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CLASSIFICATION OF ECONOMIC INDICATORS: AN ALTERNATIVE APPROACH

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For the post World War II period, 68 NBER indicators are classified using methods of numerical taxonomy, a technique which simultaneously utilizes all turning point timing information. A set of hierarchical groups of indicators, identified at various levels of similarity, is formed, which corresponds closely to the NBER classification of leading, roughly coincident, and lagging. Our findings show that several indicators ought to be unclassified, since their timing characteristics are not sufficiently close to established groups. Furthermore, our results indicate that there has been some change in the timing behavior of certain (NBER) lagging indicators during the post World War II period.

I. INTRODUCTION

The selection and classification of a set of indicators which reflect the level of aggregate economic activity has been a major interest of business cycle analysts. The major work in this area was done at the National Bureau of Economic Research (NBER) by Mitchell (1927), Burns and Mitchell (1938), Moore (1950; 1961), and Shiskin and Moore (1967).[1] As a result of these studies, the NBER has compiled a list of major economic indicators and classified them with respect to their timing by comparing specific cycle turning points and movements with those in the general level of business activity (the reference cycle).[2] The result has been a classification of major economic indicators into categories of leading, roughly coincident, and lagging.[3]

In the NBER studies, the method of classification of indicators was based upon the median of the pre- and post-World War II turning point timing differences between the indicator and the reference cycle, subjectively taking into consideration the number of leads, lags, and coincidences. In contrast, we shall classify economic indicators using a method which simultaneously and objectively utilizes all the timing information of all post-World War II cycles. We use the multivariate technique of numerical taxonomy to develop a classification scheme which is based on the set of differences in timing between the indicator turning points and those of

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[1] Shiskin and Moore "grade" 122 U.S. indicators with respect to the following criteria: economic significance, statistical adequacy, conformity, timing, smoothness, and currency.

[2] The method of selecting reference cycle turning points is described in Mitchell and Burns (1938). Briefly, the turning points of all (seasonally adjusted) cyclical indicators are selected. From this scatter of dates, the center around which the months "cluster" is approximated. Then, the dates of the turns in the individual series are compared with the tentative business cycle turn selected. This tentative date is then revised on the basis of the results of the individual indicator dates.

[3] The timing is considered roughly coincident if the turning point occurs within three months of the reference cycle turn. If the indicator leads the reference cycle by more than three months, it is considered leading; if the turn occurs more than three months after the reference cycle turn, the indicator is considered lagging.

the reference cycle. So that we may compare our classification scheme with that of the NBER, we classify those indicators which Shiskin and Moore (1967) have identified as being "important and reliable." In section II, a brief description of the multivariate technique of numerical taxonomy which provides the framework for our classification analysis is presented. In section III, the data are discussed, our results are analyzed, and a comparison is made of this study's classification of indicators with that of the NBER. In the final section, we offer some summary comments and conclusions.

II. Preliminaries

In this study the methods of numerical taxonomy will be used to classify economic indicators into various groups. The multivariate methods of numerical taxonomy were developed in the 1950's and 1960's, primarily by biologists, for the purpose of object classification.[4] Since a comprehensive treatment of the development, methods, and applications of numerical taxonomy can be found in Sneath and Sokal (1973), Rohlf (1970), or Cormack (1971), only the most important aspects of this approach will be presented here.

The general taxonomy or classification problem may be described in the following way. Given a set of objects or individuals, called Operational Taxonomic Units (OTU's), which are known only by a list of properties or attributes, we attempt to find the "best" way of describing their complex patterns of mutual similarities (phenetic relationships).

