particular to the general, nor in deductive reasoning from the general to the particular. Instead, it is a process of *adductive* reasoning in the simple sense of adducing answers to specific questions, so that a satisfactory explanatory "fit" is obtained. The answers may be general or particular, as the questions may require. History is, in short, a problem-solving discipline. A historian is someone (anyone) who asks an open-ended question about past events and answers it with selected facts which are arranged in the form of an explanatory paradigm.

These questions and answers, according to Fischer, affect each other in "a complex process of mutual adjustment." The resultant explanatory paradigm—expressed as some combination of statistical generalization, narrative, causal model, or analogy—is "articulated in the form of a reasoned argument." This is the spirit of my analysis, and I repeat that those who expect "behavioral science" will not find it here.

Alker (1984:167) notes that this kind of explanation is incomplete, offering neither "sufficient causes" nor "counter-arguments as to alternative determinants." Adductive accounts thus "belong in the realm of probabilistic or contingent reasoning; they are not necessarily valid inferences. Nor are they conventional inductive statistical inferences." Yet these "practical inferences" can give a "how possible" rather than "why necessary" account of behavior, and these accounts are in fact useful in a world of imperfect information.[17]

The cumulation of knowledge, as discussed in chapter 7, relies on adduction in important ways. Since theories, according even to Popper, are never "proven" but only imperfectly corroborated, all of science is in a sense adductive. But this is more evident in such a field as long wave research than in, say, physics.

The above considerations, then, shape my overall methodological approach—an approach that stresses adduction, historical datings, descriptive statistics, and cycle time.

16. See also Alker (1984), Braudel ([1958] 1972; [1969] 1980), and Le Roy Ladurie ([1978] 1981).

17. Wallerstein (1984a) argues that cycles, like all concepts, are "a construct of the analyst." A construct "must have an empirical base" to distinguish it from fantasy, but "a construct is not a 'fact,' somehow there, irremediably objective, unmediated by collective representations and social decisions. A construct is an interpretive argument. . . . Its justification is in its defensibility and its heuristic value."

Data Considerations

The search for historical empirical evidence of long waves is greatly constrained by data limitations. Quantitative data regarding economic history are spotty (especially for preindustrial times). Most quantitative data are estimates of particular quantities at particular (occasional) years (or for such longer periods as decades). These are of little use in identifying trends over specific phase periods that do not generally correspond with the years or decades given. Long waves can be identified only by finding trends in the data over phase periods as short as ten to twenty years, and only *annual time series* data will adequately capture such relationships.[18]

Furthermore, in looking for long waves of roughly five decades' length, few meaningful conclusions can be drawn from time series of less than about one hundred years. The series should, at the minimum, pass through several adjacent phase periods—so that differences in the trend behavior within different phase periods may be identified.

Data considerations bear on the issue of what variables to include in the analysis. As I showed in Part One, past work on long waves in different theoretical schools has focused on different variables. I have included in some manner each of the seven categories of variables outlined at the beginning of chapter 4.[19] But I have been constrained by using "available data" in each category (since I did not have the resources to create new time series from primary sources). For some variables data are woefully inadequate, and for some variables the only "available" data are those developed by long wave scholars working within a paradigmatic framework that stresses both the particular variable *and* a theoretical role for that variable (particularly for innovation). Thus my empirical analysis is not free of the "debates" of Part One, since data are themselves influenced by research frameworks.[20]

Another data consideration is what time period to examine. Most past studies of long waves have restricted their analysis to industrial times. Barr (1979:677) refers to "a gap in the literature—*viz.*, the empirical study of long waves before the so-called Industrial Revolution." I have sought to include data from both before and since the beginning of industrial times, going back to 1495 (the beginning of Levy's "great power system" and approximate start of Wallerstein's world-system). But again this has been only partially possible. Data for *price* series both before and since about 1790[21] are adequate for a fairly detailed analysis. However, *production* series are available only since around 1790—and this limits the analysis. Still more spotty are time series for innovation, trade, wages, and capital investment. I have included at

18. On long time series, see Granger and Hughes (1971).

19. Prices, production, innovation, capital investment, wages/working-class behavior, trade, and war.

20. I often find that my own analysis of another long wave researcher's data confirms his or her own conclusions.

21. Again, I use the year 1790 to distinguish the preindustrial from the industrial period, since the 1790 long wave trough begins Kondratieff's part of the base dating scheme.

least two time series in each of these categories, but two series are insufficient to draw far-reaching conclusions. The capital investment area is particularly underrepresented. In these parts of the theoretical debate, then, the analysis will be able to do no more than tentatively look for consistency between alternative hypotheses and the limited data.

My data set consists of fifty-five economic time series (see table 8.1) as well as Levy's war data to be discussed below. The general type of data is annual time series for different economic variables. The time period of interest is 1495 to 1975. However, only one economic time series comes close to covering the entire 481-year period (South English consumer price index). Most of the time series are about 100–200 years long. Thus the five-century period is covered through an overlap of different series in different periods.

