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Economic Review

Federal Reserve Bank of Dallas
July 1988

This paper introduces two new measures for analyzing the Texas economy. The first measure, a composite index of coincident economic indicators, is designed to show whether the overall Texas economy is currently growing or declining. The second, a composite index of leading economic indicators, is designed to signal upcoming weaknesses or strengths in the state economy. Evaluation of the Texas coincident index shows that the index successfully combines information on the Texas economy into a smooth business cycle index. Also, an analysis of the Texas leading index shows that this index has performed well in anticipating directional changes in the state economy.

During the past 10 years, both U.S. agricultural exports and exchange rates have fluctuated considerably. Although exchange rate movements and U.S. agricultural export levels have frequently been linked, competitiveness is more accurately described by market share. In this article, simple econometric models of U.S. export shares reveal that exchange rates have generally small effects on U.S. agricultural export competitiveness. Consequently, exchange rates have probably not accounted for much of the large swings in U.S. export levels during the 1970s and 1980s.

Since the average service life of a nonresidential building exceeds thirty years, investors must form long-run expectations about economic growth in a region. In this study, expectations about population growth are shown to affect rates of nonresidential construction. In turn, these expectations are influenced by past local impacts of changes in the relative world prices of various goods and services. Although state and local governments' fiscal policies are sometimes claimed to affect regional growth, our research suggests that they have little influence on nonresidential building or on growth expectations.

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New Tools for Analyzing the Texas Economy: Indexes of Coincident and Leading Economic Indicators

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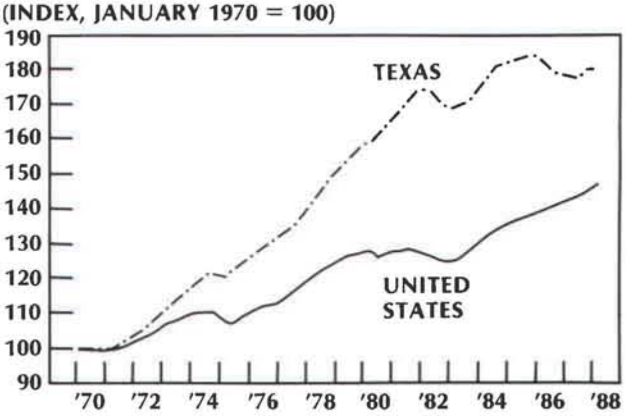
The increased volatility of the Texas economy during the 1980s has strengthened the need for improved methods of analyzing the current state of the economy as well as the economic outlook. One method is to construct econometric models to forecast growth in several measures of aggregate economic activity. An article which appeared in the January *Economic Review* used this approach.[1] Another method, treated in the present article, is the construction and analysis of composite indexes of coincident and leading economic indicators.

During the 1970s, an increasing price of oil helped bring economic prosperity to Texas. One measure of economic activity—employment—grew 58.6 percent in Texas from 1970 to 1980, as compared to 28.8 percent for the nation. The prosperity of the 1970s, however, ended abruptly in the 1980s with declining oil prices and a sluggish state economy. As shown in Chart 1, the rapid employment growth experienced in Texas during the 1970s slowed and became more variable in the 1980s. It is also apparent from the chart that while employment in the national economy had continued to grow in 1985 and 1986, in Texas it had flattened and started to decline.

During the 1980s, the growing uncertainty in the Texas economy has emphasized the need for better ways of measuring the state's economic activity and direction. The purpose of this paper is to provide two timely measures of the Texas economy that should help interpret its current and future cyclical movements. One such measure—the Texas index of coincident economic indicators—is a current measure of changes in the state's aggregate economic activity. This index, which combines changes in monthly measures of employment and output in Texas, is plotted in Chart 2, together with a similar measure available for the national economy from the U.S. Department of Commerce.[2] As is evident from this chart, the timing of cyclical movements in the Texas economy has often been similar to that in the national economy. In late 1984, however, the two began to diverge. The Texas economy began to decline while the U.S. economy continued to grow.

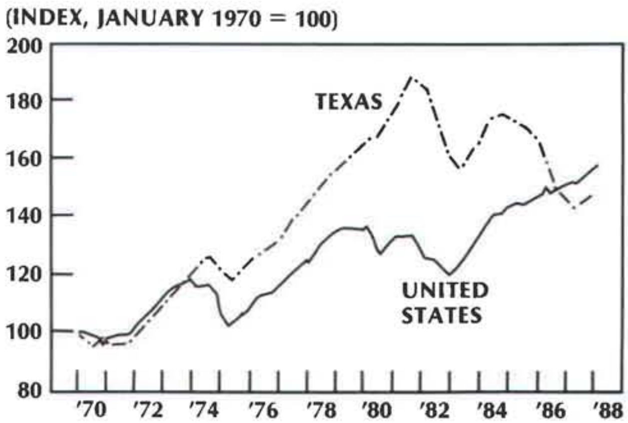
Another useful measure of the Texas economy derived in this study is the Texas index of leading economic indi-

Chart 1
Texas and U.S. Nonagricultural Employment



SOURCE: U.S. Department of Labor, Bureau of Labor Statistics.

Chart 2
U.S. and Texas Coincident Economic Indicators



SOURCES: U.S. Department of Commerce, Bureau of Economic Analysis.
Federal Reserve Bank of Dallas.

Using Business Cycle Data

Business cycle data reflect expansions in many economic activities followed by similar general contractions. Specific U.S. business cycles are defined by turning points as designated by the National Bureau of Economic Research (NBER) sometime after the turning point has actually occurred. A complete business cycle is defined as the period in which economic activity goes from a peak to a trough to another peak.

In studying U.S. business cycles, most analysts rely on the official NBER business cycle turning points. In analyzing whether overall economic activity in the economy has changed direction, the NBER studies movements in many economic series that it defines as coincident series. Included in these series are quarterly variables (such as gross national product) and monthly series (such as nonagricultural employment and the U.S. industrial production index).

The NBER analyzes these coincident series to see if the majority of the series have changed directions, and if the movements in the series are as similar in scope and magnitude as they have been in other historical turning points. Also, other factors taken into account include the perceived causes underlying the cyclical developments and the steps the government has taken that might offset or reinforce the directional change. If the NBER decides that a business cycle turning point has occurred, as a result of these evaluations and comparisons, it then decides in which particular month the turning point occurred. Although no one series or index is used to determine the timing of the turning point, composite indexes such as the coincident economic indicator index produced by the Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce are important sources of information used by the NBER.

cators.[3] As shown in Chart 3, the changes in this leading index have generally preceded changes in the Texas index of coincident economic indicators. Although data constraints have limited the historical period for which this index could be computed, present evidence shows that the index has performed well in signaling slowdowns or resurgences in the economy.

Composite indexes of coincident economic indicators

Composite indexes of economic activity are summary measures designed to signal directional changes in aggregate economic activity. These indexes are constructed from variables that represent widely different types of economic activity but show similar timing at business cycle turns (see Box). The most widely publicized composite indexes of the national economy are those of leading and coincident indicators published monthly by the Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce.

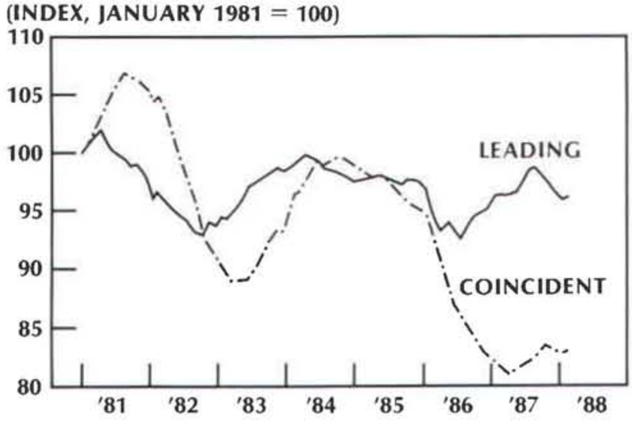
The *Business Conditions Digest* lists 84 different economic time series described as monthly cyclical indicators of the national economy. One problem for the monetary policymaker, as well as for businessmen and consumers, is how to distill from this large volume of information some assessment of how well the overall economy is currently performing. Fortunately, the BEA has simplified the process by condensing the information from the most important coincident variables into the composite index of coincident economic indicators. By using an explicit systematic scoring system, the BEA has chosen the following four variables as the components in its coincident index: (1) nonagricultural employment, (2) the U.S. index of industrial production, (3) manufacturing and trade sales in 1972 dollars, and (4) personal income minus transfer payments in 1972 dollars.

Developing a Texas composite index of coincident economic indicators

Deciding which series to include in a Texas index of coincident indicators differs, however, from the evaluation process for the respective national index. The scoring system used in evaluating and selecting variables for the national index places particular emphasis on series timing relative to official U.S. business cycle turning points as designated by the National Bureau of Economic Research (NBER). Since the Texas economy has no officially designated business cycle turning points, this method was not applicable to this study. Instead, the construction of the Texas coincident index first concentrated on finding state counterparts to national coincident indicators, as classified by the BEA. Then these state variables were analyzed to determine which of them were reported on a timely basis and had turning points that, in general, matched the turning points of the majority of the other coincident indicators. Also, in order to reduce the amount of false signals of business cycle turning points, it was required that the variables moved *smoothly* up during economic expansions and down during contractions.

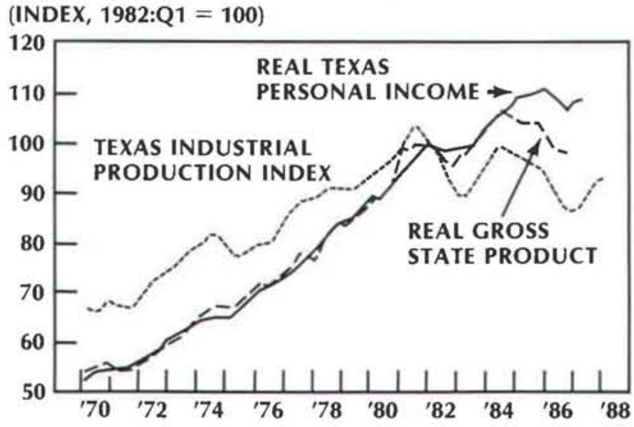
Trying to analyze the Texas economy with all the available cyclical indicators could lead to a somewhat confusing

Chart 3
Texas Leading and Coincident Economic Indicator Indexes



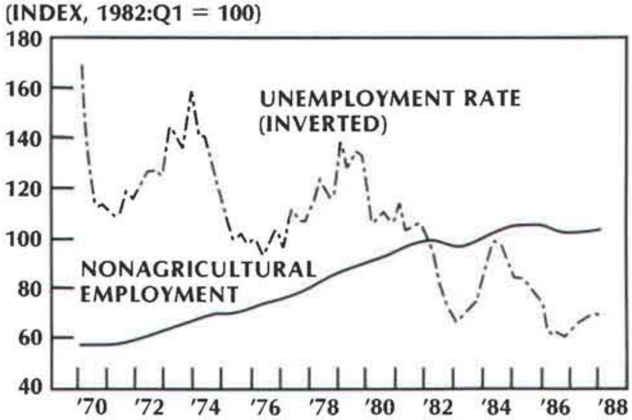
SOURCE: Federal Reserve Bank of Dallas

Chart 4
Indicators of the Texas Economy



SOURCES: Baylor University Forecasting Service (Waco).
U.S. Department of Commerce, Bureau of Economic Analysis.
Federal Reserve Bank of Dallas.

Chart 5
Indicators of the Texas Economy



SOURCE: U.S. Department of Labor, Bureau of Labor Statistics.

interpretation. The movements since 1970 of three important cyclical indicators of output in Texas—real gross state product, real personal income, and the Texas Industrial Production Index (TIPI)—are shown in Chart 4. Plotted in Chart 5 are two other important cyclical indicators that relate to employment—total nonagricultural employment and the unemployment rate (inverted).[4] Although these indicators might be expected to move similarly, they sometimes move in different directions, as is reflected in the charts.

Another way of analyzing the movements in these indicators is through the use of correlation coefficients.[5] The correlation matrix of the five cyclical indicators of the Texas economy since 1970 is profiled in Table 1. Also included in the correlation matrix is a time variable representing a linear time trend. All of these variables except the inverted unemployment rate show a high positive correlation.

Also revealed in the table is the positive time trend generally shared by the variables (except for the inverted unemployment rate). In fact, much of the correlation between the individual series may have resulted from this common trend. In order to eliminate the impact of the time trend, all of the series except the unemployment rate were converted to percent changes. Since the unemployment rate was already measured in percentage terms, simple changes rather than percent changes were calculated for this variable. The correlation of the transformed series thus represented the relationship between the cyclical movements of the series apart from their individual trends. As shown in Table 2, all of the correlations between the detrended cyclical movements in the series were positive, though generally much lower than those of the original series. Although the movements in these cyclical indicators were correlated, the correlations were significantly less than one. Thus, the indicators could—at any particular point in time—provide a differing picture of the Texas economy.

To construct a coincident index with timely information on the business cycle, it was necessary that variables in the index be reported monthly. This requirement eliminated the measures of real personal income and real gross state product. Even though these measures were considered important in analyzing the Texas economy, they could not provide timely information about the current state of the economy. The remaining three indicators—total nonagricultural employment, the unemployment rate, and the TIPI—were available on a current monthly basis.

Of the most important coincident indicators (see Table 2), the change in the unemployment rate was generally the least correlated with changes in the rest of the indicators. It should also be noted from Charts 4 and 5 that the timing of the turning points in the unemployment rate generally was not consistent with the other coincident indicators. The fact that the unemployment rate was less correlated with the other series was even more apparent in the monthly data. As can be seen in Table 3, the correlation between changes in the TIPI and changes in nonagricultural employment proved to be about twice as high as the correlation

Table 1
CORRELATIONS BETWEEN TEXAS ECONOMIC INDICATORS: QUARTERLY, 1970-87[1]

Indicator	Real personal income	Real gross state product	Nonfarm employment	Industrial production index	Unemployment rate (inverted)	Time
Real personal income	1.00	0.99	0.99	0.88	−0.72	0.99
Real gross state product	0.99	1.00	0.99	0.94	−0.66	0.98
Nonfarm employment	0.99	0.99	1.00	0.91	−0.71	0.98
Industrial production index	0.88	0.94	0.91	1.00	−0.44	0.83
Unemployment rate (inverted)	−0.72	−0.66	−0.71	−0.44	1.00	−0.78
Time	0.99	0.98	0.98	0.83	−0.78	1.00

1. Correlation coefficients are Pearsonian; see J. Johnston, *Econometric Methods*, 3rd ed. (New York: McGraw-Hill Book Company, 1984), 23-25. All coefficients are statistically significant at the 1-percent level of significance; for sources of variables, see text, n. 4.

Table 2
CORRELATIONS BETWEEN PERCENTAGE CHANGES IN TEXAS ECONOMIC INDICATORS: QUARTERLY, 1970-87[1]

Indicator	Real gross state product	Industrial production index	Real personal income	Nonfarm employment	Unemployment rate (inverted)
Real gross state product	1.00	0.59	0.59	0.54	0.44
Industrial production index	0.59	1.00	0.48	0.65	0.52
Real personal income	0.59	0.48	1.00	0.64	0.29
Nonfarm employment	0.54	0.65	0.64	1.00	0.48
Unemployment rate (inverted)	0.44	0.52	0.29	0.48	1.00

1. Correlation coefficients are Pearsonian; see J. Johnston, *Econometric Methods*, 3rd ed. (New York: McGraw-Hill Book Company, 1984), 23-25. All coefficients are statistically significant at the 1-percent level of significance; for sources of variables, see text, n. 4.