In this paper, each of the major economic indicators is considered as an OTU. The differences in timing (measured in months) between the peak (or trough) in the indicator and the peak (or trough) in economic activity (measured by the NBER's reference cycle turning point for post World War II period)[5] is taken as the set of character states for each of the indicator series (OTU's).[6]

The classification process may be described as follows. First, data are gathered on (say) m character states (attributes) for n individuais (OTU's). The result is an $n \times m$ matrix of character state evaluations for the OTU's. Next, an $n \times n$ symmetric matrix of similarity coefficients is computed which measures the relative degree of similarity between all pairs of OTU's. The measure of similarity[7] (here, actually a measure of dissimilarity, since a low value indicates a high degree of similarity) between two OTU's, (say) X_j and X_k, used in this study is the Euclidean distance measure

$$\Delta_{jk} = \left[\sum_{i=1}^{m} (X_{ij} - X_{ik})^2 \right]^{1/2},$$

[4] For applications of numerical taxonomy to problems of aggregation and classification in economics, see Fisher (1969) and Goronzy (1969).

[5] There were five cycles during this period. This means that five troughs and five peaks have been observed. Thus, there have been a total of ten turning points.

[6] The measurements (timing differences) for each character state are relative to the given set of NBER reference cycle turning point dates. If the reference dates were different, then the character state measurements would be different and would be based upon timing differences from the given reference dates.

[7] Various measures of similarity (or dissimilarity) which are often used belong to one of the following classes: distance measures, association or matching coefficients, correlation coefficients, or probabilistic similarity coefficients.

where m is the number of character states. Where there were missing data, no measure is computed. The taxonomic measure utilized here has the following heuristic interpretation: Points in the character space (i.e., OTU's) are considered similar, if they are close to each other in terms of Euclidean distance. The matrix of dissimilarity coefficients has $n(n-1)/2$ distinct elements, which is large for large n, so some summary of the information on the similarity relationships among OTU's is usually desired.

In this paper, we apply clustering methods to the dissimilarity matrix to group OTU's into classes.[8] The groups which are formed depend upon the clustering algorithm employed. The most frequently used clustering techniques in classification analysis belong to the class of sequential, agglomerative, hierarchical, non-overlapping (SAHN) clustering techniques.[9] A SAHN clustering of the symmetric dissimilarity matrix was performed by the method of unweighted pair-group arithmetic averages (UPGMA) to summarize the phenetic relationships between the economic indicators (OTU's). This clustering algorithm compares the dissimilarity (distance) between an indicator and the average (equally weighted) dissimilarity of an existing cluster of indicators and then joins the indicator to the cluster to which it is most similar (cf., Sneath and Sokal (1973), p. 230 ff.). The resulting (hierarchical) clusters reveal which series are most similar, at given distances, according to the evaluated character states. It is possible to diagram the results of this cluster analysis in the form of a tree-like structure called a phenogram which represents similarity levels at which OTU's (or groups of OTU's) join to form a new group.

The statistical reliability of a phenogram is not known; however, a measure of its effectiveness, the cophenetic correlation coefficient, has been proposed by Sokal and Rohlf (1962). The cophenetic correlation coefficient,[10] which can take

[8] Other summary methods (e.g., multidimensional scaling (ordination) and network analysis) may be applied to the similarity matrix to simplify the phenetic relationships. As a complement to the clustering methods mentioned above, a non-metric multidimensional scaling analysis was performed on the symmetric similarity matrix. The results of this analysis are presented in Broder (1974) and are available from the authors upon request.

[9] A sequential clustering process forms clusters in a regular step-wise manner rather than simultaneously. Agglomerative clustering procedures begin with pairs of similar OTU's and build up clusters in contrast to divisive methods which begin with the entire set of OTU's and partition it into subsets. Hierarchical cluster methods result in nested clusters, i.e., the OTU's are partially ordered. Nonoverlapping clusters are disjoint at any given similarity level. Examples of some common SAHN clustering techniques are single-linkage, complete-linkage, weighted and unweighted pair-group methods (cf., Sneath and Sokal (1973), p. 214 ff.).

[10] The formula for the cophenetic correlation coefficient is

$$\frac{\sum_i \sum_j (\Delta_{ij} - \bar{\Delta}_j)(c_{ij} - \bar{c}_j)}{\sqrt{\sum_i \sum_j (\Delta_{ij} - \bar{\Delta}_j)^2} \cdot \sqrt{\sum \sum (c_{ij} - \bar{c}_j)^2}}$$

where

Δ_{ij} is the (original) similarity between OTU's i and j,

$\bar{\Delta}_j$ is the average similarity between OTU j and all others,

c_{ij} is the cophenetic value, the maximal similarity between OTU's i and j implied by the phenogram. This value may be obtained from the furcation in the phenogram linking the OTU's.