The fifty-five time series comprise six *classes* of variables:

1.	Prices	28 series
2.	Production	10 series
3.	Innovation and invention	9 series
4.	Capital investment	2 series
5.	Trade	4 series
6.	Real wages[22]	2 series

To my knowledge, no comparable compilation of economic time series for Europe and the United States covering the past five centuries exists. The series have been rescaled and converted to a standard format,[23] as described in Appendix A, and are listed in Appendix B.[24]

The sources of historical economic time series data are varied and fragmentary. The fifty-five economic time series used in this study have been drawn from twenty-seven sources. Only a few of these sources compile series from different countries (Mitchell 1980; Maddison 1982). More often, an economic historian has reconstructed a time series for a particular commodity and in some cases has compiled a set of such series for a particular country (for example, Beveridge 1939; Jörberg 1972; Maddalena 1974). Some economic historians have gone on to construct indexes of

22. I had no time series data on class struggle.

23. The original data series are given in a wide variety of units, ranging from arbitrarily scaled indexes to units of national currency or of physical volume. The particular units in the original source are of no interest in analyzing the dynamic patterns of ups and downs in the series—provided one remains consistent about measurement concepts. Specifically, all the price series are expressed in current terms in the national currency (unless already converted to price indexes in the original form). All production, trade, innovation, investment, and wage series are expressed in "real" terms, i.e., in "constant prices," so changes in those series do not reflect changes in prices (with one exception, "English exports in current prices"). In most such cases the data have been converted from current prices to constant prices by the original author using some sort of deflator (an index of inflation). In no cases have I converted data to constant prices myself.

24. Appendix A describes the source of each time series, my judgment of its accuracy and consistency, and any special considerations relevant to its interpretation. It also explains what was done to transform each series from its original form to the standardized format as printed in Appendix B.

Table 8.1. List of Economic Time Series

Period	Length (years)	Variable	Source
Price indexes (14 series)			
1495-1954	460	S. English consumer price index	Phelps-Brown [a]
1495-1640	146	S. English industrial price index	Doughty (1975)
1495-1640	146	S. English agricultural price index	Doughty (1975)
1651-1800	150	New Castile textile price index	Hamilton (1947)
1651-1800	150	New Castile animal product prices	Hamilton (1947)
1661-1801	141	English producers' price index	Schumpeter (1938)
1780-1922	143	British commodity prices	Kondratieff [b]
1791-1922	132	U.S. commodity prices	Kondratieff [b]
1750-1975	226	British wholesale price index	Mitchell (1980)
1798-1975	178	French wholesale price index	Mitchell (1980)
1792-1918	127	German wholesale price index	Mitchell (1980)
1801-1975	175	U.S. wholesale price index	Fellner, Census [c]
1822-1913	92	Belgian industrial price index	Loots (1936)
1835-1913	92	Belgian agricultural price index	Loots (1936)
Commodity Prices (14 series)			
1495-1788	294	French wheat prices (Paris)	Baulant (1968)
1531-1786	256	German wheat prices (Cologne)	Ebeling and Irsig. (1976)
1658-1772	115	German bread prices (Cologne)	Ebeling and Irsig. (1976)
1597-1783	187	Amsterdam prices for Prussian rye	Posthumus (1964)
1595-1831	237	English malt prices (Eton College)	Beveridge (1939)
1622-1829	208	English hops prices (Eton College)	Beveridge (1939)
1630-1817	188	English wheat prices (Winchester)	Beveridge (1939)
1653-1830	178	English coal prices (Eton College)	Beveridge (1939)
1694-1800	107	English bread prices (Charterhouse)	Beveridge (1939)
1701-1860	160	Italian wheat prices (Milan)	Maddalena (1974)
1701-1860	160	Italian hard coal prices (Milan)	Maddalena (1974)
1732-1914	183	Swedish wheat prices	Jorberg (1972)
1735-1914	183	Swedish pine wood prices	Jorberg (1972)
1732-1914	183	Swedish iron ore prices	Jorberg (1972)
Production indexes (10 series)			
1740-1850	111	World industrial production (1)	Haustein and Neuwirth [d]
1850-1975	126	World industrial production (2)	Kuczynski (1980)
1850-1975	126	World agricultural production	Kuczynski (1980)
1850-1975	126	World total production	Kuczynski (1980)
1820-1975	156	French real gross national product	Maddison (1982)
1830-1975	146	British real gross national product	Mitchell (1980)
1889-1970	82	U.S. real gross national product	U.S. Census (1975)
1801-1938	138	British industrial production	Mitchell (1980)
1815-1913	99	French industrial production	Crouzet (1970)
1840-1975	135	Belgian industrial production	Vandermotten (1980)
Trade indicators (4 series)			
1506-1650	145	Volume of Seville-Atlantic shipping	Chaunu (1956)
1700-1775	76	British net volume of wheat exports	Minchinton [e]
1700-1775	76	English exports in current prices	Minchinton [f]
1850-1975	126	Total world exports	Kuczynski (1980)
Innovation indicators (5 series)			
1764-1975	212	List of innovations [g]	Haustein/Neuwirth(1982)
1856-1971	116	List of innovations [g]	Van Duijn (1981/83)
1904-1968	65	List of innovations [g]	Clark et al. (1981)
1879-1965	87	List of "product" innovations [g]	Kleinknecht (1981b)
1859-1969	111	List of "improvement" innovations [g]	Kleinknecht (1981b)
Invention indicators (4 series)			
1738-1935	198	Number of British patents	Haustein/Neuwirth(1982)
1790-1975	186	Number of U.S. patents (1)	Haustein/Neuwirth(1982)
1837-1950	114	Number of U.S. patents (2)	Schmookler (1966)
1837-1950	114	U.S. patents in buildings and railroads	Schmookler (1966)
Capital investment (2 series)			
1830-1957	127	U.S. private building volume	Schmookler (1966)
1870-1950	81	U.S. railroad gross capital expenditure	Schmookler (1966)
Real wages (2 series)			
1700-1787	88	Real wages for London	Gilboy (1936)
1736-1954	219	South English real wages	Phelps-Brown [a]

Notes:
a. Phelps-Brown and Hopkins (1956).
b. Kondratieff's index as listed in Van Duijn (1983). Data in Kondratieff ([1928]/1984.)
c. Fellner (1956) until 1889, then U.S. Census (1975; 1983).
d. Haustein and Neuwirth (1982), who cite Hoffmann.
e. Minchinton (1969), who attributes the source as Marshall.
f. Minchinton (1969), who attributes the source as Schumpeter.
g. Time series constructed from a list of innovations (the value for a year is zero or a small integer).

prices or other economic variables for a national economy as a whole (for example, Doughty 1975; Crouzet 1970). I drew two time series on average from each source, and no more than five from any one source.

