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Contents

New composite indexes presented in this article could prove useful in analyzing and forecasting the Mexican economy. Keith Phillips, Lucinda Vargas, and Victor Zarnowitz present composite indexes of leading and coincident indexes for Mexico. In constructing the indexes, the economists use an approach similar to that developed by the National Bureau of Economic Research to create the composite indexes of U.S. economic activity. The authors classify peaks and troughs in the Mexican business cycle since 1980. Using these business cycle turning points, the authors determine which indicators consistently turned down prior to recessions and turned up prior to expansions. Eight of the best performing indicators are combined to create a composite index of leading economic indicators.

Evan Koenig presents a model that has proved successful at reproducing the pattern of M2 growth over the first half of the decade of the 1990s. The model suggests that a large gap between long-term bond yields and M2 deposit rates contributed importantly to the slow money growth that persisted through the end of 1994. The increased availability of bond market mutual funds may also have played a role in the money growth slowdown. The model can be combined with real-time published forecasts of spending and interest rates to yield predictions of future changes in money growth. It has generally performed well in this regard. However, in 1995 a sharp flattening of the yield curve led to a more-pronounced-than-expected acceleration of M2 growth, calling the future forecasting performance of the model into question. Results for an M2 aggregate expanded to include household bond funds are similar.

A key factor in forecasting a region's growth is anticipating how a region will respond to changes in national policy. One important way national policy affects a region is through real interest rates. Forecasting regional growth, therefore, requires good estimates of the interest rate sensitivity of regional industries.

In this study, Lori Taylor and Mine Yücel use vector autoregression analysis to examine the relationship between changes in real short-term interest rates and changes in Texas industry employment. They find that while a few industries are moderately sensitive to interest rate movements, most Texas industries are insensitive to changes in real interest rates. Moreover, they find that Texas total nonagricultural employment is insensitive to changes in real interest rates. As such, their analysis suggests that real interest rate movements influence the composition of Texas employment rather than its level.

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

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To judge the usefulness of the indexes more completely, their real-time performance must be studied over long periods of time and across many business cycles. To this extent, the Center for International Business Cycle Research will be producing and monitoring a corresponding set of Mexican composite economic indexes, along with their components.

During much of the 1990s, Mexico has been in the world spotlight for being a model economic reformer. The North American Free Trade Agreement (NAFTA), which took effect in 1994, was expected to stimulate even more growth and investment in Mexico. The start of NAFTA, however, coincided with the beginning of sociopolitical strife in Mexico, which hampered much of the trade agreement's potential economic impact. Then in late 1994, a steep peso devaluation rocked the world financial community and helped send the country into a deep recession.

The dramatic changes in Mexico over the past several years illustrate that, despite Mexico's important, growth-enhancing economic reforms, the volatility of its economy appears to be little changed from the 1980s when swings in the exchange rate and oil prices created an economic roller-coaster.[1] The continued sharp swings in the Mexican economy have led to an increased demand for timely economic data to monitor business cycle developments more closely.[2]

One method of monitoring business cycles in Mexico is through the construction of composite indexes of leading and coincident indexes. The U.S. composite index of leading economic indicators, published monthly by the Conference Board (CB), is one of the economic statistics most cited by the U.S. media and has long been used as a guide to the future direction of U.S. economic activity.[3] Although the index has come under increased criticism in recent years, many analysts continue to find it quite useful in monitoring the ups and downs of the U.S. business cycle.[4]

In this article, we create composite indexes of leading and coincident indicators for Mexico that are constructed in a fashion similar to that used for the U.S. indexes. We start by analyzing various economic indicators to determine which are sensitive to swings in the Mexican business cycle. We then define a coincident index and classify peaks and troughs in the Mexican business cycle in the period since 1980. The peaks and troughs in the cycle and overall movements in the coincident index and real gross domestic product (RGDP) are then used to determine what indicators consistently lead the business cycle. We find, perhaps not surprisingly, that the peaks and troughs in the Mexican economy are often difficult to foresee. The composite indexes we present, however, should be useful tools in analyzing and forecasting the Mexican economy.

The development and use of composite indexes of economic activity

The primary motivation for the construction of composite indexes of economic activity is the belief that there is no single proven and accepted cause of all observed business cycles. If different recessions are caused by different factors, then it is likely that no one indicator will perform best over all cycles. To increase the chances of getting true signals and reduce the chances of false ones, a host of indicators is combined from a wide range of economic sectors and processes.

Another reason for constructing composite indicators is that measurement errors, if independent across series, can be reduced by combining the series. Composite indexes can also reduce signals that are not indicative of cyclical fluctuations but the result of short-term events, such as an employee strike or a one-time tax law change that lumps certain activity into the end of a tax year.