$\bar{c}_j$ is the average cophenetic value between OTU j and all others.

a value between zero and one, measures the degree of fit (or lack of distortion) of the phenogram in summarizing the phenetic relationships among the OTU's in the original similarity matrix.[11]

III. Data and Results

The indicators which are examined in this study are a subset of the 88 indicators which Shiskin and Moore (1967) have identified as "high quality" indicators of economic activity. In this study, their unclassified series are not used, since we only want to examine NBER classified indicators. Indicators which are no longer being reported are also excluded. Thus, 68 "high quality" indicators are evaluated and classified in this paper. All data for the historical series were obtained from various issues of *Business Conditions Digest*. Given the selection of economic indicators (OTU's), it was necessary to determine the difference in timing between indicator turns and reference cycle turns, i.e., evaluate the character states for each OTU. The chronology of turns in general economic activity, the reference cycle, is determined by the NBER, but is constantly undergoing revision. Consequently, the latest available revised reference cycle turning point dates were used and are presented in Table 1.

For each indicator series, the date of each peak (or trough) corresponding to the one in the reference cycle was identified.[12] The difference in timing was calculated in months. In the eleven cases where the series are reported quarterly (cf., Table 2), it was assumed that the turning point occurred in the middle month of the quarter.

TABLE 1

Dates of Reference Cycle Turning Points

Peaks		Troughs	
October	1948	October	1949
June	1953	August	1954
August	1957	April	1958
April	1960	February	1961
November	1969	November	1970

Source: Mintz (1972), p. 64; U.S. Department of Commerce, *BCD* (June 1973), p. 115.

[11] In this paper we present a *classification* of indicators in contrast to an *identification* [cf. Cormack (1971), 321, and Sneath and Sokal (1973), 383]. A *classification* allocates indicators to initially undefined classes or groups which are formed so that the indicators in a group are similar in some sense to one another. On the other hand, an *identification* would allot an unclassified indicator to one of a number of defined classes, i.e., existent groups of indicators. The methods of discriminant analysis would be appropriate for identification procedures. In this case one could evaluate the statistical reliability of the identification process.

[12] Turning points are given in the *Business Conditions Digest* (June 1973) for all indicators on the NBER short list. The remaining turning points were determined by the authors. In some cases, there was no turning point for a particular indicator which corresponded to a turning point in the reference cycle. In such cases, *NC*(no cycle) is reported.

To classify the 68 indicators into a set of homogenous groups on the basis of the ten post-war turning point timing differences from the reference cycle, the Taxon program of the NT-STS System of Multivariate Computer Programs, developed by Rohlf, Kishpaugh and Kirk (1972), was used.

From the data matrix of timing differences for the 68 indicators (OTU's), a symmetric 68×68 dissimilarity matrix was computed, using Euclidean distance as a measure of dissimilarity. The phenogram for the (UPGMA) clustering of the dissimilarity matrix of the 68 indicators listed in Table 2 is presented in Figure 1.[13] The cophenetic correlation coefficient is 0.705. This indicates a moderate correlation between the original distances and the distances implied by the phenogram.[14] For the purposes of naming and describing the branches of the phenogram, an appropriate distance level at which major groups are formed must be determined. In general, the clustering methods which we used more faithfully preserve the original phenetic relationships at lower distances (cophenetic values, cf. footnote 8) than at higher distances. By inspection a scatter plot of original distances against distances implied by the phenogram (cophenetic values), it was decided to choose the phenogram cut-off level of 24.0. This level was selected because at higher distance levels, the spread of points increases dramatically. This indicates that the amount and pattern of distortion introduced by the clustering method was greater at higher levels of dissimilarity, hence the cluster analysis ought to present a more reliable description of the phenetic relationships between indicators at levels below 24.0. Using this 24.0 level, ten groups were formed and labeled: U_{Lg}(1 member), Lg(4 members), C(26 members), L_0(21 members), U_{L0}(3 members), U_{L1}(1 member), L_1(9 members), U_{L2}(1 member), U_{L3}(1 member), and U_{L4}(1 member).[15]