For prices, twenty-eight series are included—fourteen price indexes and fourteen commodity price series.[25] In the case of commodities, some of the series were drawn from compilations of many commodities for a given national economy, and in such cases (Beveridge, Jörberg, Maddalena, Posthumus) only a few commodities were selected. The few commodities were selected on the basis of their central role in the economy, the quality of data for those particular series, and the availability of the same variable (for example, wheat prices) for different countries. Thus many more price series than are analyzed here are available if one wishes to analyze various commodity series for the same country and time period and from the same source. This was not my intent; rather, I wanted to analyze a variety of series from different sources, time periods, and countries in order to investigate common patterns in them. With regard to nonprice data, my intentions were the same, but in practice the choices were much more limited, and I generally "took what I could get."

In addition to the economic series, my data set includes several war series (severity, intensity, and incidence) as well as non-time-series war indicators (numbers and types of wars aggregated by long wave phases). The best compilation of war data that is consistent across the five centuries under study is Levy's (1983a) study of war in the "modern great power system." Levy's work traces its roots to the approach of Singer and the Correlates of War project mentioned in chapter 5. He takes the conceptual and methodological framework of the project and extends its most central indicators (participants and battle fatalities) back to 1495, instead of just 1815 as in the COW project. All my war series[26] derive from Levy's data, although I have transformed them quantitatively.

A Methodology for Long Waves

In designing an appropriate methodology for a quantitative analysis of long waves, many choices must be made. As I showed in chapter 4, there have been six major methodologies in past empirical research. The first task of this section is to sort through these methodologies and explain why I find phase period analysis to be the best approach. I will then explore the methodological issues in phase period analysis itself.

The methodological problems with each of the methodologies used in the past may be summarized as follows. First, the inappropriateness of *spectral analysis,* and related techniques based on fixed periodicities, has just been discussed. In addition to the problems mentioned, these techniques generally require transforming a time

25. The national indexes are of most interest, and prices of individual commodities of less interest, in the overall assessment of long waves. However, the commodity series are included as supplementary data covering different countries and time periods than are available in price index form.

26. With the exception of one very tangential analysis of Sorokin's war data for the period before 1495.

series to achieve stationarity (no long-term trend), raising the problems of trend deviation discussed below.

Trend deviation has been particularly problematical, due to disagreements over the correct specification of a long-term secular trend in a time series (see Reijnders 1984). Past studies that have claimed to find long waves in this manner have used unduly complicated equations for the trend and have specified the trend differently for each series. This introduces an ad hoc element and weakens the idea of long waves as simple and unified movements of the world economy.

Moving averages, as was noted in chapter 4, can introduce distortions in the cyclical character of the time series, possibly exaggerating and lengthening intermediate-range cycles.

Analysis in terms of *business cycles* also presents problems in terms of how the business cycle is measured or compared with adjacent cycles. To measure from one peak to the next (as in Van Duijn 1980) means using only one data point in each business cycle (throwing away most of the information in the data) and a data point that is probably an ''outlier'' at that (since it is a peak).

Visual inspection relies on qualitative interpretation to describe phase periods and turning points in a time series. By itself, visual inspection is not convincing since it is subjective and may tend towards ad hoc interpretations of historical data.[27]

I find *phase period analysis* the methodology most appropriate to the definition of cycles developed above. Unlike spectral analysis, trend deviation, or moving averages—all of which relate to calendar time—phase period analysis relates to cycle time. The unit of analysis is the historical phase period. This approach identifies long waves by the differences in averages, growth rates, or other attributes of a series in successive phase periods.[28]

Phase period analysis has been used most often by Marxist researchers—perhaps because it corresponds well with Trotsky's conception of long waves, which, as Day (1976:71) says, ''implied a trend broken into discontinuous periods each represented by a distinct line with a different slope.'' But Rostow's (1979) view of long waves as a ''sequence of erratic but quite clear alternating trend periods'' is a parallel statement of the same basic idea from a different theoretical camp.

Past phase period analyses have suffered from two problems. First, the dating of phases has been inadequate; many past studies have dated phases differently in each series (each according to its own unique turning points) rather than with a global dating scheme,[29] and this introduces an ad hoc element. Second, the methods of calculating trends or averages within each phase period have also been problemat-

27. The reader cannot be expected to wade through the source materials used by the analyst in making judgments through visual inspection; thus statistics should be used in order to convey to the reader overall characteristics of the data under study.

28. Statistical techniques may be used to find whether a certain set of series consistently tend toward a higher trend or average on upswing phases than on downswing phases.

29. I have criticized this in chap. 4. Note it is inconsistent with the concept of a system-wide ''cycle time.''

ical, differing from one study to another and often remaining unspecified in published articles. I will now try to resolve both problems.