Table 3
CORRELATIONS BETWEEN PERCENTAGE CHANGES IN TEXAS ECONOMIC INDICATORS: MONTHLY, 1970-87[1]

	Nonfarm employment	Industrial production index	Unemployment rate (inverted)
Nonfarm employment	1.00	0.44	0.22
Industrial production index ...	0.44	1.00	0.21
Unemployment rate (inverted)	0.22	0.21	1.00

1. Correlation coefficients are Pearsonian; see J. Johnston, *Econometric Methods*, 3rd ed. (New York: McGraw-Hill Book Company, 1984), 23-25. All coefficients are statistically significant at the 1-percent level of significance; for sources of variables, see text, n. 4.

between changes in the unemployment rate (multiplied by minus one) and changes in either the TIPI or nonagricultural employment. Also, the data plotted monthly (see Chart 6) show that the unemployment rate has not been as smooth as total nonagricultural employment and the TIPI. Because the unemployment rate proved to be relatively inconsistent and relatively volatile, it was not used in this study to construct the index. (This decision was consistent with the BEA's design for the coincident index, which also does not include the national unemployment rate.)

To combine the information from total nonagricultural employment and the TIPI into an aggregate index, this study followed the BEA's procedures in calculating the national coincident index. The calculations involved the following four steps: (1) standardizing the changes in the individual series so that the most volatile series does not dominate movements in the index, (2) selecting weights for the series, (3) combining the weighted changes in the series into an aggregate index, and then (4) trend-adjusting this index.

Consider the method used for standardizing the changes in the series. First, the symmetrical percent changes in the series, represented here by C_{it}, were calculated by the following formula:

$$C_{it} = 200(d_{it} - d_{it-1})/(d_{it} + d_{it-1}),$$

where d_{it} refers to the data for series i in period t. These monthly symmetrical percent changes were then standardized by dividing them by their average percent change, without regard to sign. The average percent change in each of the series was calculated over the period February 1970 to December 1987.

Consider next the selection of weights. As was mentioned earlier, industrial production and nonagricultural employment are included in the national index. Assuming that these variables would play a similar role in the Texas economy, the relative weights derived by BEA for these variables in the national economy could be used for the respective state variables in the Texas economy.[6] In this way, changes in total nonagricultural employment in Texas were given a weight of 0.5085, while changes in the TIPI were given a weight of 0.4915.

Once the changes in component series were multiplied by their weights and added together, they could then be used to create an index. The combined standardized changes, R_t, were made into an index, using the formula

$$I_t = I_{t-1}(200 + R_t)/(200 - R_t),$$

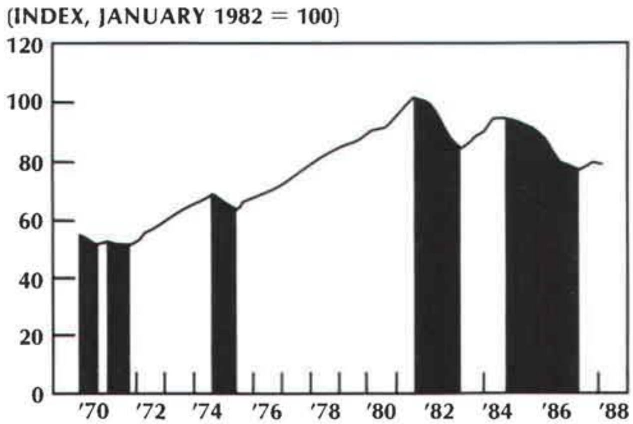
in which I_1 was assigned the value of 100. This index was then trend-adjusted.

The BEA adjusts its series trend to equal the average trend of the series components to ensure that the long-run growth will be equal to the long-run growth in overall economic activity. For the Texas index of coincident economic indicators, the long-run trend was set equal to the average of the trends (using equal weights) of total nonagricultural employment, real gross state product, real personal income, and the TIPI.[7] After the trends in these four economic series were computed, the average of these trends was determined and compared to the trend in the raw index, I. If the trend in the raw index was greater (less) than the average trend of the four economic indicators, then the difference between the trends was subtracted (added) from (to) the

Chart 6
Monthly Indicators of the Texas Economy

SOURCES: U.S. Department of Labor, Bureau of Labor Statistics.
Federal Reserve Bank of Dallas.

Chart 7
Texas Coincident Economic Indicator Index



SOURCE: Federal Reserve Bank of Dallas.

combined standardized changes, R_t, computed above. The method for computing the index discussed previously was then used to convert these adjusted changes into the trend-adjusted series.

As can be seen in Chart 7, the composite index of coincident indicators for Texas is effective in combining information on the Texas economy into a smooth business cycle index. The timing of the turning points in the index, in general, was found consistent with those of the economic indicators shown in Charts 4 and 5. (Periods of economic contraction, as defined by the coincident index, have been marked by the shaded areas in the chart.) Also, the index moves smoothly upward during expansions and downward during contractions, thus minimizing the number of false signals of business cycle turning points.

Although the index is useful in defining, on a current basis, the peaks and troughs in the Texas business cycle, it is less clear that it can be considered a good historical indicator of *levels* of economic activity. In Charts 4 and 5, for example, the real Texas personal income, real gross state product, and total nonagricultural employment are all shown to indicate an economic level greater at the end of 1984 than in 1981. Although the *long-run* trend in the Texas coincident index has been set equal to the average trend of these variables (along with the TIPI), for shorter time periods, such as 1981-84, the index's trend may diverge from the average trend of major Texas economic indicators.

Composite index of leading economic indicators

Unlike a coincident index that moves in tandem with the business cycle, an index of leading economic indicators *anticipates* movements in the business cycle. Thus, this index can serve as an early warning device signaling upcoming peaks or troughs in the business cycle.

The BEA, in constructing the national leading index, evaluated variables in terms of their relationship with official NBER peaks and troughs. Since there are no officially designated turning points for the Texas economy, this could not be done for this study. By using the Texas coincident index, though, it is possible to construct a series that would lead this business cycle indicator. To choose and weight the components, this study generally followed the BEA's guidelines for developing its national index of leading economic indicators.

The BEA scores its variables in terms of economic significance, statistical adequacy, cyclical timing, overall business cycle conformity, smoothness, timeliness, and revisions. The scoring criteria used place particular weight on cyclical timing. Although the scoring system is primarily qualitative, the BEA has systematized the procedure to reduce ad hoc judgments. In other words, the explicit scoring system has helped to ensure evaluating all of the important aspects of the economic series in a consistent and essentially replicable manner.[8]

Unlike the BEA's scoring procedure, which places particular emphasis on the timing of the series in relation to business cycle turning points, the procedure for this study placed its emphasis on the overall conformity of the series relative to the business cycle. This focus was necessary because data constraints reduced the number of turning points present in the Texas variables as compared with the national series. This smaller number of business cycles limited the amount of information that could be derived by evaluating the series only at turning points. Also, the measure of conformity used in this study evaluates the relationship between every observation of the variable relative to every observation of the business cycle. The measure of conformity used by the BEA, however, studies only the relationship between movements in the variable and NBER peaks and troughs. Thus, the measure of conformity used in this study utilizes more information about the relationship between changes in the variable and changes in the business cycle.

To measure the overall conformity of the candidate series for the Texas leading index, correlations were calculated between changes in the past values of the candidate variables and changes in the current values of the coincident index.[9] Where the resulting correlation coefficients between changes in the current values of the coincident index and past changes of at least two months in the candidate series were statistically different from zero, that was taken as evidence of a leading relationship between the candidate variable and the coincident index.

Particular weight was given to this statistical result within the general framework of the BEA's scoring system. The scores derived by this process were first used to select and then to weight the index components. Fourteen candidate variables were evaluated and nine were selected.[10] In the selection process, it was noted that 11 of the 14 variables related directly to the Texas economy. Three of these Texas-related variables—new unemployment compensation claims (inverted), average weekly hours in manufacturing, and the help-wanted index—related directly to state employment levels. Two of the other Texas variables—housing permits and the total value of residential building—attempted to capture any leading relationship between the important construction sector and the overall Texas economy. The drilling rig count, real oil prices, and well permits represented indicators of another important sector that might lead the state economy as a whole. Real retail sales

Table 4
VARIABLES USED IN THE INDEX OF LEADING ECONOMIC INDICATORS FOR TEXAS[1]

Variable	Weight
Texas	
Average weekly hours of production Workers in manufacturing	1.03
Help wanted index	1.05
Real Texas77 stock market index	1.02
New unemployment compensation claims (inverted)	1.03
Real retail sales (three-month moving average)	0.97
Number of well permits issued	1.00
Real price of oil	0.99
National	
Index of leading economic indicators	0.98
International	
Texas-weighted real value of the dollar (inverted and lagged six months)	0.92

1. In computing the index, the weights are divided by 9.

served as a proxy for final demand for goods and services in the state, while new business incorporations and the Texas stock market index served directly as measures of the outlook for business profits and indirectly as measures of the outlook for economic growth.

The other three non-Texas variables—two related to the national economy and one tied to international trade—attempted to capture the leading relationship that the national economy and international trade have to the Texas economy. The two national variables—the BEA's composite indexes of leading and coincident indicators—represented national demand for Texas output. Movements in the final candidate variable, the Texas trade-weighted value of the dollar (inverted), represented changes in the price of Texas output to foreigners.

Based on the BEA's general scoring approach, the present study did not include the following variables in the Texas index of leading economic indicators: (1) housing permits, (2) the total value of residential building, (3) the national coincident index, (4) the rig count, and (5) new business incorporations. Although housing permits and the total value of residential building showed a slightly significant leading relationship to the coincident index, the monthly changes in these measures were highly erratic. Three-month moving averages were calculated in an effort to smooth these series, and thus reduce the likelihood that movements in these indicators might often give false signals of a forthcoming recession or recovery. But an evaluation of these averages showed no statistically significant relationship between the coincident index and either past values of housing permits or the real value of residential building.

None of the correlation coefficients between the coincident index and lags of new business incorporations were statistically significant. Although a three-month moving average was calculated to try to eliminate some of the noise from this series, the results using this smoothed series did not show any improvement. The drilling rig count showed only some slight statistical evidence of a lead relationship to the coincident index. Since two other measures of the energy sector—well permits and real oil prices—provided a much better result, the rig count was not included.

The national indexes of coincident and leading indicators both represent the national business cycle, but at different points in time. These were both included in the list of potential indicators in order to choose the more effective one of the two. The national coincident indicator was not used because the results of the statistical tests demonstrated that the national leading index was better than the national coincident indicator as a leading indicator of the Texas economy.

The variables selected are shown in Table 4 along with their calculated weights. Real retail sales was measured as a three-month moving average because the test of smoothness used in the scoring process showed this series to be highly variable and thus likely to give false signals of upcoming turning points. The three-month-moving-average process was able to eliminate much of the noise from the series without significantly reducing its leading relationship to the coincident index. Also, the Texas trade-weighted value of the dollar was lagged six months to keep its lead relationship consistent with the other variables while allowing it to be reported on a timely basis.

As in the coincident index, the leading index combined the standardized, linear, symmetric percent changes in the selected variables through the use of estimated weights. The BEA also adjusts the index's trend to be consistent with that in the coincident index. Besides trend-adjusting the index, the BEA standardizes the amplitude of the index by standardizing the percent changes in the leading index. This makes the sum of the absolute changes in the leading index equal to the sum of the absolute changes in the coincident index. The amplitude standardization thus facilitates the use of the two indexes as a consistent system.[11] The BEA computed factors for the leading index trend adjustment and amplitude standardization for the period 1948-81, and these are not changed on a month-to-month basis.

Adjustments can help make consistent the long-run trends and overall amplitudes of the two series. Although the trend and amplitude adjustments both serve a purpose in the BEA's index of leading economic indicators, neither adjustment was appropriate for the leading economic indicator index for Texas, primarily because of the short time period for which the Texas leading index was calculated. Because the Texas leading index is only calculated from 1981, it is not possible to estimate a long-run trend or long-run average amplitude. Even without these adjustments, though, the index is effective in its central purpose of foreshadowing turning points in the coincident index.

Evaluation of the Texas index of leading economic indicators

As can be seen in Chart 3, the Texas index of leading economic indicators is smooth and generally leads movements in the coincident index. A peak in the leading index led the August 1981 peak in the coincident index by four months and led the October 1984 peak by six months. A trough in the leading index led the March 1983 trough in the coincident index by six months and led the April 1987 trough by nine months. Thus, in this limited period, the index led peaks by an average of five months and led troughs by an average of seven and a half months.

Although, from the historical data, it is fairly easy to note the occurrences of peaks or troughs in the leading index, it may be difficult on a month-to-month basis to detect turning points. A common rule used with the BEA's leading index is that three months of consecutive declines signals an upcoming recession and three months of consecutive increases signals an upcoming recovery.

If the three-month rule is used to analyze the Texas index of leading economic indicators, then the lead time following this signal for the peak in August 1981 was one month. For the peak in October 1984, it was three months. In the five months prior to the trough in March 1983, the leading index increased during three of the five months. But since these increases were not consecutive, the three-month rule did not predict the trough until two months after its actual occurrence. On the other hand, the lead time for the trough in April 1987 was six months. Thus, on average, this signal has led both peaks and troughs by two months.

It is also interesting to use the three-month rule to evaluate whether the leading index has given any false signals of turning points. For the period January 1981-July 1987, a consecutive three-month decline or increase in the index never falsely predicted an upcoming recession or recovery.

It should also be noted that the leading index declined for five consecutive months beginning in September 1987. Although the coincident index declined slightly for three months beginning in November 1987, preliminary estimates for February 1988 showed the coincident index was increasing. If the coincident index continues to increase, however, the decline in the leading index may have predicted only a mild slowing of the Texas economy rather than a general downturn.

It is also useful to evaluate the relationship between the leading and coincident indexes by the correlation estimation procedure used in evaluating the individual series. Results showed a strong, statistically significant leading relationship between changes in the leading index and changes in the coincident index. Another useful test is to see if the leading indicator index improves the forecast of changes in the coincident index. In other words, in order for the leading index to be useful, it must not only predict changes in the coincident index, but it must be a better predictor than just the past movements in the coincident index. A model was constructed that used only past changes in the coincident index to predict current changes. Then, past changes in the leading index were added and tested to see if they significantly improved the model's one-period-ahead predictive ability. The results of this procedure showed that the leading indicator is useful in predicting future movements in the Texas economy.[12]

A major problem in evaluating the index in this study was its short time period. In order to evaluate business cycle relationships, it is best to study that relationship over a long period of time and over many business cycles. Because the help-wanted index only began in 1981, this restricted the time period for this series. Although each individual series was tested for its ability to lead the coincident index from the earliest possible date, no series was tested prior to 1970. Because the predictive ability of the leading index was evaluated over only a short time period, this relationship possibly might not hold in the future. The BEA, in evaluating the variables that it uses in its index of leading economic indicators, has scored its variables over seven complete business cycles during the 32-year period 1948-80. The performance of the leading economic indicator index for Texas derived in this article thus will best be judged in years to come.