[13] Two alternative SAHN clustering methods using Euclidean distance were also applied: single-linkage (SINGLE) and unweighted pair-group centroid method (UPGMC). These methods are discussed in detail in Sneath and Sokal (1973), p. 216 ff. Briefly, in the single-linkage (nearest neighbor) cluster method, an OTU which is a candidate for an existent cluster has similarity to that cluster equal to its similarity to the closest member within the cluster. Thus clusters are formed by single-links between OTU's and tend to be long and straggly (in contrast to the compact clusters formed under UPGMA and UPGMC methods). The cophenetic correlation between the original OTU distances and the cophenetic values under SINGLE was 0.592, showing that SINGLE introduces great distortion in summarizing the phenetic relationships. In the UPGMC cluster method, an OTU which is a candidate for an existent cluster has similarity to that cluster equal to the similarity between the OTU and the centroid of the cluster. While geometrically pleasing, the resulting phenogram may show reversals, i.e., the cophenetic values within a cluster are not monotonic. The cophenetic correlation between the original OTU distances and the cophenetic values under UPGMC was 0.770. The correlation between the cophenetic values under UPGMA and UPGMC was 0.862, which is indicative of the similar phenetic relationships implied by the two methods.

[14] The above analysis was also performed on differences in timing at peaks and differences in timing at troughs. Classifications based on these sets of data were made to determine whether there were any differences in behavior at peaks and troughs. We found that the classification based on peaks only was nearly identical with that based on all turns (i.e., peaks and troughs), while that based on troughs only was substantially different from that based on all turns. Our results tend to confirm Moore's (1964) observation that there is a difference in the performance of many indicator classifications when troughs in the business cycle occur in contrast to when peaks occur. These results are reported in Broder (1974). In addition, an analysis was performed on the NBER's "short list" of indicators to determine whether there are differences in classification between the short list and the longer list of indicators (OTU's), which there appears not to be. The results of these studies are available from the authors upon request.

[15] The 24.0 cut-off level is judgmental and is based on the scatter plot discussed in the text. If a different distance level had been used (say 20.0), a different number of groups would have resulted (18).