My approach for dating turning points between phases begins with a single set of dates that applies to the core of the world system—to different countries and different variables. For these dates I use the base dating scheme developed in chapter 4, which comes reasonably close to a consensus of datings drawn from thirty-three long wave scholars.[30] The base dating scheme thus defines cycle time for my long wave analysis.[31]

Estimating Growth Rates

The method of measuring trends within a given phase period is not straightforward. What distinguishes the alternating phases of the long wave? What characteristic of the expansion and stagnation phases should be measured, and how should it be measured to compare the two phases? These are not trivial questions, since different scholars have used different methodologies to measure long wave expansion and stagnation phases and have arrived at different results (see chapter 4). Like most phase period analyses, I stress *growth rates* as the characteristic that distinguishes expansion from stagnation phase periods. The growth rate of prices (inflation rate) and other economic variables is higher in expansion phases and lower or negative in stagnation phases. But how, given the dates of a historical phase period, should the growth rate of the series in that period be estimated?

This turns out to be difficult. As indicated in chapter 4, five Marxist studies using phase period analysis claimed to find long waves in production variables (Mandel 1975; Gordon 1978; Kleinknecht 1981a; Kuczynski 1982; Screpanti 1984).[32] These authors typically report a figure for the "average growth rate" of some variable during a particular set of years but do not fully explain their methodology for measuring the average growth rate during that period.[33]

I will first discuss four methods I chose *not* to use and why each one is problematical. Then I will explain the method I use to estimate growth rates in a phase period.

1. Probably the most common method of measuring an "average growth rate" for

30. For reasons explained in chap. 10, I eventually changed the last turning point in the base dating scheme from 1968 to 1980 to reflect new insights (production peak around 1968, price peak around 1980). The results reported here use the 1980 date for consistency, except where otherwise noted. An earlier set of results using the 1968 date differed little (only one or two phase periods in a few series are affected by the change). In a rare few instances, as noted, I failed to rerun a 1968 result using 1980, and I report the 1968 result instead—but never with any substantive effect.

31. The dates of turning points are explicitly drawn from sources other than the particular data series under analysis. Certainly I could have developed a statistical routine to find the "best" dates to fit a given set of time series. This is much better than dating the ups and downs of *each* series separately. But drawing that dating scheme from the particular set of economic time series analyzed would still introduce an ad hoc element in the analysis. The base dating scheme, on the other hand, is largely independent of the time series I analyze except in the (unresolvable) sense that there is only one history from which both my data and other scholars' datings derive.

32. One other study using a similar methodology found no long waves (Van der Zwan 1980).

33. Although studies of prices generally have not used phase period analysis, similar concerns arise in making a phase period analysis for prices (as I will do below) as for production.

a phase period is to convert the time series to annual growth rates[34] and then average these annual growth rates for all the years in the phase period. The problem here is that the average of the annual growth rates is not necessarily a good indicator of the overall growth of the series during the phase. This is because a percentage growth rate when the series rises is not the same as the percentage (negative) growth rate when it falls again by the same amount. To illustrate this problem, consider a hypothetical series that alternates between 100 and 125 each year, without any trend up or down, over a phase period of twenty years. The series is in fact stationary, but the "average annual growth rate" would be 2.5 percent[35] and would hence be indistinguishable from a series showing steady growth.

2. This problem with annual percentage growth rates can be solved by converting the series to annual *changes* on a fixed scale (not percentages), thus giving equal weight to upward and downward changes. However, in such a methodology the net change during a given historical phase period is by definition equal to the difference between the starting and ending points. This is identical to the following methodology.

3. The growth rate of a phase could be defined by the turning point years alone, as the change (or the percentage change) from the trough to the peak, or vice versa. However, this approach relies on just one data point for each phase, throwing away the rest of the data in the series—data that could provide much richer information about the structure of trends in the data. It is also unduly sensitive to the exact specification of turning points, which have been defined as inexact within a few years in either direction.

4. A methodology that resolves all the problems with the above three approaches uses statistical regression to estimate the slope of the data curve within a phase period. Several past studies have estimated growth rates by logging the data series and then fitting a straight line to the series within a phase period.[36] Van der Zwan (1980:191) argues for this method. Bieshaar and Kleinknecht (1984:282) also use a methodology along these lines. They estimate (through linear regression) the slopes of the log-linear trend curves of national production series within each phase period.[37] They also constrain the trend lines so that they intersect at the turning points, forming a zigzag pattern for the sequence of trend lines.[38]

34. Each year's data point being expressed as a percentage change from the previous year's data point.

35. The growth rate on the up years is 25/100, or 25%, while that on the down years is −25/125, or −20%. The average is 2.5%. Fluctuations of this magnitude are common in many price series, especially in preindustrial commodity prices.

36. Logging the data means that a growth curve is transformed to a linear increase and that the slope of the line should in theory represent the growth rate of the series.

37. The phase periods are "assumed to be known a priori from the literature" (p. 284) are hence predefined in terms of the study. They use Mandel's dates of turning points (p. 286), except that the turning point in 1968 is changed to 1974 (p. 288).

38. The estimation is done through an iterative process to find the best-fitting linear slopes (with logged data) subject to the restraint that values of slope lines in adjacent periods must be equal at the turning point. This constraint I find undesirable because it complicates the estimation and puts too much importance on the particular years chosen as turning points.