It should also be noted that peaks in the BEA's leading economic indicator index have not always been followed by recessions. On at least three occasions since 1948, peaks in the index have been followed by a slowing of growth rather than by a recession. In the case of the Texas economy, periods of decline in the Texas leading index also could point to a slowdown in growth rather than to a recession. This may be true of the decline shown at the end of 1987. In either case, though, the Texas leading economic indicator index should provide a good warning device to signal weakness in the Texas economy, whether the growth declines or actually becomes negative.

Summary conclusion

The increased economic uncertainty that the Texas economy has experienced during the 1980s has emphasized the need for good measures of the current state of the economy and the outlook for the future. This study has calculated two series—the index of leading economic indicators and the coincident index—that should help businessmen, policymakers, and consumers better evaluate movements in the Texas economy.

The Texas coincident economic indicator index is a measure designed to indicate, in a timely manner, directional changes in aggregate economic activity in the state. A comparison of its past values with other indicators such as gross state product shows that the coincident index generally is consistent with other state indicators in defining periods of cyclical upturns and downturns in the Texas economy.

The second index, the Texas leading economic indicator index, is designed to signal directional changes in the state economy. This index is composed of state, national, and international variables that play an important role in anticipating the future economic direction for Texas. Although the index has performed well since 1981, this is a relatively short period by which to judge a business cycle indicator. Much of the judgment about the usefulness of this indicator is yet to come as the Texas economy moves into the future.

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1. See William C. Gruben and William T. Long III, "Forecasting the Texas Economy: Applications and Evaluation of a Systematic Multivariate Time Series Model," *Economic Review*, Federal Reserve Bank of Dallas, January 1988, 11-25.

2. The BEA also produces an index of lagging economic indicators which is used to confirm business cycle turns. Also, there are other, less-publicized leading indexes such as the Duncan leading indicator index and the Mitchell leading indicator index. (See *Weekly Letter*, Federal Reserve Bank of San Francisco, 26 April 1985.)

3. Currently, two agencies in Texas—the Texas Comptroller of Public Accounts and the Bureau of Business Research at the University of Texas at Austin (BBR-UT)—estimate leading indicators that relate to the Texas economy. The Texas Comptroller's index is constructed to lead employment in mining, manufacturing, and construction, while that of the BBR-UT is used to lead total employment in Texas. The leading index constructed in the present study is designed to lead changes in aggregate economic activity in the state as measured by the Texas coincident economic indicator index.

   Since each of the indexes purports to lead different measures of economic activity, it is difficult to judge which is the best leading indicator. All three, though, contain many of the same variables and thus move in a similar manner. The index developed here, however, rules out several of the variables included in the other indexes. It also includes national and international variables that have an effect on the state economy but are not included in the other two indexes.

   The leading index produced by the BBR-UT contains the following five state variables: (1) average weekly hours of production workers in manufacturing, (2) real retail sales, (3) housing permits, (4) the oil price, and (5) initial unemployment compensation claims divided by nonagricultural employment. The Comptroller's leading index contains these same variables, except that initial unemployment compensation claims are not divided by another series. This index also includes the help-wanted index, the Texas77 stock index, and new business incorporations.

4. All variables are seasonally adjusted. Real gross state product is estimated by M. Ray Perryman of the Baylor University Forecasting Service (Waco); total nonagricultural employment and the unemployment rate are estimated by the U.S. Department of Labor, Bureau of Labor Statistics; and real personal income is estimated by the U.S. Department of Commerce, Bureau of Economic Analysis (BEA). The Texas Industrial Production Index used in this study is a recently revised series estimated by the Federal Reserve Bank of Dallas. (The revised index will appear in a future issue of the *Economic Review*, published by the Federal Reserve Bank of Dallas.)

Although the national unemployment rate is not classified by the BEA as a coincident indicator, the Texas unemployment rate is an important economic variable that is often used as a coincident indicator. Because of this, the Texas unemployment rate was evaluated for this study along with the other variables that are classified on the national level as coincident indicators.

5. A correlation coefficient is simply an index number between zero and one, with zero indicating no tendency for a variable to move with another and with one indicating a perfect direct relationship between the two variables.

6. By using estimates of real gross state product by sector, the study determined that the industries included in the Texas Industrial Production Index (TIPI) represent about one-third of the total state output. This percentage is similar to that of the national output represented by the U.S. industrial production index. It was assumed that total nonagricultural employment plays a role in Texas similar to what it does in the nation and that the TIPI and the U.S. industrial production index also play a similar role in their respective economies. It was thus assumed that the relative weights of these variables in Texas could be well represented by the corresponding national weights.

7. The long-run trends in the series were estimated using the business-cycle-average method. Let C_f and C_l represent the averages of the series for their first and last complete cycles (as measured from peak to peak) that are present in the data. The trend is computed using the compound interest formula

$$Trend = [(C_l/C_f)^{1/m} - 1]100$$

where m is the number of months from the center of the initial cycle to the center of the terminal cycle.

8. For a more detailed explanation of the BEA's scoring system, see Victor Zarnowitz and Charlotte Boschan, "Cyclical Indicators: An Evaluation and New Leading Indexes," *Business Conditions Digest,*, series ES1, no. 75-5 (May 1975): v-xv, which is also reprinted in U.S. Department of Commerce, Bureau of Economic Analysis, *Handbook of Cyclical Indicators: A Supplement to the Business Conditions Digest* (Washington, D.C.: U.S. Government Printing Office, 1977).

9. To eliminate any spurious correlations from both series having followed similar autoregressive patterns, the candidate series were transformed to white-noise series using the appropriate ARIMA process. The coincident index was then "prewhitened" using the ARIMA process of the candidate series. (See Walter Vandaele, *Applied Time Series and Box-Jenkins Models* (New York: Academic Press, Inc., 1983), 267-300.)

10. All of the variables that contained seasonal patterns were seasonally adjusted. All variables measured in dollars and not available on a real basis were adjusted by the U.S. consumer price index. The following is a list of the variables with their sources: (1) new state unemployment compensation claims, from the Texas Employment Commission; (2) the Texas help-wanted index and the Texas77 stock market index, from the Texas Comptroller of Public Accounts; (3) real retail sales and total housing units authorized by permits in Texas, from the U.S. Department of Commerce, Bureau of the Census; (4) new business incorporations in Texas, from Dun and Bradstreet Corporation; (5) the number of active drilling rigs in Texas, from the Hughes Tool Co.; (6) the U.S. indexes of leading and coincident economic indicators, from the U.S. Department of Commerce, Bureau of Economic Analysis; (7) the average weekly hours of production workers in manufacturing in Texas, from the U.S. Department of Labor, Bureau of Labor Statistics; and (8) the total value of single-family building in Texas, from the McGraw-Hill Information Systems Co., F.W. Dodge Division.

Prior to 1983, the change in the oil price was calculated from data on the refiners' cost of domestic crude oil provided by the U.S. Department of Energy. For data after 1983, the change in the oil price was calculated from figures on the price of West Texas Intermediate Crude oil supplied by the Federal Reserve Bank of Dallas.

The series on well-permit applications was provided by the Texas Railroad Commission. In August 1983, when the number of well permits jumped over 328 percent in one month, the sudden increase resulted not from a jump in planned drilling but from a change in the pricing of well-permit applications scheduled to take effect the following month. Thus, the well-permit data for 1983 do not reflect the normal relationship between well permits and drilling activity. To smooth over these noncharacteristic data, an ARIMA model estimated for the period 1973-82 was used to predict well permits for 1983.

In calculating the Texas exchange rate index, first the exchange rate indexes for U.S. industries are derived by taking the real dollar/foreign currency exchange rates and weighting them by their importance to the particular industry group. Then these are weighted by their importance to Texas. (See W. Michael Cox and John K. Hill, "Effect of the Lower Dollar on U.S. Manufacturing: Industry and State Comparisons," *Economic Review*, Federal Reserve Bank of Dallas, March 1988, 1-9.)

11. See U.S. Department of Commerce, Bureau of Economic Analysis, *Handbook of Cyclical Indicators: A Supplement to the Business Conditions Digest* (Washington, D.C.: U.S. Government Printing Office, 1987), 65-69.

12. Lags of one through four were found to be appropriate in predicting changes in the coincident index based solely on past changes of itself. When lags of one through twelve for changes in the leading indicator index were added to this equation, the predictive power of the equation, as measured by the adjusted R2, increased from .4491 to .5646. An F test on the significance of the lags of changes in the leading index was significant at the 1-percent level.

U.S. Agricultural Export Competitiveness: Export Levels, Trade Shares, and the Law of One Price

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The 1970s constituted a golden decade for U.S. agriculture. U.S. agricultural exports during that time increased at an annual rate five times that for the previous 30 years. In 1981 the boom reached its zenith, with agricultural exports and land values peaking simultaneously. U.S. agricultural exports declined for several years thereafter and have only recently shown modest increases. During the period of declining agricultural exports, the foreign exchange value of the dollar was rising. As a consequence, there has been a surge of studies estimating exchange rate effects on the levels of U.S. exports. A small body of literature has developed in which different agricultural exchange rate indexes have been constructed. These new indexes have been plugged into the earlier models or into new single-equation models to get a measure of exchange rate effects on the volume of farm exports.

The problem with applying new exchange rates to old models is at least twofold. First, they are not the exchange rates that were used to estimate the original models. Second, the models themselves were estimated over the agricultural export boom of the 1970s. Therefore, using new exchange rate indexes and older-model elasticities is likely to overstate the responsiveness of U.S. agricultural exports to movements in exchange rates. Further, levels of agricultural exports are imperfect indicators of market competitiveness. Changes in levels are not necessarily indicative of changes in competitiveness.

One way to model U.S. agricultural competitiveness would be to look at the share of agricultural exports captured by U.S. producers. The movement in the share over time should largely be invariant to demand-side factors but, rather, would concentrate on price and nonprice competition between exporters.

This article first argues that shares are superior to levels in analysis of agricultural exports, particularly for looking at agricultural competitiveness. Second, a graphical model of the agricultural export-share determination is presented. Next, the critical role of the Law of One Price (LOP) in modeling agricultural exports is examined. The LOP is empir-

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ically tested for wheat, corn, and rice—all important U.S. agricultural export crops. Finally, using LOP results, bilateral export-share equations are estimated by logit techniques. The empirical results show that although the LOP does not strictly hold in some cases, it is a very close approximation to reality. Moreover, with one exception, the estimated elasticities for U.S. export share with respect to exchange rates are small. These results indicate that the dramatic drop in U.S. agricultural exports was probably not due to a lack of competitiveness but, rather, was attributable to demand-side factors.

Exports: levels, shares, and indexes

Research attention to agricultural exports has generally concentrated on the factors influencing the levels of U.S. agricultural exports and the magnitude of their effects. The gyrations in both agricultural exports and exchange rates in the 1980s have spawned refinements in exchange rate indexes, but the questions of competitiveness and export share have received proportionally less interest.

The advantage of using export-level models is that elasticities of demand with respect to different variables can be estimated. The dependent variables in these models are quantities exported, so the elasticities estimated are percentage changes in the level of exports given the percentage changes in, for example, domestic prices or some exchange rate index.[1] At least two factors caution the use of level-derived exchange rate elasticities of demand for determining policy.

First, almost without exception, the data used by the export-level models were largely drawn from the 1970s.[2] Although the stellar U.S. agricultural export performance during the 1970s was hopefully regarded at the time as a permanent condition, that period is now largely perceived as an aberration.[3] Consequently, there is the problem of how relevant the period's elasticity estimates are in out-of-sample period forecasts. In a forecasting sense, data values describing future export markets are likely to be far from the means of these variables that are calculated for the 1970s. If they are, the forecast errors would be large.

The second factor possibly diminishing the usefulness of export-level elasticities as a policy tool is that they focus attention on a potentially misleading interpretation of export performance. It is quite possible, for instance, to have world and U.S. exports falling because of demand-side factors but, because of increasing competitiveness of U.S. exports, the U.S. *share* of world exports may be rising.

Changes in world levels of agricultural exports are dependent on variables, such as importing countries' incomes and liquidity, that are generally outside the realm of U.S. agricultural policy action. Moreover, changing the values of these variables would be quite costly, and there would be no guarantee that the United States would garner the additional export sales. A more focused (and perhaps more attainable) policy action would be to concentrate on maintaining or enlarging the U.S. *share* of the export market.

While U.S. export competitiveness as measured by export share has received little attention, construction of agricultural exchange rate indexes has become popular.[4] The idea behind the indexes is to isolate exchange rate changes against U.S. agricultural export competitors or import customers or both. These indexes can then be used to investigate claims that prices of U.S. agricultural products became more competitive during the 1970s and less competitive in the early 1980s.

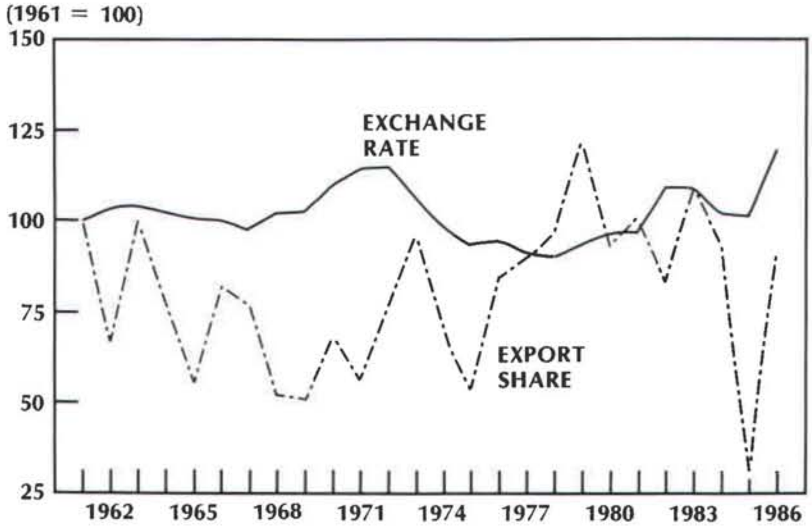
Again, it helps to distinguish between levels and shares. Charts 1 through 4 show the movement of indexes of U.S. export shares and crop-specific export-weighted real exchange rates (foreign currency units per dollar) for cotton, wheat, corn, and rice. There seems to be some correspondence: for example, the corn export share seems to rise in the 1970s as the corn exchange rate falls. It is hard, however, to see much of a pattern for cotton. The results of simple correlations between the indexes of export shares and exchange rates for the four commodities show that, as a first approximation, the shares and exchange rates are negatively and significantly related (at the 5-percent level) except for cotton.[5]

If the focus is shifted to export competitiveness and away from percentage changes in the levels of exports, many of the factors helping to determine levels are irrelevant in determining market shares among competing exporters. For example, importing-country crop production, so crucial in level determination, probably plays little role in deciding export competitiveness.