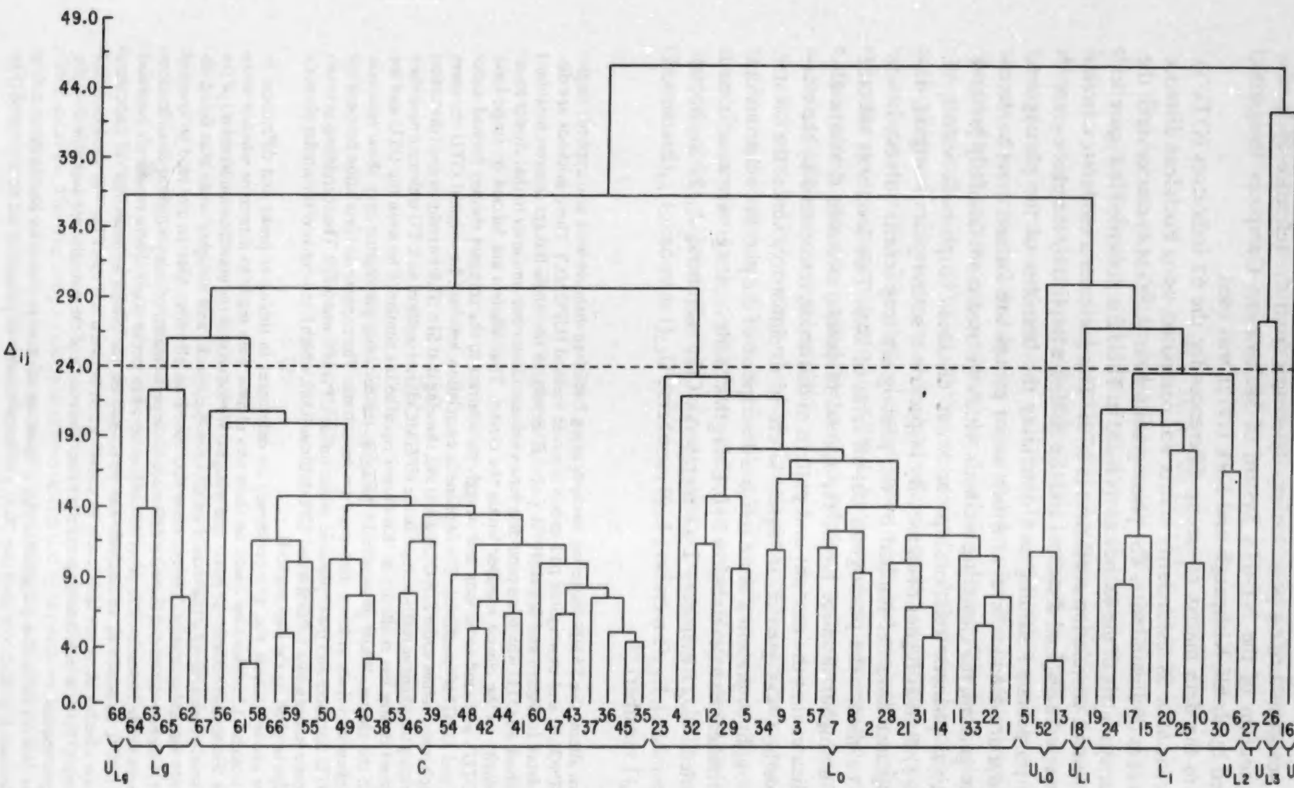

Figure 1. Phenogram based on an unweighted pair group method of cluster analysis using arithmetic averages (UPGMA) for economic indicator data described in text. The similarity scale (Euclidean distance) is shown on the abscissa. Numbers at the tips of the phenogram represent indicator names and can be found in Table 2. The names at the right of the indicators' numbers indicate the subclass based on timing differences from the reference cycle at all post WW II turns. The cophenetic correlation coefficient for this phenogram is 0.705.