While this approach of estimating log-linear slopes comes close to the ideal, I do not find the log transformation necessary or useful, because it assumes an underlying form to the series (exponential growth).[39] This may not be the best model of underlying change, particularly in stagnation phases and particularly for price series. I prefer to avoid making such assumptions about the underlying trend or form of the series, if possible.

My solution, then, is to estimate the linear slope of the (unlogged) data within each phase period and then standardize that slope to the mean of the series in that phase period, giving a number equivalent to a growth rate.

The growth estimation procedure is as follows: Starting with the historically defined phase periods given by the base dating scheme, each phase period is treated as a separate segment ten to forty years long.[40] For each of these segments the best-fitting slope is estimated by linear regression.[41] No attention is paid to inferential indicators of how well the slope line fits the data (R squared) but only to the descriptive indicator (the slope itself). I converted these slopes (expressed in term of whatever units the series is in) to growth rates by dividing each slope by the mean of the series during that period.[42] A series whose slope line increases two units per year at a mean level of one hundred units has an estimated growth rate of 2 percent during the period.

This method for estimating growth rates allows trends during phase periods to be compared from one phase period to another and from one variable to another. It is not overly sensitive to the particular dating of turning points, since the moving of the turning point by a year weights the regression by the addition or deletion of only one data point. The trend line is not forced to intersect the data point for any particular year. The methodology makes fullest use of all the data points in the time series and does not require any rigid assumptions about the structure of the underlying long-term secular trend.

This methodology is compatible with a variety of theoretical models of the underlying form of long waves, since all have in common a difference in slope between adjacent phase periods. Figure 8.1 illustrates five different conceptions of the underlying model of long waves: (1) a stationary series of up and down phases (of unequal length), (2) a rising secular trend with alternate rising and stagnating phases,

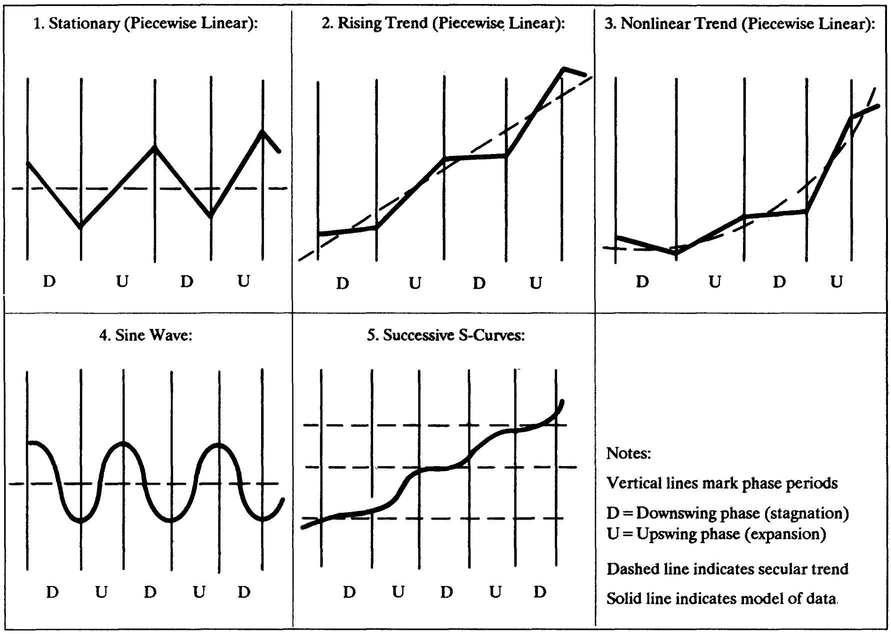
39. As chapter 4 showed, such assumptions can be controversial.

40. If the beginning or end of the time series falls within a particular phase period, then that segment will consist of a shorter series covering only part of the phase period. I ran a set of analyses in which phase periods containing data for less than half the years were first included and then excluded, and the results showed no substantial differences. The results I report are those in which all periods are included for which the time series is at least five years long. Note also that in those few series extending to 1980 the year 1980 was included erroneously in the last phase period (as though 1981 were the peak). The effect was negligible.

41. The ordinary-least-squares regression procedure was used. The slope of the best-fitting line (i.e., the coefficient estimated by the regression, with no restraint on the intercept) represents the best estimate of the series trend during the phase period, expressed in terms of the units in which the series is measured.

42. A slope of 2 when the mean of a series is 100 will be equivalent to a slope of 20 when the mean is 1000.

Figure 8.1. Phase Periods in Five Long Wave Models



(3) a long wave defined around a more complicated secular trend (exponential, S curve,[43] and so forth, (4) a long wave defined as a sine wave (with time-invariant periodicity), and (5) a long wave defined as successive S curves of growth. These models all have in common that the growth rates between turning points (defined by mean-standardized slopes) are higher during upswing than downswing phases. Thus my methodology works under a variety of theoretical specfications, not just for one model.