Export competitiveness

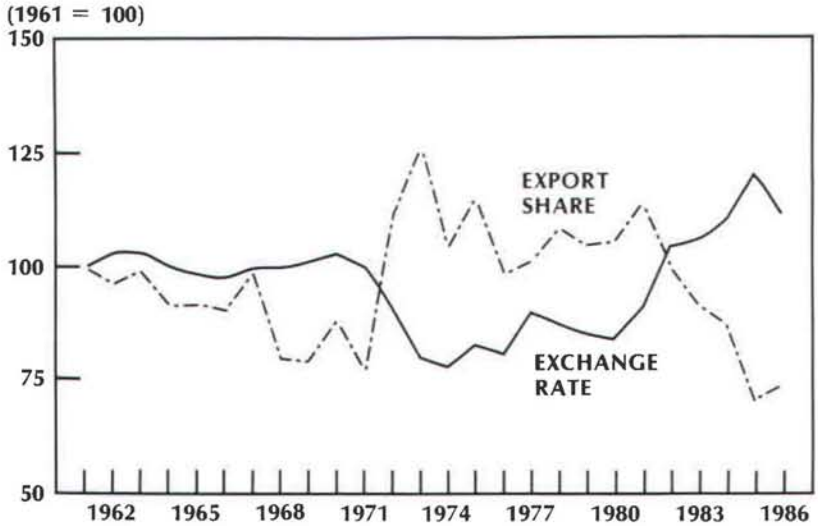
One of the most convenient measures of competitiveness of an individual country or company is movements in market share. In the absence of trade distortions and by abstracting from transportation costs, product differentiation, and the like, the problem of export-share competition can be reduced to two export competitors—for example, the United States and foreign exporters in the wheat market—and an aggregate importing-country sector. Further, it is taken as given that wheat is a world commodity priced in U.S. dollars. Chart 5 presents five panels to illustrate how the three prices work to determine market share. These diagrams show that exporting-country exchange rate effects

Chart 1
U.S. Cotton: Export Share and Exchange Rate



SOURCES OF PRIMARY DATA: International Monetary Fund
U.S. Department of Agriculture

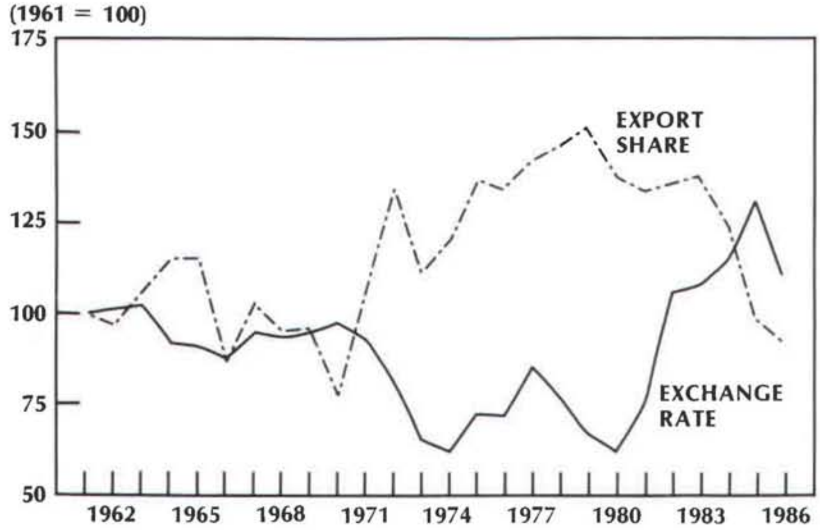
Chart 2
U.S. Wheat: Export Share and Exchange Rate



SOURCES OF PRIMARY DATA: International Monetary Fund
U.S. Department of Agriculture

Chart 3

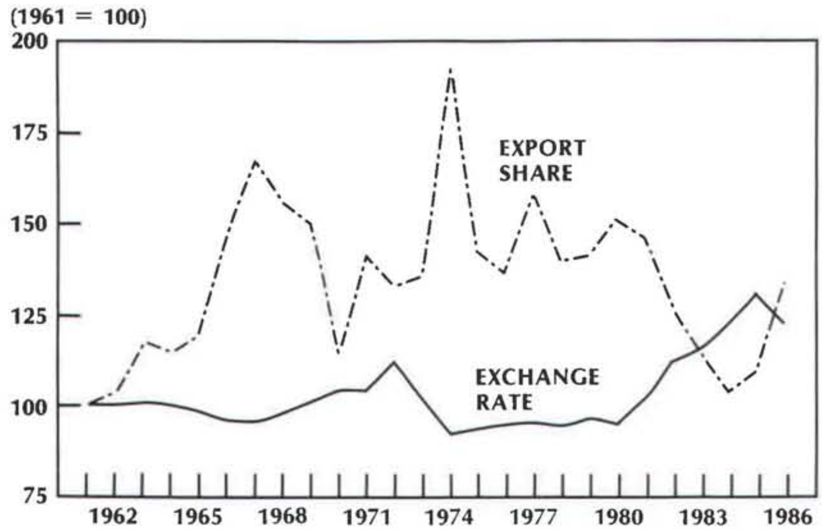
U.S. Corn: Export Share and Exchange Rate



SOURCES OF PRIMARY DATA: International Monetary Fund
U.S. Department of Agriculture

Chart 4

U.S. Rice: Export Share and Exchange Rate



SOURCES OF PRIMARY DATA: International Monetary Fund
U.S. Department of Agriculture

on U.S. share are unequivocal and that the direction of price correlation depends on the forces at work in the market.

In the leftmost diagram of Panel A, the net world excess demand for wheat facing the United States is shown as the downward-sloping line NXD^w. Excess demand at each price is total world demand for wheat imports less the world (foreign) supply of exportable wheat. Similarly, XS^{us} is the excess supply of U.S. wheat, or the excess of the U.S. wheat supply over domestic demand above the no-trade domestic price. The intersection of the two curves gives the quantity of U.S. wheat exported and the unit price.

The middle diagram shows the excess demand curve XD^i for importing countries. The rightmost diagram shows the excess supply curve (XS^{ex}) for foreign wheat exporters. These two diagrams are linked to the first by the relation

$$NXD^W = XD^i - XS^{ex}. \tag{1}$$

Panel A shows a situation that characterized much of the 1970s: outward shifts of the U.S. excess supply curves caused by policy changes that encouraged U.S. farmers to plant fencerow to fencerow. U.S. export prices would fall (from P_0 to P_1) and export quantities would rise under a free-market scenario (from Q_0^{us} to Q_1^{us}). Whether total revenues increased would depend on the elasticity of the excess demand curve. The second and third diagrams in Panel A show that import demand would increase (Q_0^i to Q_1^i) at the lower U.S. price and that foreign exports would fall (Q_0^{ex} to Q_1^{ex}); the foreign share of the export market (U.S. plus foreign) would fall proportionally more. Thus, as expected, declines in U.S. domestic price caused by supply expansion would be associated with increases in U.S. export share and would be matched by declines in export competitor prices.

The second outcome with an expansion of U.S. supply occurs if P_0 is a U.S. Government support price. In that event, potential additional export quantities move into government stocks ($Q_2^{us} - Q_0^{us}$), and the increase in supply is, in effect, neutralized in the short run. If U.S. supply variations were offset by government stockholding behavior, then U.S. prices would contain little information on U.S. supply-based shocks.

In Panel B, an outward shift in the foreign excess supply curve would increase foreign exports and export share by lowering internal foreign wheat prices. If P_0 were acting as a floor price, foreign share would increase more than if the U.S. price were allowed to decline fully. Implicit in the diagrams so far is that the exchange rate has a value of unity and that the exchange rate fully equilibrates prices across countries.

The third price to be considered is the currency exchange rate. Although both appreciations and depreciations of the dollar could be illustrated, the cases are symmetrical, and only depreciations will be considered here.

In Panel C, if the U.S. dollar depreciates against world currencies as it did in the late 1970s, then the excess supply curve for foreign wheat will rotate to the left.[6] After such a rotation, a given world dollar price of wheat buys fewer foreign bushels, and downward pressure is placed on internal foreign wheat prices. Further, importer excess demand rotates to the right. The comparative static results are that after a devaluation of the U.S. dollar, the net excess demand facing U.S. exporters shifts outward. The new equilibrium consists of higher U.S. dollar prices for wheat, lower foreign local-currency prices for wheat, and a larger share of the market for U.S. exporters.

During the 1970s, importers' demand for agricultural commodities grew when the importing countries experienced rapid economic growth and borrowed money on easy terms. The middle diagram of Panel D shows the importers' excess demand curve rotating outward. Wheat prices will rise, as will the U.S. share, if the U.S. supply response is more elastic than the response of foreign exporters. Given U.S. agricultural policies before 1985, that possibility has substance. The effects are exactly the reverse when importer excess demand curves rotate inward as a consequence of an exogenous decline in importer demand.

As a very crude indication of the relative elasticities, logarithms of world exports of wheat, corn, and rice were separately regressed on logarithms of U.S. exports of wheat, corn, and rice. The results are displayed in Table 1. While these results are only correlations, rather than the underly-

Table 1
REGRESSION OF WORLD EXPORTS ON U.S. EXPORTS, 1961–85

Log of world exports	Intercept	Elasticity[1]	R^2	Durbin-Watson statistic[2]
Wheat ...	2.36	.92	.91	1.06
	(2.34)	(15.45)		
Corn.....	4.65	.76	.98	1.05
	(10.84)	(30.16)		
Rice	7.31	.60	.66	1.29
	(5.63)	(6.72)		

1. Elasticities shown are percentage changes in world exports with respect to percentage changes in U.S. exports.
2. None of the estimated first-order autocorrelation coefficients were significant at the 5-percent level.
NOTE: Figures in parentheses are t statistics.

Chart 5
Exports, Prices, and Exchange Rates

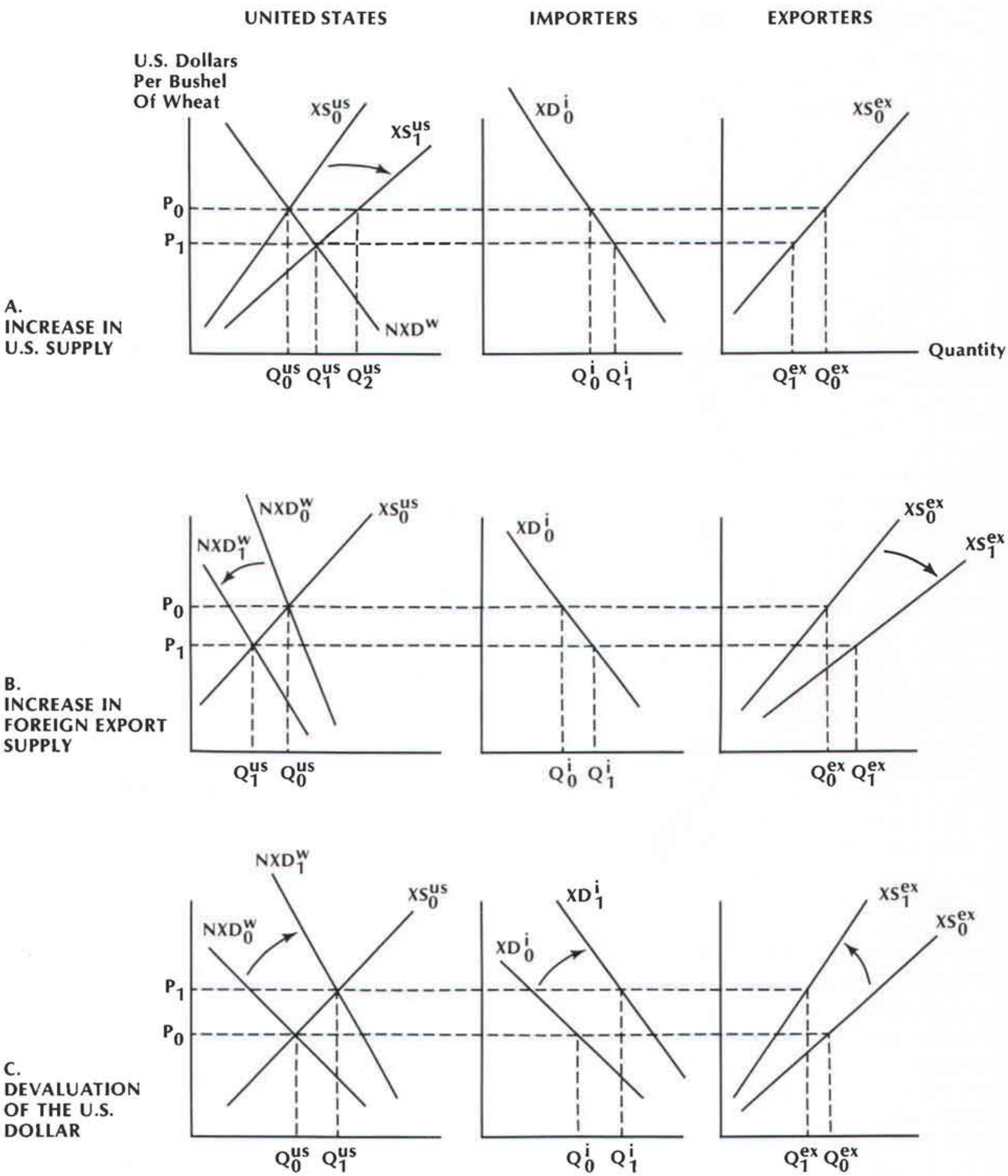
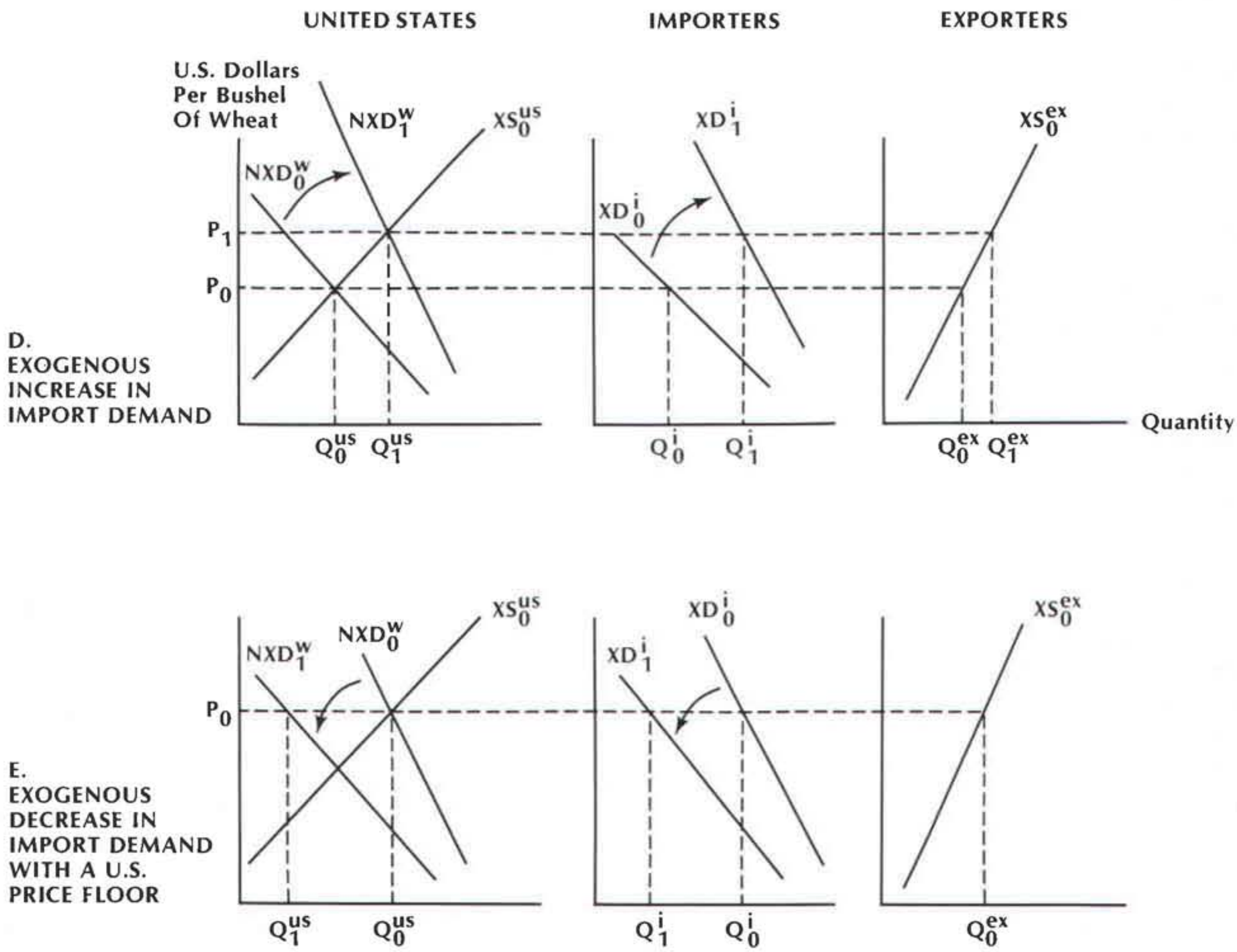


Chart 5—*Continued*

Exports, Prices, and Exchange Rates



ing supply elasticities, the estimates are consistent with the notion that the U.S. supply response is more elastic. The elasticity estimates show that percentage changes in world exports are smaller than those for U.S. exports. For example, a 10.0-percent increase in U.S. corn exports is associated with a 7.6-percent increase in world exports.