By using simple, general theoretical arguments, but apart from any specific theory of the causes of business cycles, it is possible to find indicators that consistently lead, lag, or coincide with business cycle turning points. Leading indicators often represent future economic commitments, such as new orders for capital goods or building permits. The indicators also can embody expectations about future activity, such as help-wanted advertising, stock price indexes, and consumer confidence surveys. Coincident indicators typically represent broad economic measures, such as employment, output, and income.[5]

The popularity of the U.S. leading index has prompted the development of similar indexes for other countries. Klein and Moore (1985) describe how a broad set of economic indicators that have been shown to be strong cyclical indicators in the United States also performs strongly in a variety of market-oriented economies. As shown in Table 1, the performance of the indicators varies somewhat, but in general, the timing of the series is consistent across countries at both peaks and troughs of the growth cycles.[6] The evidence in Table 1

Table 1, Part 1

Median Lead (–) or Lag (+) of Individual Indicators at Growth Cycle Peaks in Months, Eleven Countries

Indicators: U.S. classification and U.S. titles	United States	Canada	United Kingdom	West Germany	France	Italy	Japan	Australia	Taiwan	South Korea	New Zealand	All countries
Leading indicators												
Average workweek, manufacturing	−3	−3	0	−8	−4	0	−4	−2	−8	−7	0	−3
New unemployment claims	−1	−1	NA	+2	−41	NA	NA	NA	NA	NA	NA	−1
New orders, consumer goods	−2	−2	NA	NA	−11	−8	NA	NA	+6	NA	0	−2
Formation of business enterprises	−11	NA	−8	−8	NA	−4	−10	−8	NA	NA	NA	−8
Contracts and orders, plants, and equipment	+1	+3	−3	−6	NA	NA	−5	−2	NA	−1	0	−2
Building permits, housing	−6	−3	−11	−10	−9	−2	−12	−5	−3	NA	+2	−6
Change in business inventories	0	0	−4	−4	+2	NA	−1	NA	NA	NA	−6	−1
Industrial materials price change	−8	−2	+3	−5	−2	0	−4	−5	NA	NA	−3	−3
Stock price index	−4	−3	−5	−6	−3	−6	−8	−7	0	−6	−7	−6
Profits	−4	−5	−4	−8	NA	NA	−10	−2	NA	NA	NA	−4
Ratio, price to labor cost	−8	+1	−14	−9	−4	+2	−2	−14	NA	NA	0	−4
Change in consumer debt	−6	−2	−16	−21	NA	NA	−9	−10	NA	NA	−3	−9
Median	−4	−2	−5	−6	−4	−5	−6	−5	−4	−2	0	−4
Coincident indicators												
Nonfarm employment	+1	+2	+2	+3	+6	+6	+2	+3	+1	+5	+9	+3
Unemployment rate	0	+1	+1	+3	0	+1	0	+1	+3	−6	0	+1
Gross national product	0	0	−13	0	−1	+1	−5	0	−10	+2	0	0
Industrial production	+3	0	0	0	0	0	0	0	0	+2	NA	0
Personal income	−1	+1	−4	−6	NA	NA	−9	−3	−4	NA	−4	−4
Manufacturing and trade sales	−1	−2	−3	−3	−2	−1	−8	−2	+2	0	0	−2
Median	0	0	−2	0	0	+1	−2	0	−1	+2	0	0

SOURCE: Center for International Business Cycle Research, Columbia University.

Table 1, Part 2

Median Lead (–) or Lag (+) of Individual Indicators at Growth Cycle Troughs in Months, Eleven Countries

Indicators: U.S. classification and U.S. titles[a]	United States	Canada	United Kingdom	West Germany	France	Italy	Japan	Australia	Taiwan[d]	South Korea[e]	New Zealand	All countries
Leading indicators												
Average workweek, manufacturing	–2	–5	–2	–1	–3	+4	–4	–4	–12	–10	+3	–3
New unemployment claims[b]	–5	–2	NA	–3	NA	NA	NA	NA	NA	NA	NA	–3
New orders, consumer goods[c]	–2	0	NA	NA	–12	–9	NA	NA	–13	NA	–3	–6
Formation of business enterprises	–1	NA	–10	–4	NA	–7	–14	–8	NA	NA	NA	–8
Contracts and orders, plants, and equipment[c]	–5	0	–1	0	NA	NA	0	0	NA	–2	–4	0
Building permits, housing	–9	–9	–10	+2	–7	–2	–6	–7	–7	NA	–2	–7
Change in business inventories[c]	–2	0	–6	–1	+1	NA	–4	NA	NA	NA	–2	–2
Industrial materials price change	–4	–4	+3	+1	–1	+1	–7	+1	NA	NA	+3	+1
Stock price index	–4	–6	–8	–8	–9	–8	–4	–4	0	–1	–10	–6
Profits[c]	–2	–2	–3	–12	NA	NA	–10	–2	NA	NA	NA	–2
Ratio, price to labor cost	–7	0	–9	–6	–3	+1	–2	–9	NA	NA	+5	–3
Change in consumer debt[c]	–4	–11	–15	–18	NA	NA	–6	–6	NA	NA	–6	–6
Median	–4	–2	–7	–3	–5	–8	–5	–4	–6	–4	–2	–4
Coincident indicators												
Nonfarm employment	+1	0	+2	+6	+7	+8	+2	+4	0	+7	0	+2
Unemployment rate[b]	+1	+2	+1	0	+1	+7	+2	0	0	0	0	+1
Gross national product[c]	–1	–1	0	0	–4	–1	–2	0	0	+2	+2	0
Industrial production	0	0	0	0	–3	0	0	0	0	0	NA	0
Personal income[c]	0	0	–3	+6	NA	NA	+1	+1	+1	NA	+3	+1
Manufacturing and trade sales[c]	0	0	–1	0	0	–7	–1	–2	–4	0	–4	–1
Median	0	0	0	0	0	0	0	0	0	0	0	0