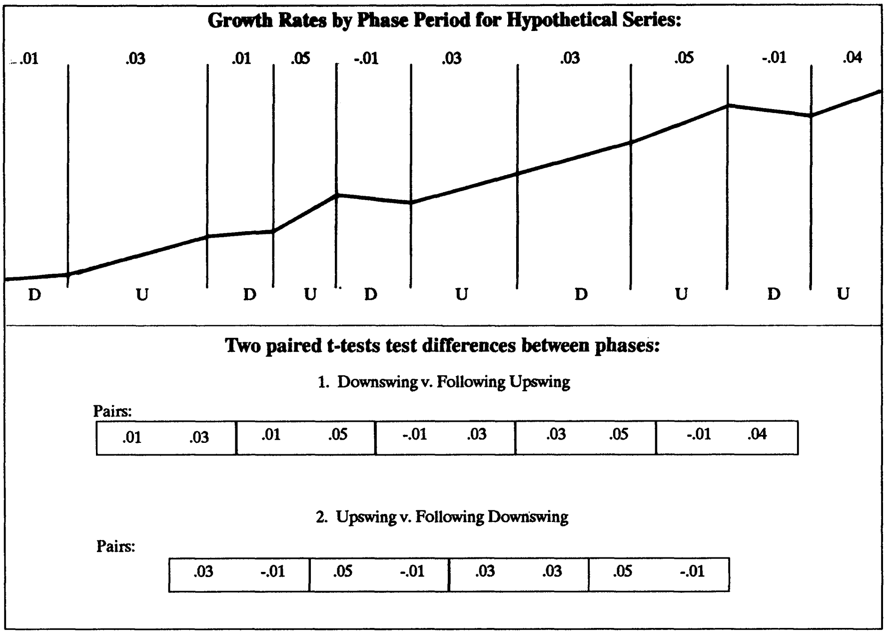
Testing for Differences in Alternate Phases

These methods allow us to compare, for a single series, the growth rates in successive phase periods (in order to look for an alternating pattern). However, since the data set includes hundreds of phase periods, it is also useful to summarize the growth rates on upswing and downswing phases for an entire class of series at once. This requires a statistical method to summarize both the overall difference in slopes between the upswing and downswing periods and the likelihood that such a difference would result from random differences in growth rates in different phases.

The appropriate statistical tool for this purpose is the *paired t-test.* A t-test looks

43. Van Duijn (1980:224) suggests that long waves be conceived as fluctuations around long-term S curves.

Figure 8.2. Paired T-tests



for a statistically significant difference in the means of two groups of numbers. The groups in this case are the growth rates on upswing and downswing phases for a class of series. Since successive phases of a system cannot be assumed to be independent of each other (a requirement of the ordinary t-test), I use a paired t-test in which data points from the two groups are paired with each other.[44]

As shown in figure 8.2, this requires two paired t-tests—one pairing each downswing against the following upswing, and one pairing each upswing against the following downswing.[45] I use these tests for each class of variables and (for prices where data permit) for different time periods within the five centuries under study.[46]

44. This is the appropriate methodology for a before-and-after analysis—in this case the growth rate before and after a turning point is passed.

45. Sometimes there are more pairs in the down/up test (the first one in figure 8.2) than in the up/down test, or vice versa, and generally the test with more pairs (more degrees of freedom) shows stronger results (chaps. 9 and 10).

46. When the direction of the difference in means is hypothesized ahead of time, a one-tailed t-test is appropriate rather than the more common two-tailed test, which simply indicates a significant difference in means in either direction. This applies to prices, production, and capital investment (all presumed to increase on the upswing) but not to innovation, wages, or trade, where both directions of correlation were hypothesized by different scholars (chap. 7). For these latter variables I have used two-tailed probabilities (the two-tailed probability of error is twice that of the one-tailed distribution). In actual practice I was able to perform t-tests only on prices, production, innovation, and wages. The first two of these were one-tailed and the last two were two-tailed.

Identifying Lagged Correlations

The approach just outlined disaggregates the long wave into only two phases per cycle and tests whether actual data series do in fact follow the trends defined by the dating of those phases. However, there are two major reasons for trying to examine the timing of the long wave in more detail than just the two phases.

First is simply that some hypotheses specify more exact timing than can be tested using a two-phase framework alone. For example, to distinguish between the following two hypotheses requires resolution down to a period of one-fourth of a cycle:

Innovations cluster late in the downswing. [A]
(Gordon, Schumpeter)

Innovations cluster early in the upswing. [A]
(Kondratieff, Mandel, Freeman et al.)

And the following hypothesis could require even greater resolution:

Production increases precede price increases. [A]
(Imbert)

The second reason for looking more closely at the timing within long waves is that variables defined differently may appear to lead or to lag each other, obscuring their correlation with the long wave. Figure 8.3 illustrates two definitions, which have not been closely distinguished in past long wave research. The first, which I generally follow, defines a long wave upswing phase as a period of increased *growth* in the series, lasting from a trough until a subsequent peak. The second model defines an upswing phase as a period of higher *levels* in the series, or a *cluster* of discrete events.[47]

As figure 8.3 indicates, this difference in definition has the effect that for a single series the phases defined in terms of growth rates *lead* the phases defined in terms of levels by about one-fourth of a cycle (half a phase).[48] This principle can be understood intuitively since there is a lag after a rate change before levels "catch up."

The effect of this lag on the phase period analysis is potentially serious, since using the "wrong" definition[49] will shift the correlation by about one-fourth of a cycle. This shift could "wash out" any correlation with the long wave phases (since each