Panel E shows the effects of an exogenous decrease in import demand (caused, say, by foreign debt problems), with P_0 acting as a floor price. This case could be considered a stylized partial-equilibrium representation of what happened in the first half of the 1980s. U.S. wheat exports, share, and importer demand all fell sharply, while foreign export declines were relatively smaller.

From this elementary analysis come some hints about the complexity of the causal relationships among prices and export share. The price of wheat is negatively associated with increases in U.S. share, primarily for the cases of exogenous changes in U.S. supply. That relationship is weakened when U.S. production controls or support prices are binding. For exogenous changes in foreign export supply, for appreciations/depreciations of the dollar, and for changes in the import demand when export response is more elastic for the United States than for other countries, U.S. prices and export share move in the same direction. The role of the exchange rate is less equivocal. Depreciations in the U.S. dollar against exporting countries' currencies raise U.S. share, while appreciations lower it. The quantitative significance of these results, however, depends on whether the Law of One Price holds.

U.S. agricultural exports and the Law of One Price

The Law of One Price (LOP) states that for a given commodity, one price—adjusted by exchange rates—will prevail across countries. Symbolically, the LOP is represented for the United States by

$$(2) \qquad P^{us} = e\,P^{for},$$

where

P^{us} = U.S. dollar price of some homogeneous good,
e = exchange rate in U.S. dollars per unit of foreign currency, and
P^{for} = foreign-country price of the good.

Empirically, there are several ways to test the LOP.[7] The simplest is to test what has been called the weak long-run LOP hypothesis by first putting equation 2 in logarithmic form:

$$(3) \qquad \ln(P^{us}) = \alpha_0 + \alpha_1 \ln(e) + \alpha_2 \ln(P^{for}) + u_t,$$

where u_t is an error term.

Equation 3 is then estimated. Given the likelihood of simultaneous determination of foreign and U.S. prices, a two-stage procedure can be used to purge the foreign price term of simultaneity bias. With either ordinary least squares or a two-stage procedure, it is necessary to test the restriction

$$H_0: \alpha_1 = \alpha_2 = 1.$$

If the null hypothesis is not rejected, then there are two implications for the determination of U.S. market share. The first is that the static analysis as presented here is not rejected by the data. The second implication is that among the two commodity prices and exchange rate, there are only two unique pieces of information.

Modeling U.S. market share

This investigation examines the extent to which prices and exchange rates determine market shares, but other variables could play a role. Trade policies are probably the prime nonprice influence affecting shares in a systematic way, but they are difficult to capture empirically. Other influences, such as production or domestic consumption variations, will likely show up as random fluctuations in the error term.[8]

To formalize the model notation,

$$(4) \qquad S_i = f(\underset{-}{ER_i},\ \underset{?}{P_i^{us}},\ \underset{?}{P_i^{for}}),$$

where

S_i = U.S. share of exports of commodity i;
ER_i = real exchange rate, in terms of currency units of foreign exporting countries per U.S. dollar;
P_i^{us} = U.S. real price of commodity i; and
P_i^{for} = real price of commodity i in foreign exporting countries.

The signs under the variables indicate the expectations of the signs given by the static analysis. Depreciation of the U.S. dollar against exporting-country currencies is predicted to have a positive effect on U.S. share. The sign of the price term is not determinate. As described in the discussion of Panel A in Chart 5, increases in U.S. supply, other forces remaining constant, should produce lower U.S. prices and, hence, a greater market share for U.S. exports. The correlation between U.S. prices and U.S. export share is likely to be positive in most other circumstances: changes in foreign supply, changes in the value of the dollar against exporting-country currencies, and changes in foreign import demand when U.S. supply response is more elastic than the response of competing exporters.

As with any reduced form, the net correlation of price and share depends on the magnitude of the above effects, about which theory is silent. Should the estimated sign on the price coefficient be negative, then as a summary measure, the parameter value and the associated elasticity would have useful policy implications. A positive U.S. price coefficient, however, would indicate that U.S. supply effects on price are sufficiently damped to allow the other forces (foreign demand and supply changes, exchange rate effects) to dominate. With a positive sign, the price coefficient shows correlation, not causation, and hence is empty of policy relevance. The expectations for the sign of foreign price depend on whether LOP holds. If LOP cannot be rejected, U.S. and foreign prices are assumed to move in concert, diverging from each other only as exchange rates move. Further, if the LOP is found to hold, then including foreign prices with U.S. prices and the exchange rate is superfluous.[9] If LOP does not hold, then higher foreign prices, other things remaining the same, would mean an increase in U.S. export share.

Table 2
TEST OF THE LAW OF ONE PRICE

	Tests of coefficient restrictions							
	$ER = 1$	$P = 1$	$ER = P = 1$	$ER = .95$	$P = .95$	$ER = P = .95$	$ER = P$	Predicted $ER = P = 1$[1]
Wheat								
Canada	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Australia	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Argentina ...	No	No	No	No	No	No	No	No
Corn								
Argentina ...	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Rice								
Thailand	No	No	No	No	No	No	No	Yes

1. Test conducted with predicted foreign price variables.
NOTE: ER = exchange rate coefficient.
P = foreign-country price coefficient.
"Yes" indicates that the 1961–86 data were unable to reject the restriction in the column heading; "no" indicates the reverse.
All tests were at the 5-percent significance level.

Table 3
LOGIT SHARE ESTIMATION RESULTS

	Intercept	Exchange rate	U.S. price	$\bar{R}^2$	Durbin-Watson statistic	Chow F-test[1]
Wheat						
Canada	−0.13	−0.94*	0.80*	.50	1.46	3.92*
	(−0.79)	(−3.04)	(5.11)			
Australia	0.25	−0.53*	1.14*	.45	2.11	0.29
	(1.16)	(−2.14)	(4.54)			
Argentina	1.24*	0.006	0.97*	.16	1.78	0.50
	(3.35)	(0.47)	(2.11)			
Corn						
Argentina	1.35*	−0.052*	1.53*	.59	1.86	1.34
	(7.06)	(−5.95)	(4.10)			
Rice						
Thailand, 1961–85...				.56	2.27	4.25*
1961–72...........	10.53	−1.05	−2.84*			
	(0.94)	(−0.38)	(−2.26)			
1973–85...........	4.02	−1.92	0.69*			
	(0.92)	(−1.50)	(2.32)			

1. $F(3,19) = 3.13$, testing for coefficient stability at the .05 level, 1961–85 and the two subperiods 1961–72 and 1973–85.
* Significant at the 5-percent level.
NOTE: Figures in parentheses are t statistics.

Estimation and results

The first test is whether the Law of One Price holds. Annual data were gathered for U.S. wheat, corn, and rice prices; Canadian, Australian, and Argentine wheat prices; Argentine corn prices; Thai rice prices; and exchange rates.[10] Table 2 shows the results of estimating the LOP equation for the years 1961-86. Several coefficient tests were performed: (1) test of whether the coefficient on the exchange rate is equal to 1, (2) test of whether the coefficient on the foreign price term is equal to 1, (3) test of whether the two coefficients are jointly equal to 1, and (4) test of whether the two coefficients are equal to each other. The first three tests were repeated for 0.95, an arbitrarily chosen value close to 1. Further, test 3 was also conducted using predicted values of the foreign price variable to control for endogeneity.[11]

The LOP results are mixed. Only the Argentine corn passed the joint test of both coefficients equal to 1. Canadian and Australian wheat passed the 0.95 joint test, but Argentine wheat and Thai rice rejected both the 1.0 and 0.95 tests. Three of the five LOP equations were unable to reject the test that the exchange rate and price coefficients were equal (though not necessarily equal to 1). Similarly, in tests using predicted values of the foreign price, three of the five LOP equations were generally unable to reject the joint 1.0 test.

For the share equation estimations, the LOP tests mean that although LOP was not strictly confirmed, in large measure the theory is approximate to reality. That being the case, the share equations are estimated with only real U.S. price and real exchange rate as regressors; the foreign price is dropped as being unnecessary.[12] The share variables are the U.S. proportion of the sum of bilateral annual exports for wheat, corn, and rice.[13] Thus, three wheat equations, one corn equation, and one rice equation were estimated.

The dependent variable is a proportion. As with any share variable, the bounds are 0 and 1. Distribution of the share variables is truncated and, thus, is not strictly normal. The cumulative logistic probability function is a good candidate because its extremes are 0 and 1. It has the further advantage of transforming the dependent variable from one contained within the (0,1) interval to one bounded only by the $(-\infty, +\infty)$ interval. For this application the logistic function is

$$(5) \qquad S_i = \frac{1}{1 + \exp(-Z_i)},$$

where

S_i = U.S. share of bilateral exports in period i,
exp = natural log exponential operator, and
$Z_i = \beta_0 + \beta_1 \ln(ER_i) + \beta_2 \ln(P_i^{us})$.

Multiplying through by the denominator and collecting terms yields

$$(6) \qquad e^{Z_i} = \frac{S_i}{1 - S_i}.$$

Taking the log of both sides and substituting for Z_i gives the estimating equation:

$$(7) \qquad \ln\left(\frac{S_i}{1 - S_i}\right) = \beta_0 + \beta_1 \ln(ER_i) + \beta_2 \ln(P_i^{us}).$$

All models were estimated over the years 1961-85, using yearly data. Further, each of the models was examined using a Chow test for a change in structure coinciding with the switch from fixed to flexible exchange rates. The results of the estimation are displayed in Table 3.

The Chow F-test statistic for stability of the coefficients over the entire sample period indicates that only for Canadian wheat and Thai rice is the restriction of constant coefficients rejected.[14] For Canadian wheat, individual coefficient t-tests reveal no significant differences in coefficient values over the period, so the values reported are for the entire sample period. For Thai rice, there were significant differences for individual coefficients, and values are reported for each subperiod.

Turning to the individual coefficients, the exchange rate terms have the expected signs and are significant in three of the six reported regressions. The exchange rate coefficient is only marginally significant in the 1973-85 rice regression and is insignificant in the Argentine wheat regression and the 1961-72 rice regression.

The coefficients for U.S. price variables are significant and positive in sign for all regressions except 1961-72 Thai rice. With positive signs, the coefficients should not be interpreted as indicating a causal relationship of price to share but, rather, as indicating that both share and price are being moved in the same direction. These results show that U.S. supply shocks are sufficiently damped by government policy that price changes are too small to move U.S. export share and/or that the effects of U.S. supply-induced price movements on share are swamped by other factors, such as foreign supply and demand changes and exchange rate movements.

Given that the dependent variable was formed as a logit variable, the parameter estimates are not derivatives, as is the case in regular ordinary-least-squares regressions. The

Table 4
LOGIT ESTIMATION ELASTICITIES

	U.S. price	Exchange rate
Wheat		
Canada		−.3134
		(−2.94)
Australia		−.1214
		(−2.17)
Argentina		.0007
		(9.84)
Corn		
Argentina		−.0057
		(−2.69)
Rice		
Thailand, 1961–72	−1.4128	−.5211
	(−6.82)	(−5.17)
Thailand, 1973–85	0.3482	−.9689
	(4.95)	(−4.50)

NOTE: Elasticities shown are percentage changes of the U.S. share of bilateral export totals with respect to percentage changes in the indicated variables. The elasticities were evaluated at the means for the 1976–85 period except as indicated. Figures in parentheses are *t* statistics. The asymptotic standard errors used to compute the *t* statistics were derived from a formula in Henri Theil, *Principles of Econometrics* (New York: John Wiley & Sons, 1971), 373–74.

derivatives and elasticities must be calculated separately. The calculated elasticities are reported in Table 4.

On the whole, the elasticities indicate that the U.S. shares of agricultural exports, expressed as a proportion of the bilateral total, are relatively inelastic. For example, for Canadian wheat, a 10-percent appreciation of the U.S. dollar would cause the U.S. share of Canadian-U.S. wheat exports to decline 3.1 percent. The results for Australian wheat are even more inelastic: a 10-percent appreciation of the U.S. dollar against the Australian dollar would decrease the U.S. share of Australian-U.S. exports by 1.2 percent.

For Argentine corn, the exchange rate elasticity is minute. A 100-percent appreciation of the U.S. dollar would cause only a 0.57-percent decrease in the U.S. share.

For Thai rice, the Chow test indicated that the coefficients were not stable over the 1961-85 period, so elasticity estimates are reported for two subperiods, 1961-72 and 1973-85. The negative and significant price term coefficient for the earlier period indicated that U.S. share was very responsive to price movements caused by U.S. supply shocks. The elasticity estimate is that during the 1961-72 period, a 10-percent increase in U.S. domestic price resulted in a 14.1-percent decline in the U.S. share of Thai-U.S. rice exports.

The U.S. rice export share is also more sensitive to exchange rate movements than are other crop shares. For a 10-percent appreciation of the U.S. dollar, the U.S. share would decline more than 5 percent. For the 1973-85 period, the sign of the price coefficient in the logit regression becomes positive, as does the corresponding elasticity. For the exchange rate elasticity, percentage changes in exchange rates induce percentage changes of nearly equal size in the U.S. share.

Conclusions

Overall, the results seem to indicate that the Law of One Price does hold, at least to an approximation. The cumulative effects captured in the price signal, however, cannot be disentangled in this single-equation model. One of the qualitative results coming from estimation of the price terms is that the domestic supply effects do not seem to dominate other effects, such as changes in foreign supply or demand. Given the U.S. Government's program of support prices and stockholding, domestic prices are not a reliable barometer of domestic supply-demand conditions.

As for exchange rates, their effect on share is inelastic in all statistically significant cases except rice for the 1973-85 period. Thus, it would appear that the 1982-86 decline in U.S. agricultural exports was only marginally related to the change in export competitiveness brought about by appreciations of the dollar against currencies of U.S. export competitors. Demand-side factors are likely to provide the answer.