TABLE 2
CLASSIFICATION OF ECONOMIC INDICATOR

Code Number	Indicator	NBER Clas-sification	New Clas-sification	Median Timing Difference
1	Average Workweek, Prod. Workers, Mfg.	L	L_0	−5.0
2	Accession Rate	L	L_0	−4.5
3	Initial Claims, Unemployment Ins. (Inv.)	L	L_0	−5.0
4	Layoff Rate (Inv.)	L	L_0	−5.0
5	Index of Net Business Formation	L	L_0	−7.0
6	New Business Incorporation	L	L_1	−9.5
7	New Orders, Durable Goods Industries	L	L_0	−3.5
8	Contracts and Orders, Plant and Equipment	L	L_0	−5.5
9	New Capital Appropriations, Mfg., Q	L	L_0	−4.0
10	New Orders, Machinery and Equipment Industries	L	L_1	−5.5
11	Construction Contracts, Comm. and Indus. Floor	L	L_0	−5.0
12	New Building Permits, Private Housing Starts	L	L_0	−9.5
13	Change in Business Inventories, All Indus., Q	L	U_{L0}	−2.0
14	Change in Book Value, Mfg. and Trade Inventories	L	L_0	−4.5
15	Purchased Mater., % Reptg. Higher Inventories	L	L_1	−5.0
16	Change in Book Value, Mfg. Inventories of Materials and Supplies	L	U_{L4}	−9.0
17	Buying Policy, Mater. % Reporting Commitment 60+ days	L	L_1	−5.0
18	Vendor Performance, % Reporting Slower Delivery	L	U_{L1}	−7.0
19	Change in Unfilled Orders	L	L_1	−12.5
20	Industrial Material Prices	L	L_1	−4.5
21	Stock Prices	L	L_0	−5.0
22	Corporate Prices, After Taxes, Q	L	L_0	−5.0
23	Ratio, Profits to Income Orig., Corp., All Indus. Q	L	L_0	−7.0
24	Profits per $ Sales, Corp., Mfg., Q	L	L_1	−2.0
25	Ratio, Price to Unit Labor Cost, Mfg.	L	L_1	−5.5
26	Change in Money Supply and Time Deposits	L	U_{L3}	−18.5
27	Change in Money Supply	L	U_{L2}	−15.5
28	Total Private Borrowing	L	L_0	−8.0
29	Change in Consumer Installment Debt	L	L_0	−6.0
30	Change in Bank Loans to Businesses	L	L_1	−5.0
31	Change in Mortgage Debt	L	L_0	−8.5
32	Liabilities of Business Failures (Inv.)	L	L_0	−9.0
33	Delinquency Rate, Installment Loans (Inv.)	L	L_0	−4.5
34	Help-Wanted Advertising	C	L_0	−1.0
35	Man Hours in Non-Farm Establishments, Employees	C	C	+1.0
36	Employees in Non-Agricultural Establishments	C	C	0.0
37	Total Non-Agricultural Employment	C	C	−2.0
38	Unemployment Rate, Total (Inv.)	C	C	0.0
39	Insured Unemployment Rate (Inv.)	C	C	0.0
40	Unemployment Rate, Married Males, (Inv.)	C	C	−2.0
41	GNP, Expend. Est., Current $, Q	C	C	−0.5
42	GNP, Expend. Est., Constant $, Q	C	C	−1.5
43	Industrial Production	C	C	−1.0
44	Personal Income	C	C	−1.0
45	Labor Income in Mining, Mfg., and Construction	C	C	+0.5
46	Final Sales, Current $, Q	C	C	+0.5
47	Manufacturing and Trade Sales	C	C	−0.5
48	Sales of Retail Stores	C	C	−0.5
49	Manufacturers Unfilled Orders, Durable Goods Industries	C	C	0.0
50	Backlog of Capital Appropriations, Mfg., Q	C	C	0.0
51	Wholesale Prices, Excl. Farm Products & Food	C	U_{L0}	−1.0
52	Wholesale Price Index, Manufacturers Goods	C	U_{L0}	−0.5
53	Treasury Bill Rate	C	C	+2.0

TABLE 2—continued

Code Number	Indicator	NBER Classification	New Classification	Median Timing Difference
54	Corporate Bond Yields	C	C	+0.5
55	Treasury Bond Yields	C	C	+1.0
56	Municipal Bond Yields	C	C	0.0
57	Free Reserves	C	L_0	−6.5
58	Unemployment Rate, Persons Unemployed 15+ Weeks, (Inv.)	Lg	C	+2.5
59	Business Expenditures, New Plant & Equip., Q	Lg	C	+1.0
60	Machinery and Equip., Sales, Bus. Const. Expend.	Lg	C	+0.5
61	Book Value, Mfg. and Trade Inventories	Lg	C	+3.0
62	Book Value, Mfg. Invent., Finished Goods	Lg	Lg	+4.0
63	Labor Cost per $ Real Corp. GNP., Q	Lg	Lg	+8.5
64	Labor Cost per Unit Output, Mfg.	Lg	Lg	+10.0
65	Consumer Installment Debt	Lg	Lg	+4.5
66	Commercial and Industrial Loans Outstanding	Lg	C	+2.0
67	Bank Rates on Short Term Business Loans	Lg	C	+4.5
68	Mortgage Yields, Residential	Lg	U_{Lg}	+3.0

L = Leading
C = Roughly Coincident
Lg = Lagging
U = Unclassified
Q = Quarterly Series
Inv = Inverted Series