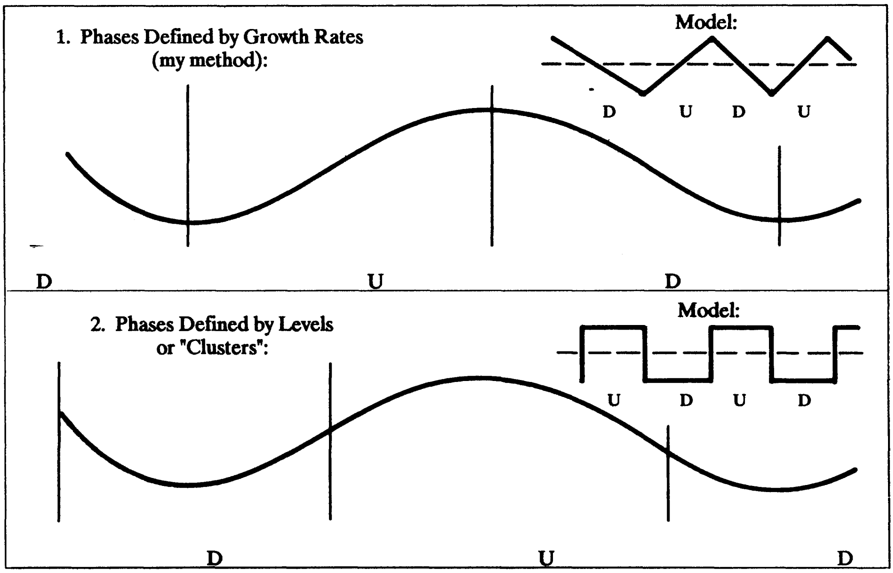
47. The first definition has often been used for continuous variables like prices and production, while the second has been used for correlating discrete events, such as innovations and wars, with the long wave. A statement such as "more innovations (wars) occur during the downswing (or upswing) phase" is based on the second model of levels rather than growth rates. But the distinctions can be unclear even for price or production series when, for example, the series has been "detrended." The hypothesis that the curve is above the trend line during upswings reflects the second model (levels, not rates).

48. This is a deductive conclusion and not drawn from actual data, although it can be found in the data as well.

49. That is, using levels when rates are actually correlated with the historical phases, or vice versa.

Figure 8.3. Phases Defined by Rates v. Levels

Two ways to date schematic curve are shown:
First based on phases defined by growth rates, then on phases defined by levels.



Note that the phase periods in #1 lead those in #2 by 1/4 cycle.

phase will have data drawn half from an upswing, half from a downswing). Only by looking at more detailed timing relationships, not just two phases, can such correlations be recovered. This was a second reason to disaggregate the timing beyond just two phases.

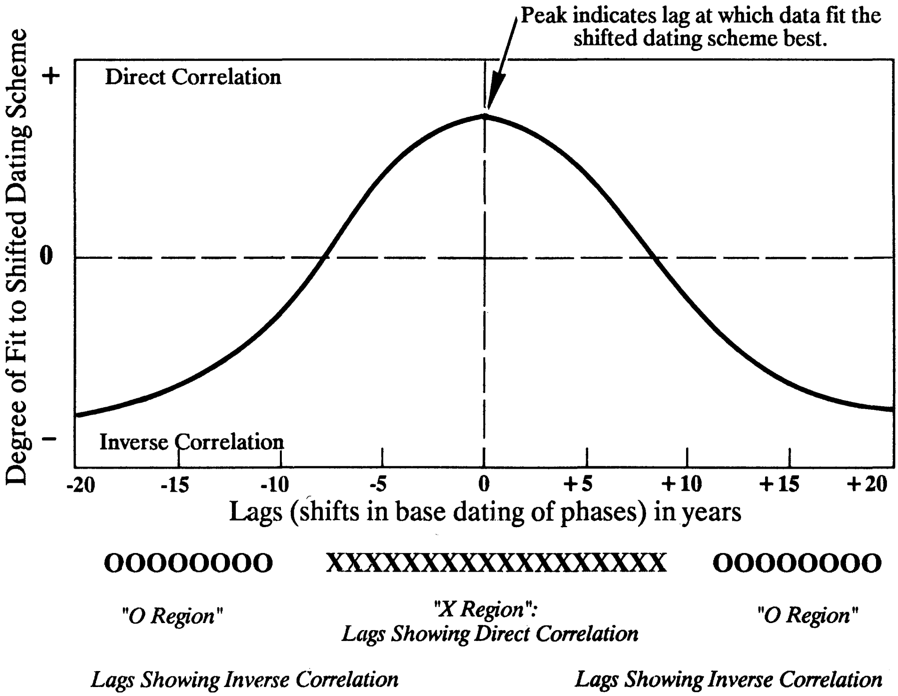
To this end, I developed a methodology to identify *lagged correlations* of a series with the base dating scheme. To identify lagged correlations within cycle time, I developed a descriptive statistic that I call the "lag structure" of a time series. Figure 8.4 is a schematic diagram of a lag structure. The lag structure is a curve showing how well the data series fits the upswing and downswing phases as a function of shifting the base dating scheme backward and forward a year at a time.[50] The goodness of fit indicator derives from the difference between growth rates on the upswing phases and those on the downswing phases for the series.[51] This approach

50. The horizontal axis goes from −20 to +20 years of shift in the dating scheme; the vertical axis represents the goodness of fit (of the data to the shifted dating).

51. In calculating the fit to the dating scheme, I used a method similar to that of the t-tests described above (with only one series there are not enough cases to do the t-test for the growth rates for each lag). For each lagged dating scheme, the average change in growth rate at peaks and the change at troughs are calculated, as is the difference between these. If indeed growth rates are higher on upswings than on downswings, then the mean change at peaks will be negative and at troughs positive. The difference will be positive, and that difference is the indicator of the fit of a series to a particular dating scheme. As the dating scheme is shifted through time, this indicator should be maximum at the time lag that "best fits" the data.