1. See Walter H. Gardiner and Praveen M. Dixit, *Price Elasticity of Export Demand: Concepts and Estimates*, Foreign Agricultural Economic Report no. 228, U.S. Department of Agriculture, Economic Research Service (Washington, D.C., February 1987), for a review of elasticity methodology and a survey of studies.

2. One well-known paper that models agricultural exports during the 1970s is Robert G. Chambers and Richard E. Just, "Effects of Exchange Rate Changes on U.S. Agriculture: A Dynamic Analysis," *American Journal of Agricultural Economics* 63 (February 1981): 32-46.

3. G. E. Rossmiller, "Farm Exports: An Historical Perspective," *Choices*, Third Quarter 1986, 24-25.

4. For example, David Henneberry, Shida Henneberry, and Luther Tweeten, "The Strength of the Dollar: An Analysis of Trade-Weighted Foreign Exchange Rate Indices with Implications for Agricultural Trade," *Agribusiness* 3, no. 2 (1987): 189-206; John Dutton and Thomas Grennes, "Measurement of Effective Exchange Rates Appropriate for Agricultural Trade," Economics Research Report no. 51, North Carolina State University, Department of Economics and Business (Raleigh, November

1985); and O. Halbert Goolsby and Ronald R. Roberson, "Exchange Rate Developments and Their Impact on U.S. Agricultural Exports, 1970-84," FAS Staff Report no. 5, U.S. Department of Agriculture, Foreign Agricultural Service (Washington, D.C., May 1985).

5. The estimated simple correlation coefficients for the indexes of export shares and exchange rates for the 1961-86 period are −0.118 for cotton, −0.770 for wheat, −0.476 for corn, and −0.532 for rice.

6. A simple mathematical representation of this graphical model shows that the sign on the partial derivative of the U.S. share with respect to the U.S.-foreign exporter exchange rate is negative. The sign of the U.S. share derivative with respect to the U.S.-foreign importer exchange rate is ambiguous. In this model, therefore, the U.S.-foreign importer exchange rate is assumed either to move in tandem with the U.S.-foreign exporter exchange rate or to remain constant.

7. For extensive tests of LOP and for a good set of references to other relevant LOP literature, see Aris A. Protopapadakis and Hans R. Stoll, "The Law of One Price in International Commodity Markets: A Reformulation and Some Formal Tests," *Journal of International Money and Finance* 5 (September 1986): 335-60.

8. For a widely cited model of U.S. agricultural trade that considers cross-price effects, expectations in supply, and stockholding, see Jim Longmire and Art Morey, *Strong Dollar Dampens Demand for U.S. Farm Exports*, Foreign Agricultural Economic Report no. 193, U.S. Department of Agriculture, Economic Research Service (Washington, D.C., December 1983).

9. This proposition holds only for a log-linear estimation form. Given that LOP is a multiplicative relationship, $P^{us} = e\,P^{for}$, then a log-linear estimating equation, $\ln(P^{us}) = \ln(e) + \ln(P^{for})$, preserves the mathematical equality that a purely linear equation, $P^{us} = e + P^{for}$, does not.

10. Foreign-country prices in local currency are difficult to get. The nominal commodity prices used in this study were provided by the U.S. Department of Agriculture (USDA). Foreign-country prices were converted by the USDA from local currency units to dollars. This conversion was reversed by the author for the LOP tests, using the appropriate exchange rates. Exchange rate data came from *International Financial Statistics* (International Monetary Fund) tapes.

11. J. A. Hausman detailed an exogeneity test for variables in "Specification Tests in Econometrics," *Econometrica* 46 (November 1978): 1251-71. The test involves including a predicted variable of the suspect variable as an additional variable on the right-hand side of the regression. The estimated value of the included variable coefficient, if significantly different from zero, indicates endogeneity. The data for the study here were unable to reject the null hypothesis of exogeneity for the prices of wheat, corn, and rice. Thus, the method of least squares was applied to test LOP. Nevertheless, the two-stage least squares method was used in some of the LOP tests for comparative purposes.

12. Trial estimations including all three LOP variables showed severe multicollinearity.

13. Data on exports were gathered from Food and Agriculture Organization of the United Nations, *FAO Production Yearbook*, FAO Statistics Series (Rome, Italy), for various years.

14. The Chow test was constructed using the sum of squares from the restricted model and the sum of squares from the unrestricted model (additive dummy variable for the intercept, multiplicative dummies for the independent variables). The dummy-variable coefficients in the unrestricted model were examined for significance when the Chow test indicated coefficient instability. A separate *F*-test showed that the assumption of homoscedasticity could not be rejected by the data.

Interstate Shifts in Nonresidential Construction

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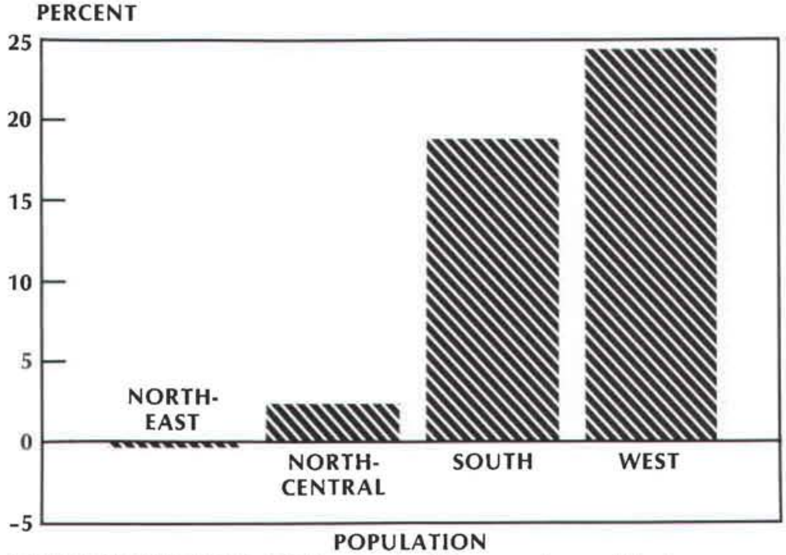
In nonresidential construction, aggregate fluctuations are strongly influenced by national factors—such as changes in tax laws—and by international events such as fluctuations in interest and exchange rates. But despite the importance of both in explaining these growth-rate fluctuations, much rate variation occurs among regions and over time. During 1985-87, for example, when nonresidential construction contract values fell in the Eleventh Federal Reserve District while growing nationally, the District share of national construction declined. The reverse was true in the decade prior to 1983 when the District share of national construction increased greatly because the District's nonresidential construction outpaced the nation's.

In this study, we examined the factors that led to regional variations over time in the relative growth rates of nonresidential construction across regions. Our results suggest that interregional shifts in nonresidential construction investment shares are explained by labor migration patterns. These, in turn, appear to be determined primarily by factors linked to prospects for overall growth in output, including the relative strength of the state's most dominant industries and by major external shocks. During the 1973-83 time period we studied, the most important of these exogenous shocks were probably the abrupt movements in oil prices. A major factor in determining the population flows and nonresidential investment over this period proved to be how much that each region had participated in energy production.

These results suggest that the relative performance of a region's economy depends on its industrial structure and the nature of exogenous shocks. Of greater importance is the fact that our results indicate that one of the most significant determinants of nonresidential investment was the change in an area's population in response to a given shock.

In the first section of this article, we describe the particular characteristics of structures that distinguish them from other investments and other productive factors. In the second section, we show how shocks can cause shifts in investment patterns through their impact on growth expectations. We develop a stylized two-equation model of nonresidential-structures investment in the third section. The results from the pooled estimation of the two-equation

Figure 1
Percentage Change in U.S. Population, by Region, 1973-83



SOURCE OF PRIMARY DATA: U.S. Department of Commerce, Bureau of the Census.

system constitute the fourth section, followed in the fifth section by the conclusions.

Characteristics of nonresidential structures

Whether a particular nonresidential structure houses manufacturing operations, offices, stores, schools, or theaters, it is simply one input used to produce goods or services. Nevertheless, structures clearly do differ from other productive inputs. One distinctive characteristic of structures is their long life in productive processes, typically more than thirty years as opposed to less than ten for most equipment investments. A second distinctive characteristic is that the lags occurring between changes in the desired and actual stock of structures are longer than is common for other investment types.[1]

For both reasons, the policy decisions to invest in nonresidential structures depend on long-term expectations about future returns. Furthermore, investment expectations may be formed under greater uncertainty because of long structure life and decision lags between investment and construction project completion.

Shocks and regional investment patterns

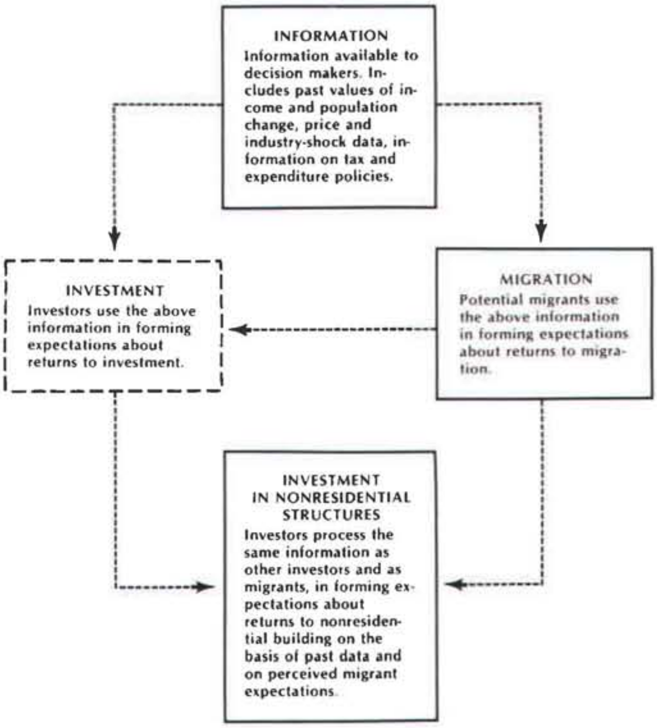
Focusing attention on investment in nonresidential structures is important because of these special characteristics, particularly the implied longer-term commitment. Thus, in analyzing fluctuations in a region's share of nonresidential construction, we also identified influences on long-term expectations about regional growth.

The 1973-83 time period for this study had significant shifts in regional growth patterns. Generally, as shown in Figure 1, the states in the West and South had faster-than-average population growth while those in the East and Midwest slipped by comparison.

Although there are numerous explanations for this regional shift, it appears that changing energy prices accelerated the rate.[2] Higher energy costs are blamed for raising the cost of production in the colder states, thus encouraging the movement to Sunbelt states. Likewise, the concentration of energy extraction activity in Sunbelt states—together with the shift in shares of personal and business consumption expenditures toward energy and away from other products—meant a reallocation of overall spending toward this region. The positive impact on oil-rich areas went beyond the immediate employment effects in energy-related industries, suggesting that energy shocks affected long-run expectations about relative growth potential.

This point suggests an important aspect of differential regional growth. A sudden increase in a commodity's price should raise profitability and cause growth in states that specialize in producing it. But the full effect of the price shock on area growth also includes the information it con-

Figure 2
Information Cycle on Nonresidential Investment



veys about the area's overall relative growth prospects. Thus, real shocks to production or prices may be more important than other common arguments (including those related to regional fiscal policies or factor price differentials) in explaining shifts in resource flows.

Other studies have suggested that variables under the control of the region's agents, such as fiscal policies, may be important in determining where the factors flow, once decisions are made to move them.[3] Nevertheless, the relocation motivation is often linked to real shocks that significantly affect the expected profit potential of a region's industrial mix.

More generally, the relative growth of national factor shares in a region is largely determined by expectations about future returns to these factors. When a positive price shock occurs and its impacts are concentrated in some regional subset, then persons elsewhere might try to evaluate what this event could mean to their own income prospects. An individual will migrate if he decides that the shock will be persistent enough to raise the present value of his expected income. Likewise, an investor who surmises that the shock means that returns to his capital will be higher in the shocked area will move his capital.

In this study, the same processes were assumed to hold true for agents—individuals, firms, or governments—who invested in regional nonresidential structures. The same data that induced agents to invest or migrate also might be used to generate the expectations on which investment decisions would be made. Although past events clearly influence expectations, it is the expectations factor that actually determines labor migration or capital investment.

Modeling investment in nonresidential structures

Our model attempted to capture the process by which a potential investor, under uncertainty, would choose a particular type of investment in a specific location. The model assumed a recursive form in order to capture an important element of investor expectations. An initial equation was used to explain changes in population by state. Measures of price shocks, state and local government fiscal variables, and regional industrial characteristics were used to explain differentials between national population growth rates and those of individual states or regions.

A second step equation in this recursive system was used to explain regional variations in rates of growth in nonresidential construction. Explanatory variables in this second equation included the predicted values derived from the first equation that were used to proxy investor expectations about changes in population. Since this second equation also included variables that appeared in the first equation, their direct impact upon nonresidential construction—beyond what they contribute indirectly as arguments to population growth—might also be considered. The pattern of investor decision making that this recursive estimation procedure was intended to capture appears in Figure 2.

A hypothesized chain of causality for information used in making nonresidential investment decisions also appears in Figure 2. As is shown, part of the investment decision involved assessing related factor-reallocation decisions that affect both regional growth and the nonresidential investment returns. It was assumed that investors realize that the same events that would affect their investment decisions might also influence the migration decisions of potential laborers. Thus, investors would incorporate into their investment decisions information that might explain population growth.

This formulation of the problem, however, assumed that investors would place different weights on their information sets than would migrants, even though both groups would have access to much the same information. That assumption motivated both the recursivity of this model and the inclusion of some of the same variables in both equations.

Implicit in this formulation was the assumption that information is imperfect and costly to obtain. In such an environment, an investor faced with a long-term investment would have more of an incentive to obtain information than would a migrant, who could more easily reverse his decision to move. Investors thus would be more likely to make their decisions conditional on their expectations about migration, while migrants would be more likely to take business investment as an exogenous process and not predict future investment per se.[4] Consequently, expectations about population were included in the investment equation, but expectations about investment were not included in the population equation.

Based on the conceptual development of the problem shown in Figure 2, we formulated a model of nonresidential construction investment as a two-equation system:

$$\dot{n}_{it} = f[E(\dot{w}_{it} \mid \Phi_t)] \tag{1}$$

$$I_{it} = g[E(r_{it}[\dot{n}^e_{it}, o_{it}] \mid \Phi_t)]\,. \tag{2}$$

In the first equation, the relative growth of population in the region, $\dot{n}_{it}$, was determined by expectations about the growth of a vector of wage and amenity characteristics, $\dot{w}_{it}$, given the information available at time t, Φ_t. As new information became available that would change the expected geographical distribution of returns, population would move to areas where the wage potential was higher, or where other characteristics of the region would become more highly valued relative to other regions.[5]

As shown in equation 2, the decision to invest in region i, I_{it}, would depend on the potential return to an investment relative to the return elsewhere, r_{it}, and expectations about the relative return to capital would be determined by the investor's expectations about the relative abundance of factors, including population and other inputs, o_{it}. Interregional shifts in investment flows would be expected, therefore, when changes in relative conditions in one region favorably affected the expected return to investment. This gain in relative return potential might result significantly from perceptions about migration flows.

In our nonresidential construction model, we assumed a recursive structure. We further assumed that investors would first form expectations about relative population growth and then use those expectations to choose their level of nonresidential construction investment.[6] In the next two sections, we examine the variables likely to be important in each of these decision steps.