The group labels are interpreted as follows. We do not identify or describe any of the U groups, i.e., indicators in the U groups are called "unclassified." These groups each contain only one indicator (except for U_{L0} which has three).[16] The singleton groups each contain indicators which exhibit erratic fluctuations in timing differences at various turning points. However, from the phenogram in Figure 1, one can see the hierarchical relationship between indicators and that the classified and "unclassified" groups of indicators join at higher levels of dissimilarity. The subscripts on the U groups at the 24.0 level are suggestive of this relationship. Thus, the 24.0 level classification contains a total of eight unclassified indicators: Change in Business Inventories, All Industries (No. 13), Change in Book Value, Manufacturer's Inventories of Materials and Supplies (No. 16), Vendor Performance, Percent reporting slower delivery (No. 18), Change in Money Supply and Time Deposits (No. 26), and Change in Money Supply (No. 27), all of which are classified as leading by the NBER; Wholesale Prices, Excl. Farm Products and Foods (No. 51) and Wholesale Price Index (No. 52), which are classified by the NBER as roughly coincident; Mortgage Yields, Residential (No. 68), which is classified by the NBER as lagging.

The remaining 60 series are classified into four groups: Lg, C, L_0, and L_1. We shall now interpret these groups and determine whether they are related in any way to the NBER classification of leading, coincident, and lagging indicators.

[16] The group U_{L0} contains indicators No. 13 (no missing observations), No. 51 (two missing observations), and No. 52 (six missing observations). Due to the number of missing observations, no attempt was made to interpret this group.

For each indicator, the median of the timing differences between the indicator and reference cycle turning points (X_m), is presented in Table 2. In Table 3, we present the range of the median timing differences for each classified group of indicators.

TABLE 3
CLASSIFIED GROUP RANGES OF MEDIAN TIMING DIFFERENCES (AT 24.0 LEVEL)

Group	Range of Median Timing Differences (Months)
Lg	$4.0 \leq X_m \leq 10.0$
C	$-2.0 \leq X_m \leq 4.5$
L_0	$-9.5 \leq X_m \leq -1.0$
L_1	$-12.5 \leq X_m \leq -2.0$

Based on the range of the median for each of these groups, indicators in group Lg can be considered to be "lagging," indicators in group C can be considered to be "roughly coincident," and indicators in groups L_0 and L_1 can be considered to be "leading." It should be noted that we have used the range of a univariate measure, the median, solely to name the classified groups which were formed on the basis of multivariate phenetic relationships between indicators. For example, at the 24.0 level, indicators in groups L_0 and L_1 are considered to be "leading" on the basis of the range of the median timing differences. However, from the phenogram in Figure 1, we see that those indicators in group L_0 are more similar on the basis of multivariate phenetic relationships to those in group C than to those in group L_1 at higher levels of dissimilarity. While the distinction is not sharp, one might say, for naming purposes, that the indicators in group L_0 are "short-leading" and those in group L_1 are "long-leading."

Now we shall determine how the groups obtained by this method of classification compare with those under the NBER's classification. In Table 2, the list of indicators with their median timing difference, NBER classification, and our classification are presented. All indicators classified here as Lg are also classified as lagging by the NBER. Twenty out of twenty-six indicators classified here as C are also classified as roughly coincident by the NBER. Nineteen out of twenty-one classified here as L_0 are also classified as leading by the NBER. All indicators classified here as L_1 are also classified as leading by the NBER. Consequently, 52 of the 60 classified series coincide with the NBER classification. The differences occur for: Unemployment Rate, Persons Unemployed 15+ Weeks, Inv. (No. 58), Business Expenditures, New Plant and Equipment (No. 59), Machinery and Equipment Sales, Bus. Constr. Expend. (No. 60), Book Value, Manufactur. and Trade Inventories (No. 61), Commercial and Industrial Loans Outstanding (No. 66), and Bank Rates on Short Term Business Loans (No. 67), which are all classified as lagging by the NBER, but are classified as roughly coincident here, and Help Wanted Advertising (No. 34) and Free Reserves (No. 57), which are both classified as roughly coincident by the NBER, but are classified as leading here.

The results of our classification quite clearly indicate that the NBER's method of classification is reasonable. The differences between our classification and that of the NBER might be explained by the fact that our analysis includes observations only for the post World War II cycles. Except for indicator 67, Bank Rates on Short Term Business Loans, each of the indicators classified by the NBER as lagging, which we classified as roughly coincident, has, in the post war period, a median turning point timing difference from the reference cycle turning point of three months or less. This also suggests that factors other than timing considerations might have influenced the NBER classification of these indicators.