Figure 8.4. Schematic Lag Structure

(Example shown is for a series unlagged, directly correlated to base dating.)



thus examines small shifts in calendar time (years) within each phase, while remaining in cycle time (base dating scheme phases) overall.[52]

For each variable's lag structure (see fig. 8.4) several points or regions on the horizontal axis are labeled. First is the maximum point, the lag for which data fit dating scheme best. Second, I identify with an "X" the lags for which a minimal fit to the dating scheme is found.[53] A set of such minimally fitting lags I call the "X region" of the lag structure. Conversely, the lags for which a minimal inverse correlation is found are called the "O region," and the minimum point of the lag structure indicates the best fit for an inverse correlation.[54]

52. This is an adequate but not ideal solution, since shifts of up to 20 years in either direction may or may not bring one into the next phase. But since the data are annual I cannot break down each phase into cycle-time subunits such as 1/10-phase (about 2.5 years, but variable). Therefore I live with calendar time as the secondary units within cycle time, and I find this works reasonably well within 10–15 years of each turning point.

53. The difference between growth rates on downswings and those on subsequent upswings is positive; between rates on upswings and subsequent downswings, negative.

54. Because of the nonsynchrony of cycle time and calendar time, as noted above, the maximum/minimum points and the "X" and "O" regions are more reliable close to zero lags and less so near the left or right edge (−20 lags or +20 lags).

These time shifts also indicate the sensitivity of the long wave to turning points. If small shifts in the dating scheme (along the horizontal axis) cause sudden changes in how well the data fit the periods (along the vertical axis), then the fit is too sensitive to the particular turning points chosen and not *robust* (the word I will use for this particular kind of time stability).[55]

The purpose of the lag structures is to identify possible lagged correlations with the base dating scheme in different series. As a final step, in cases where a class of variables seems to follow a certain lagged correlation, I then return to the paired t-test to find out whether the class as a whole does in fact correlate well with a lagged dating scheme. I calculate the growth rates by phases for all the series in the class, using an appropriately lagged dating scheme,[56] then use t-tests as above (and compare these results to the earlier t-tests). The interpretation of probability levels in these lagged t-tests is problematical, since I choose the "best" lags for the test;[57] therefore these t-tests are weak. They are included both to facilitate comparison between unlagged and lagged results for a class of variable and to support the adduction of the most plausible theory based on lagged correlations.[58]

Methodologies for War Data Analysis

In the analysis of war data in chapter 11, all of the above methodologies will be brought into play. However, because of the different nature of these data (originally given as discrete events in time, converted to time series by me), I have also drawn on a variety of other methodologies. I will reserve explanation of these methodologies for chapter 11, but in summary there are four additional approaches used. The third and fourth methodologies listed pertain to short-term relationships among variables, not to long cycles per se.

First, since wars may be seen as discrete events rather than a continuous flux in a system, I supplement the analysis of growth rates in phase periods by looking at *levels* (counting events) in each phase period.[59] A variety of war indicators are

55. In the base dating scheme, the dates of turning points were said to be approximate within a few years in either direction. Thus it is important that the statistical analysis not be too sensitive to the particular dating of turning points. In addition to the use of lag structures, the basic method using best-fitting slopes within each period (unconstrained by data in adjacent periods) minimizes sensitivity to turning points.

56. As suggested by the "best" lags in individual series in the class. Only lags at 5-year intervals (5, 10, 15, etc.) were experimented with—I felt that the data would not support a more exact specifications of lags than this and wanted to minimize the ad hoc nature of looking around for particular lags that might happen to fit better than others.

57. This increases the probability that a random difference in upswing and downswing growth rates will be interpreted as a lagged long wave correlation. In practice, the problem is not as serious as it might appear, since in most cases the lag structure is fairly "robust" and the "X" region of adequate fit to a long wave pattern covers ⅓ to ½ of the 41 lags. Also, I do not select the best lag for each series but a 5-year-interval lag for an entire class of series together.

58. They are not, to repeat, a test against the null hypothesis in the usual sense. The lag structure is intended as a descriptive statistic; it "uses up degrees of freedom" and thus weakens statistical confidence.

59. The same, incidentally, is done for innovations, which are also given as discrete units (see chapter 10).

tabulated for each phase period, allowing a comparison of war levels in upswing versus downswing phases. This allows such hypotheses as "more wars occur on upswings" to be tested.

Second, in the course of reinterpreting the findings of Levy (1983a), who followed the COW approach methodologically, I use a technique based on periodicity (Auto-Correlation Functions) to look at war cycles defined in calendar time. The results provide new insights into the research on war periodicity.

Third, in order to identify connections between war and price data over rather short periods (a few years), I use visual inspection of graphs showing annual fluctuations in war and price series over long time periods. Some of these graphs are reproduced in chapter 11.

Fourth, for the same purpose of identifying war-price connections, I use a methodology called Granger Causality, which aims to identify the effect of one time series on another. Although somewhat flawed for this purpose,[60] it nonetheless provides corroborating evidence for the relationships identified through visual inspection.

In the next three chapters, I will take up long waves in prices, in real economic variables,[61] and in war, respectively.[62]

60. The long-term autocorrelation in the war series as I have constructed it goes against assumptions of the model.

61. A "real" variable is one defined in terms of physical volumes, not monetary values, and hence does not reflect price movements.

62. Statistical packages used in this study include the following: (1) on the MIT IBM VM/SP mainframe, TROLL ARIMA (for ACFs) and TROLL graphing routines (for war graphs); (2) on the Sloan School of Management PRIME computer, NAG Fortran library (for growth rates by phase period), SPSSX (for paired t-tests), and SHAZAM (for Granger causality analysis).