Forming expectations about population growth

In constructing the population model equation, we applied what has been characterized as a migration-in-disequilibrium-systems approach. In this approach, interregional differentials in returns to labor were assumed to be the result of disequilibrium.[7] This disequilibrium would encourage migration from low-wage to high-wage regions that would, in turn, narrow the differential. In this section, we present arguments for a population-growth equation in which expected income differentials among regions generate migration and thus differential rates of regional population growth. The variables in the equation were not used as expectations variables per se, but were assumed to comprise data on which potential migrants might base their expectations of future returns.

One determinant of agents' expectations about potential earnings in different regions might be the degree to which current actual wages or per capita income in a region deviated from the national average. Whenever a region exceeded the nation in per capita income, the widening of this differential could be expected to induce increased rates of inmigration and, therefore, of population growth.

Relative energy costs also might affect population flows. Increases in regional over national energy costs (in the case of natural gas—because of regulatory factors; and in the case of electricity—because of differences in types of fuels used for generation) would negatively affect returns to labor net of these costs. These effects would be factored into agent calculations of the utility of migration.[8] Thus, as costs of heating and cooling rise in one particular region over others, migration rates to the affected area might fall.

State and local governments are often assumed to play a role in affecting the region's economic growth and thus its population growth.[9] The "Tiebout hypothesis" in the public finance literature predicts that an agent will move where the mix of governmental spending and tax priorities best reflects his demands for publicly provided goods and services.

In some research, relatively high expenditures in social spending (including expenditures on education and hospitals) and expenditures on economic overhead capital (including investments in streets and roads and in other classes of publicly owned infrastructures) have been shown to be positively linked to economic growth.[10] If agents perceived that high per capita expenditures in these areas were tied to opportunities for growth in their own personal income, they might be more likely to migrate there. Conversely, high per capita expenditures on welfare might discourage migration because of implied higher tax rates.

The past findings on these relationships have not been uniform either across types of spending or within one type of spending in different studies. One topic at issue is the direction of causality between growth in these various classes of government spending. In some studies, social overhead capital and economic overhead capital spending have been characterized more as responses to past growth than as generators of future expansion. In others, the opposite relationship has been postulated. It has also been argued that where population is growing, the demand will be greater for economic overhead capital than for social overhead capital.[11]

In addition to these other factors, price shocks and perceptions about the relative strength of a region's industries are likely to affect an agent's migration decision. As indicated earlier, the role played by price shocks as signaling devices suggests that for the period under study, oil prices might have significantly affected agents' expectations. When agents base expectations about their returns to migration on events that might affect particular industries in a region, then areas dominated by industries that could profit from oil price shocks should receive particularly acute attention.

To capture this effect, it was necessary to construct a proxy composed of two factors. First, the relative importance of the energy sector had to be determined. Expectations about the effect of an oil shock on a state were likely to depend on the perception of that state's dependence on oil extraction. Second, the direction and size of the shock might be expressed through the growth rate of oil prices. In our interaction of two effects (the difference in the share of employment in the extraction industry in the state from the nation, as well as the growth of oil prices), a proxy emerged that would be positive for energy states and negative for nonenergy states when oil prices rose.

Even during the period under consideration, however, the U.S. economy was subject to other technological and price shocks that might have had only tenuous links to energy-price shocks. Innovations in electronics and communications and in the organization of business enterprises played significant roles in altering the economic landscapes nationally and regionally. Thus, more general considerations based on past industrial performance in a region also should have received attention by agents who were considering migration or investment at this time.

We modeled these latter considerations by a methodology similar to what we applied to energy shocks. Agents were assumed to associate the region's industrial strength with the relative performance of its two most dominant industries. We identified an industry's degree of dominance in a state as the difference between the industry's state and national employment shares. The greater the degree to which an industry's state employment share exceeded its national share, the more dominant that industry would be for the state.

We created a proxy for the health of these dominant industries. Our first step was to take the difference between an industry's state and national employment shares. Our second step was to multiply that difference by the ratio of growth in the industry nationally to the average growth rate for all U.S. industries. Summing this individual industry variable for the two dominant industries in a state yielded the overall positive or negative expression of dominant industry health for each state (see Appendix A for a list of the two dominant industries for each state).[12]

Even though we hypothesized that agents would give particular attention to the roles of regionally dominant industries, we also assumed that these agents considered information about the remaining industries as well. Agents were assumed to evaluate the relative strength of a region's economy by examining its average performance. This performance was proxied by the previous year's employment growth relative to the national average for all industries, but weighted by the degree to which the region's employment share in a given industry differed from the national average. Instead of summing over only two industries, as with the dominant industry variable, we summed over all nondominant industries. The values of this variable took on negative signs if the nondominant industries were shrinking nationally (or if their shares happened to be smaller than the national average). The variable took on a positive sign if the nondominant industries were both declining and had smaller-than-average shares in the state.

Modeling changes in nonresidential construction spending

In the nonresidential investment equation, we identified that the expected growth of the region's population relative to the national average was one of the most important determinants of regional shifts in nonresidential construction investment. Population changes also were seen as particularly useful as a growth measure because recent literature reports population leading jobs rather than the reverse.[13]

We hypothesized two key links between population growth and nonresidential construction. First, we projected the expected population variable to capture expectations about overall regional growth. The same factors that could have generated high rates of inmigration to a region also might have incurred high rates of growth in nonresidential building there.

Second, we could postulate a direct link between growth in population and in structures. That is, in a production regime where variations in the capital-labor ratio were limited, increasing demands for labor would imply increasing requirements for capital in general and for structures in particular.[14]

We further noted that these relationships could depend on the demographic characteristics of the migrating population, however. For example, overall growth in population resulting from any demographic subcategory could induce investment in nonresidential structures, because of the increased demands for goods and services implied by a rising population. In particular in this study, expected population growth might have been linked to expansion in nonresidential structures, to the degree that growth was also linked to the expected work force group.

Since most of the work force is under the age of 65, it could be expected that relative growth in the under-65 population would be an important factor in determining the pattern of regional nonresidential investment. Such investment would be more likely to be positive in regions in which the share of under-65 population was expanding faster than average.

A heavy reliance on business taxes, however, might have discouraged investment. Since low business taxes often suggest a business climate more conducive to expansion, investment would likely have migrated to areas where the business sector had lower-than-average shares of total taxes.

We also hypothesized that other migration decision factors might have direct impacts on nonresidential construction. The dominant industry's strength could yield direct investment gains in addition to the induced migration effect. Likewise, secondary industries might have other direct effects, and shocks might have an independent role in the equation, besides effects feeding through the population equation.

Results

The results from our time-series generated-regressor model, developed as a two-step pooled cross-section, are shown in Table 1, with the variables fully described in Appendix B. We expressed the variables generally as a state's performance deviations from the national average.

The two endogenous variables—population growth and nonresidential construction expenditures—were measured as differences in state and national (average) growth rates. When we were considering the behavior of states of different sizes, we avoided scale problems by structuring the variables in this form. It also allowed us to focus on arguments that addressed comparative regional growth rather than concentrating on the absolute growth among many regions.[15]

We assumed that both the variables for population growth and the nonresidential construction expenditures would respond in a partial-adjustment framework. In both cases, a shock to a given exogenous variable triggers an adjustment that persists for more than one period. The simplest way to model such a process was through the inclusion of a lagged endogenous variable in each equation.

We employed a two-step generated-regressor estimation procedure using a pooled data set to obtain the results from the model. For the time period 1973-83, the data set included state-level annual observations for 45 states (Alaska, Delaware, Hawaii, Idaho, and Kentucky were excluded because of incomplete data). In the first step, generalized least squares (GLS) procedures were used to construct the population model. The model then was used to generate esti-

Table 1
RESULTS OF ESTIMATION PROCEDURES POPULATION EQUATION

Variable name	Coefficient value	t statistic
LAGPOP	0.9029	47.93*
INCOME	0.0013	0.80
ELEC	0.0001	0.31
GAS	−0.0015	−2.42*
BUSTAX	0.0008	0.15
SOC	−0.0006	−0.33
EOC	−0.0014	−2.04*
WELFARE	−0.0003	−0.28
DOM	0.1262	2.19*
SECOND	0.0369	0.82
OILPRICE	0.1191	2.89*

$R^2 = .88.$

NONRESIDENTIAL CONSTRUCTION EQUATION

Variable name	Coefficient value	t statistic
LAG-STRUCT	0.4932	12.61*
POPHAT	0.8866	2.27*
U65	18.8069	4.77*
BUSTAX	−0.1010	−1.00
DOM	0.9839	0.85
SECOND	−1.5477	−1.39
OILPRICE	−0.3146	−0.33

$R^2 = .44.$

* Significant at the 5-percent level.

mates of population growth. In the second step, we used GLS procedures to build a nonresidential construction equation that included the estimates of population growth generated from the first equation. These estimated values of population growth were intended to serve as a proxy for investor expectations of population growth.[16]

The results offered clear evidence of the significant effect of price shocks and industrial structure characteristics upon population growth and of the influence of expected population growth upon investment in nonresidential structures. The results also seemed to confirm the findings of some researchers that state and local government fiscal policies have, at most, only secondary influences upon relative rates of regional growth.[17] We also noted that variables which explained relative population growth contributed little to explaining changes in residential structures investment beyond their influence on population-growth expectations.

We found that the population-growth equation explained 88 percent of the variation in the difference between a state's population growth and that of the nation. Of the 11 variables in the equation, the coefficients of 7 took on the expected sign. The coefficients on 4 of the variables took on unanticipated signs but, of the 4, only 1 variable had a significant *t* statistic. Of the 11 variables, only 5 had *t* statistics that were significant at the 5-percent level.

One of the most striking aspects of the population equation was the relative importance of price and industry-related variables, compared with fiscal policy variables and with the relative income-growth variable. The oil-price shock variable (*OILPRICE*) and the dominant industry variable (*DOM*) both had the expected positive signs and were significant at the 5-percent level. Aside from the lagged dependent variable, only the gas cost variable (*GAS*) matched the explanatory power of either of these two variables.[18]

The lack of significance of the income variable suggested that expectations about future income prospects in a region were chiefly affected by information related to price (*OILPRICE*) and industry (*DOM*) shocks. Even the secondary industry (*SECOND*) variable, which was of the expected positive sign but not significant, had a higher *t* statistic than the *INCOME* variable. Once the information about price and industry shocks was processed, the differences in per capita income had little influence on expectations about the relative population-growth rates.

Of the remaining variables, two were believed to affect the expectations about potential income differentials among regions and thus population growth. Both variables took on unexpected signs. The social spending (*SOC*) and economic overhead capital (*EOC*) variables were expected to have positive values, based on the literature supporting positive effects of spending on income generation. Instead, the signs were negative, with the *EOC* significant. These unexpected negative signs could suggest that high per capita expenditures imply unacceptably high tax rates to potential inmigrants, so that these factors could really be seen as costs of doing business. That three out of the four fiscal policy variables had coefficients that were not significantly different from zero suggested that changes in most state and local governmental fiscal policies might have only limited effects on the relative attractiveness of an area to potential inmigrants, particularly when other factors that might influence expectations about earnings potentials were taken into consideration.

Of the four variables that we hypothesized were related to the cost of doing business in a state, only the cost variable for natural gas (*GAS*) was significant. Of the three others, those that characterized relatively large shares of business taxes (*BUSTAX*) and relatively high electricity costs (*ELEC*) took on unexpectedly positive signs, but their coefficients still were not significantly different from zero. The variable that characterized relatively large state welfare costs was also insignificantly different from zero, but its negative sign was expected.

Thus, despite some unexpected results in the population equation, we found that the role of price and industry shocks in determining relative growth rates was clear. It was no surprise that differentials in regional growth rates might be explained significantly by shocks to prices and industries that were important to the region. What could be surprising, however, was the dominant role such shocks played when compared to other arguments.

The nonresidential construction equation also offered both anticipated and unanticipated information about nonresidential investment decisions. Not only were the expected values of population growth a positive and significant determinant of relative rates of growth in nonresidential construction, but none of the variables that appeared in both equations were significant in the nonresidential construction equation. The shared variables in the two equations generally had little explanatory power left for the second equation after their contribution to the population equation.

Aside from the lagged dependent variable, (*LAGSTRUCT*), only the estimated population-growth variable (*POPHAT*) and the age-composition variable (*U65*) proved significant. Both of them had the expected signs.[19]

Conclusion

Factors related to industry and price shocks play a highly significant role in explaining interregional variations in population growth and nonresidential construction. These factors leave only a secondary role to be played within the control of state and local governments. Furthermore, it appears that changes in factors linked to fluctuations in the work force size—and generally to the under-65 population portion—could serve as especially strong determinants of expectations about returns to nonresidential investment. Apparently, investors in nonresidential structures perceive that the ratio of this space to the work force size varies within rather narrow limits.

The results of our study indicate that, because of the extreme variations among regions and over time, focusing an explanation of nonresidential construction activity on a strictly national interpretation may mask important determinants of the actual investment decision-making process. While national and international variables (such as federal tax policies and worldwide fluctuations in interest rates) are clearly important determinants of construction activity nationally, the differential impact of supply shocks upon the regional relative-growth expectations will be important in determining where such nonresidential construction is likely to occur.

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1. For example, Dale W. Jorgenson and James A. Stephenson, in "The Time Structure of Investment Behavior in United States Manufacturing, 1947-1960," *The Review of Economics and Statistics* 49 (February 1967): 16-27, estimate an average lag of about two years between changes in desired capital and actual changes in total investment expenditures for manufacturing. When Robert E. Hall and Dale W. Jorgenson, in "Tax Policy and Investment Behavior," *The American Economic Review* 57 (June 1967): 391-414, focused on manufacturing investments in structures alone, they estimated an average lag of four years.

2. See, for example, Thomas R. Plaut and Joseph E. Pluta, "Business Climate, Taxes and Expenditures, and State Industrial Growth in the United States," *Southern Economic Journal* 50 (July 1983): 99-119.

3. Plaut and Pluta (1983), and L. Jay Helms, in "The Effect of State and Local Taxes on Economic Growth: A Time Series—Cross Section Approach," *The Review of Economics and Statistics* 67 (November 1985): 574-82, provide regression results that offer evidence of this pattern of change.

4. This interaction between migration and investment decisions explains why single-equation models typically fail to find significant relationships between nonresidential investment and many variables other than population. Because population is largely determined by many of the right-hand-side variables, the multicollinearity robs the explanatory power of the other variables.

5. Although investors were assumed to process new information as it became available, our construction of the model did not accommodate a re-estimation of the coefficients after each new observation. In this study, agents were assumed to process information in accordance with a paradigm that involved constant weights for each variable over the observation period. Thus, each time additional information became available over time that might affect their expectations about changes in population, they were assumed to weight the new information in accordance with the same regression coefficients at any point in time. We considered this interpretation consistent, for example, with the idea that agents have some implicit model of how migration and other population-growth-related decisions are made. It also follows that—having settled into this set of perceptions—agents would not subsequently alter their perceptions of the contributory importance of a given change in a variable's value to overall relative population growth. During the estimation period for our study, for example, agents were assumed to believe that a given percentage price shock would have the same effect, *ceteris paribus*, whenever it occurred.