IV. Summary and Conclusions

In this paper, we have presented an objective method for classifying cyclical indicators of economic activity on the basis of their timing characteristics at reference cycle turns. While our method of classification is based on all turning point timing differences from the reference cycle for each indicator for the period under consideration, rather than the NBER's use of a single summary measure and other subjective considerations (other than timing), the results of the two classification procedures are very similar. Our numerical taxonomic methods of classification, however, do not impose a trichotomy on the classification, rather a number of (hierarchical) groups are identified at particular levels of similarity. While the classification presented here corresponds closely to that of the NBER, our results indicate that several indicators ought to be "unclassified," since their timing characteristics are not sufficiently similar to established groups. Furthermore, our resuits tend to indicate that there has been some change in the timing behavior of certain (NBER) lagging indicators during the post World War II period.

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References

[1] Broder, I. (1974), "Statistical Analyses of Cyclical Indicators," unpublished doctoral dissertation, State University of New York at Stony Brook.
[2] Cormack, R. M. (1971), "A Review of Classification," with discussion, *J.R. Statist. Soc. A.*, 134, 321–367.
[3] Fisher, R. G., W. T. Williams, and G. N. Lance (1967), "An Application of Techniques of Numerical Taxonomy to Company Information," *Economic Record*, 43, 566–587.
[4] Fisher, W. D. (1969), *Clustering and Aggregation in Economics*, Baltimore: Johns Hopkins Press.
[5] Goronzy, F. (1969), "A Numerical Taxonomy on Business Enterprises," in A. J. Cole (ed.), *Numerical Taxonomy*, Proceedings of the Colloquium in Numerical Taxonomy held in the University of St. Andrews, September, 1968, New York: Academic Press, 42–52.
[6] Mintz, I. (1972), "Dating American Growth Cycles," in V. Zarnowitz (ed.), *The Business Cycle Today*, National Bureau of Economic Research, New York: Columbia University Press, 39–88.
[7] Mitchell, W. (1927), *Business Cycles: The Problem and Its Setting*, New York: National Bureau of Economic Research.
[8] ——— and A. Burns (1938), *Statistical Indicators of Cyclical Revivals*, Bulletin 69, New York: National Bureau of Economic Research.
[9] Moore, G. (1950), *Statistical Indicators of Cyclical Revivals and Recessions*, Occasional Paper 31, New York: National Bureau of Economic Research.
[10] ———, ed. (1961), *Business Cyclical Indicators*, Volume 1, National Bureau of Economic Research, Princeton: Princeton University Press.
[11] ——— (1964), *Statistical Indicators, NBER 45th Annual Report*, New York: National Bureau of Economic Research.

[12] ——— and J. Shiskin (1967), *Statistical Indicators of Business Expansions and Contractions*, Occasional Paper 103, National Bureau of Economic Research, New York: Columbia University Press.
[13] Rohlf, F. J. (1970), "Adaptive Hierarchical Clustering Schemes," *Systematic Zoology*, 19, 58–82.
[14] ——— (1972), "An Empirical Comparison of Three Ordination Techniques in Numerical Taxonomy," *Systematic Zoology*, 21, 271–280.
[15] ———, J. Kishpaugh, and D. Kirk (1971), NT-SYS. *Numerical Taxonomy System of Multivariate Statistical Programs*, Tech. Rep. State University of New York at Stony Brook.
[16] ——— and R. R. Sokal (1962), "The Description of Taxonomic Relationships By Factor Analysis," *Systematic Zoology*, 11, 1–16.
[17] Sneath, P. H. A. and R. Sokal (1973), *Numerical Taxonomy*, San Francisco: Freeman.
[18] Sokal, R. R. and F. J. Rohlf (1962), "The Comparison of Dendograms by Objective Methods," *Taxon*, 11, 33–40.
[19] U.S. Department of Commerce, *Business Conditions Digest* (1971–1973).