6. For our model, we used population rather than employment as the variable of principal concern for several reasons. First, we regarded population as a better measure of the labor supply than employment. Employment is a reflection of the *use* of a factor, but population is an *actual shift* in the presence of factors that are available in an area, just as nonresidential construction is a shift in the *availability* of a factor rather than in the *use* of the factor. This role of population helped to explain hypotheses and findings in the literature that population growth leads, rather than follows, employment growth (see n. 13). Accordingly, it was hypothesized that once expectations were formed about population growth, expectations of labor growth rates were formed, in part, on the basis of expectations of population growth.

   Variables directly related to employment were not overlooked in our analysis, however. Measures of expected employment growth were captured in both the population and nonresidential construction equations in the form of the dominant and secondary industry variables in subsequent sections of this article. Thus, anticipated employment may be seen as factored into expectations of population growth and as arguments in the nonresidential construction equation apart from the population-growth equation.

   In addition, expected population growth may be taken as a close and available measure for expected overall growth in the economy. This measure may be more useful than employment-related variables in explaining nonresidential construction because not all population movements are directly related to job growth (though certainly indirectly related). For example, if a shift in amenities led to a substantial movement of retired persons to an area and a series of retirement-related industries appeared, the associated nonresidential construction was hypothesized to be posited initially on expected shifts in population. These shifts would be followed by the expected expansions in employment.

7. See, for example, the related discussions in Michael J. Greenwood, "Human Migration: Theory, Models, and Empirical Studies," *Journal of Regional Science* 25 (November 1985): 521-44.

8. These price shocks might be capitalized into asset prices in the regions that are negatively affected. Values of assets would fall. Suppose that agents see total returns to assets decline, even though rates of return in the context of the diminished value of the assets may not. These agents may then expect that further declines are possible. Some agents will respond to these amended expectations by migrating, particularly if home ownership is the agents' principal form of investment. That is, since income includes the appreciation of the value of one's assets, and expected income includes the expected appreciation of the value of one's assets, then the resulting decline in expected income motivates some persons to migrate.

9. In addition to Plaut and Pluta (1983), and Helms (1985), see also Gerald A. Carlino and Edwin S. Mills, "The Determinants of County Growth," *Journal of Regional Science* 27 (February 1987): 39-54; and Stephen P. A. Brown, "New Directions for Economic Growth: Redesigning Fiscal Policies in Louisiana, New Mexico, and Texas," *Economic Review*, Federal Reserve Bank of Dallas, July 1987, 13-20.

10. Robert Looney and Peter Frederiksen, in "The Regional Impact of Infrastructure Investment in Mexico," *Regional Studies* 15 (August 1981): 285-96, show that investments in social overhead capital, such as hospitals and schools, and economic overhead capital could both generate income growth, but that the two classes of investment would make different relative contributions to growth in accordance with the level of development of the region in question. In less-developed regions, social overhead capital is a more effective stimulus, while economic overhead capital is more effective in regions that are at an intermediate stage of development. Helms (1985) finds that when state and local revenues are used to finance improved public services, such as education, highways, and public health and safety, the favorable impact on location and production decisions provided by the enhanced services may more than counterbalance the disincentive effects of the associated taxes.

11. Niles M. Hansen, in "The Structure and Determinants of Local Public Investment Expenditures," *The Review of Economics and Statistics* 47 (May 1965): 150-62, argues that economic overhead capital and social overhead capital are to a significant degree determined by past growth, although he does not deny that such investment may generate growth.

12. In creating the dominant industry statistic, the state percentage employment share of each of industry, minus the percentage employment share of the same industry nationally, was multiplied by the percentage change in U.S. employment in the industry. The product of this multiplication for the most dominant industry was added to that of the second most dominant industry. This sum constituted the dominant industry statistic. (See Appendix A for the two dominant industries for each state.)

13. This point is made by Carlino and Mills (1987), and by Donald N. Steinnes, in "Causality and Intraurban Location," *Journal of Urban Economics* 4 (January 1977): 69-79.

14. A caveat about the role of business taxes is that in a state where business taxes are high but overall tax effort is low, possibly even a high business tax proportion of total taxes may not discourage investment or the migration of entrepreneurs. (See n. 17 for further discussion related to this issue.)

15. This structuring of the data also has the advantage that it washes out much of business cycle and national taxation effects, because the variation is benchmarked from national data.

16. Because of the recursive structure of the model, it was possible to estimate the equations sequentially. This sequential approach is identical to standard two-stage least squares procedures, given the recursive structure of the system. (The estimation procedure, developed using the SAS Matrix language, is available upon request from the authors.)

    In the case of the present model, the population equation was first estimated with generalized least squares estimates calculated after correcting the data for heteroskedasticity. The approach to model construction is based on a paper by Jeffery W. Gunther and Ronald H. Schmidt, "Increasing the Efficiency of Pooled Estimation with Block Covariance Structure," Federal Reserve Bank of Dallas, Research Paper no. 8703, June 1987. Gunther and Schmidt show that in cases of pooled cross-section time series generalized least squares regression, where the number of observations of cross-section data is greater than that of time series data, the standard procedures in the literature are inapplicable. Their results indicate that while some gain may be achieved by developing a block covariance structure for some regional groupings, a pure heteroskedasticity correction model performed nearly as well. Accordingly, the GLS estimates correct the data for differences in cross-sectional variances only.

    The assumed properties of errors in the regression equation are that covariance across states is assumed to be zero and that variance in each state is different from every other state. Autocorrelation is assumed to be zero. Thus, where i and j signify states and t and s signify time, then

$$E[\varepsilon_{it}\varepsilon_{js}] = 0 \quad \text{for } i \neq j \text{ or } t \neq s$$
$$\text{and} \qquad = \delta^2 \quad \text{for } i = j \text{ and } t = s.$$

Given the population coefficient estimates, a predicted population-growth variable can be created by applying the coefficients to the raw data. The raw data, rather than the transformed data, are used to create the predicted population series because the heteroskedasticity across equations is assumed to be different for the transformed data than for the raw data. The same GLS procedure as used in the population equation was then applied to the nonresidential construction equation using the predicted population variable in place of population growth.

It should be noted that in dealing with the nonresidential construction equation, all inferences must be posited on the assumption that expectations are equal to the predicted values. That is, using an estimated value of population growth to proxy expected population growth may represent a measurement with sampling error for which we have not provided a correction. Corrections for this general class of sampling error exist in the literature; see Kevin M. Murphy and Robert H. Topel, "Estimation and Inference in Two-Step Econometric Models," *Journal of Business and Economic Statistics* 3 (October 1985): 370-79; Adrian Pagan, "Two Stage and Related Estimators and Their Applications," *Review of Economic Studies* 53 (August 1986): 517-37; and Adrian Pagan, "Econometric Issues in the Analysis of Regressions with Generated Regressors," *International Economic Review* 25 (February 1984): 221-47. However, a correction procedure has yet to be developed that is applicable to pooled cross-section and time series generalized least squares models.

17. Carlino and Mills (1987) exemplify this interpretation, and a number of studies suggest that the role of taxes in business location decisions is small. See, for example, William V. Williams, "A Measure of the Impact of State and Local Taxes on Industry Location," *Journal of Regional Science* 7 (Summer 1967): 49-59; W. Douglas Morgan and W. Elliott Brownlee, "The Impact of State and Local Taxation on Industrial Location: A New Measure for the Great Lakes Region," *The Quarterly Review of Economics and Business* 14 (Spring 1974): 67-77; Thomas Vasquez and Charles W. deSeve, "State/Local Taxes and Jurisdictional Shifts in Corporate Business Activity: The Complications of Measurement," *National Tax Journal* 30 (September 1977): 285-97; and Advisory Commission on Intergovernmental Relations, *Regional Growth: Interstate Tax Competition* (Washington, D.C.: U.S. Government Printing Office, 1981).

    Helms (1985) argues that despite these arguments and studies that find no relationship between taxes and growth, fiscal policies can be shown to have a role in determining economic growth if both taxation arguments and variables that delineate differences in state and local government spending patterns are considered jointly in regression equations used to characterize growth. In order to account for these arguments in our own study, we not only included the business tax variable, but also variables that accounted for major components of government spending. Our equation generally showed these variables did not have significant expanatory power. While the economic overhead capital (EOC) variable was significant, it was of the unexpected sign in the population equation.

    In order to account more fully for the significance of taxation in determining economic growth—but to avoid overparameterization caused by including all of Helms's variables together with others that we hypothesized as important—we also constructed regression equations that included a measure of tax effort for all states and years. This variable was the difference between total state and local taxes and fees as a percentage of state personal income and the national average for this percentage. It was placed as an argument in equations that included all other variables we discussed. This variable took on a countertheoretically positive sign in both the population and residential construction equations. Furthermore, its inclusion did not result in any other formerly insignificant variables becoming significant. Likewise, the inclusion of this variable did not result in any other formerly significant variables becoming insignificant.

    Helms's results are different from ours in what they suggest about the role of fiscal policy. This may be the result of his assumptions and resulting model construction, which differ greatly from ours in their treatment of supply shocks. Helms characterizes supply shocks as falling within the set of nationwide time-specific factors that do not have significant region-specific impacts and are thus not treated explicitly in his equations. Our study, however, is postulated on the assumption that such shocks could have explicit regional effects. Our results show that when such shocks are treated explicitly, they may be seen to dominate fiscal impacts that are specific to a state or region.

18. It should be noted that the high coefficient value of the lagged dependent variable implies that the adjustment procedure is subject to very long lags. More to the point, it can be shown that 70 percent of the total adjustment does not take place until 11.8 years have passed.

19. The lagged adjustment process is such that 70 percent of total adjustment takes place within 1.7 years.

Appendix A

Dominant Industries, by State

State	Industry 1	Mean	Industry 2	Mean
Alabama	Apparel	2.88	Textiles	2.65
Arkansas	Food products	2.60	Lumber and wood	2.42
Arizona	Services	2.36	Trade	2.35
California	Services	3.26	Elec. equip.	1.02
Colorado	Services	2.52	Trade	2.47
Connecticut	Trans. equip.	3.85	Fab. metal	2.23
Delaware	Chemicals	11.87	Food products	1.39
Florida	Services	5.22	Trade	4.70
Georgia	Textiles	5.08	Apparel	2.27
Iowa	Nonelec. mach.	3.09	Trade	2.86
Idaho	Lumber and wood	4.93	Food products	3.76
Illinois	Nonelec. mach.	1.99	Elec. equip.	1.25
Indiana	Primary metal	3.71	Elec. equip.	3.11
Kansas	Trans. equip.	2.84	Trade	1.87
Kentucky	Mining	3.16	Apparel	1.04
Louisiana	Mining	4.43	Pub. util.	2.59
Massachusetts	Elec. equip.	1.70	Instruments	1.48
Maryland	Trade	1.96	Primary metal	0.60
Maine	Leather	5.01	Paper	3.95
Michigan	Trans. equip.	9.04	Fab. metal	2.16
Minnesota	Trade	2.51	Nonelec. mach.	2.24
Missouri	Trans. equip.	1.48	Pub. util.	1.32
Mississippi	Apparel	4.05	Lumber and wood	2.43
Montana	Trade	3.53	Pub. util.	2.37
North Carolina	Textiles	11.02	Furniture	3.17
North Dakota	Trade	5.81	Services	2.65
Nebraska	Trade	3.70	Food products	2.59
New Hampshire	Leather	2.92	Elec. equip.	2.83
New Jersey	Chemicals	3.12	Apparel	0.54
New Mexico	Mining	4.73	Services	1.92
Nevada	Services	25.51	Pub. util.	0.61
New York	Services	4.62	Finance	3.10
Ohio	Nonelec. mach.	2.35	Primary metal	2.21
Oklahoma	Mining	5.00	Trade	1.27
Oregon	Lumber and wood	7.38	Trade	1.62
Pennsylvania	Primary metal	2.86	Apparel	1.48
Rhode Island	Textiles	2.44	Rubber and plastic	1.21
South Carolina	Textiles	12.54	Apparel	2.97
South Dakota	Trade	4.81	Services	3.25
Tennessee	Apparel	3.23	Chemicals	2.13
Texas	Trade	2.92	Mining	2.77
Utah	Mining	2.13	Trade	1.45
Virginia	Textiles	1.30	Furniture	0.87
Vermont	Services	4.39	Elec. equip.	3.84
Washington	Trans. equip.	3.39	Lumber and wood	2.87
Wisconsin	Nonelec. mach.	3.86	Paper	1.79
West Virginia	Mining	9.36	Chemicals	2.95
Wyoming	Mining	14.48	Pub. util.	3.10

NOTE: The dominant industry is defined as that industry with an average employment share of nonagricultural employment (excluding construction and government) that exceeds the national average share of employment in that industry by the difference in shares. The average shares are based on annual observations for the period 1973-84.

Appendix B

Definition of Variables

A given state in the United States is referred to as state i. A given industry is referred to as industry j. Current time, a given year, is referred to as time t. A year earlier is referred to as time $t-1$. The variables are defined as follows.

ELEC	=	Percent deviation in state's average price per kilowatt hour of electricity from the national average for industrial consumers.
GAS	=	Percent deviation in state's average price per thousand cubic feet of gas from the national average for industrial consumers.
SOC	=	Percent deviation of state per capita expenditures from the national average per capita expenditures on social capital (expenditure categories are education, health and hospitals, police protection, and fire protection).
EOC	=	Percent deviation of state per capita expenditures from the national average per capita expenditures on economic overhead capital (expenditure categories are highways, sewerage, and sanitation other than sewerage).
WELFARE	=	Percent deviation of state per capita expenditures from the national average per capita expenditures on welfare (expenditure categories are public welfare, financial administration, and general control).
BUSTAX	=	[(% Share of State Taxes Derived from Corporate and Severance Tax Collections) − (National Average % Share for All States)].
DOM	=	[(% Employment Share of j in i at t) − (% Employment Share of j in U.S. at t)][(% Change in Share of U.S. Employment in j between t and $t-1$)]. Where j = two industries with largest share in i.
SECOND	=	[(% Employment Share of j in i at t) − (% Employment Share of j in U.S. at t)][(% Change in Share of U.S. Employment in j between t and $t-1$)]. Where j = all industries in i that are not in *DOM*.
OILPRICE	=	[(% Employment Share in Fuel Mining in i at t) − (Average % U.S. Share in Fuel Mining at t)][(% Change in U.S. Refinery Price of Crude Oil between t and $t-1$)].
INCOME	=	[(State Per Capita Income − National Per Capita Income)/(National Per Capita Income)] $\times$ 100.
U65	=	[(% Change in Share of Population in the State under Age 65) − (% Change in National Average Share of Population under Age 65)].
POP	=	[(% Change in Population in i between t and $t-1$) − (% Change in U.S. Population between t and $t-1$)].
POPHAT	=	Estimated population growth from the first equation.
NONRES	=	[(% Change in Nonresidential Construction Expenditures in i between t and $t-1$) − (% Change in U.S. Nonresidential Construction Expenditures between t and $t-1$)].

SOURCES OF PRIMARY DATA: American Gas Association.
Edison Electric Institute.
U.S. Bureau of the Census, *Government Finances.*
U.S. Bureau of the Census, *Population Estimates and Projections, Current Population Reports.*
U.S. Bureau of Economic Analysis, *Survey of Current Business.*
U.S. Bureau of Labor Statistics, *Employment and Earnings.*
U.S. Department of Energy, *Monthly Energy Review.*

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