[a] The series available for each country are sometimes only roughly equivalent in content to the U.S. series. In some cases, two series are used to match the U.S. series and the median. The table includes all observations for both series. The periods covered vary for each indicator and each country but all are within the years 1948–87.

[b] Inverted.

[c] In constant prices.

[d] Additional leading indicators for Taiwan and medians at peaks and troughs are exports,[c] –9, –3; money supply,[c] –4, –4. Additional coincident indicators are freight traffic, 0, –4; bank clearings,[c] –4, –8.

[e] Additional leading indicators for South Korea are accession rate, –1, –5; letter of credit arrivals,[c] –2, –8; inventories to shipments,[b] –1, –3.

NA = no indicator available.

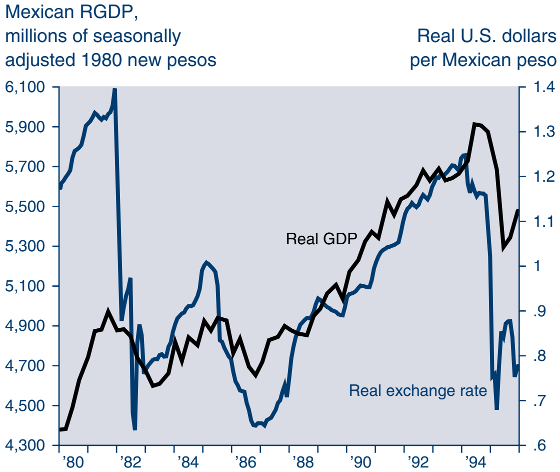
SOURCE: Center for International Business Cycle Research, Columbia University.

suggests that it would be useful to study these same indicators for Mexico.

It is also useful to examine variables that are specific to the dynamics of the Mexican economy. Changes in oil prices and the value of the peso have been important to the Mexican economy over the past two decades, as shown in Figures 1 and 2. A surge in oil prices from 1979 to 1981 fueled strong economic growth and government spending. In 1982, oil and oil-related products represented 77.6 percent of Mexico's total merchandise exports. When the price of oil began a sustained decline in 1982, a decreased supply of foreign exchange led to a dramatic depreciation of the Mexican peso. A recession soon followed.

In 1986, oil prices plunged, further weakening the real value of the peso, which had already begun to decline earlier in the year. Once again, Mexico entered a sharp recession. The dramatic decline in oil prices in 1986 resulted in a shift in merchandise exports to non-oil-related products. Although oil's share of merchandise exports declined to 12.2 percent in 1994, this industry remains an important source of economic activity in Mexico, and large swings in oil prices likely will have important impacts for many years to come. The important role that oil and international trade have played in the Mexican economy over the past two decades suggests that any study of the Mexican business cycle should include a close look at variables pertaining to these factors.[7]

Figure 1
Exchange Rates Play a Critical Role in Mexico



SOURCES: INEGI and Federal Reserve Bank of Dallas.

Choosing and evaluating the cyclical indicators

To choose the components of the Mexican leading and coincident indicators, we use an evaluation technique similar to the one the National Bureau of Economic Research (NBER) developed and used. Historically, the NBER has applied six criteria in the selection of components of composite indexes of cyclical activity. Each potential series has been analyzed for economic significance, statistical adequacy, timing at turning points, overall conformity to the business cycle, smoothness, and timeliness of release date. As Zarnowitz (1992) describes, these criteria address the following questions: How well understood and how important is the indicator in the formation of business cycles? How well does the series measure the economic variable or process in question? How consistently has the series led or coincided with business cycle turns? How well has the series conformed to measures of the business cycle over all points? How promptly can a cyclical turn in the series be distinguished from a shorter, temporary change? How promptly are the statistics available, and how frequently are they reported?

In using these six criteria, the cyclical timing and business cycle conformity measures are given more weight than the other measures. Moore and Shiskin (1967) first developed and applied a formal, detailed weighting scheme according to these criteria. Zarnowitz and Boschan (1975) and Zarnowitz (1992) explain the scoring system in detail. In choosing the components of the Mexican leading and coincident indexes, we use a similar evaluation technique based on measures of the last four of the NBER's six criteria.[8]

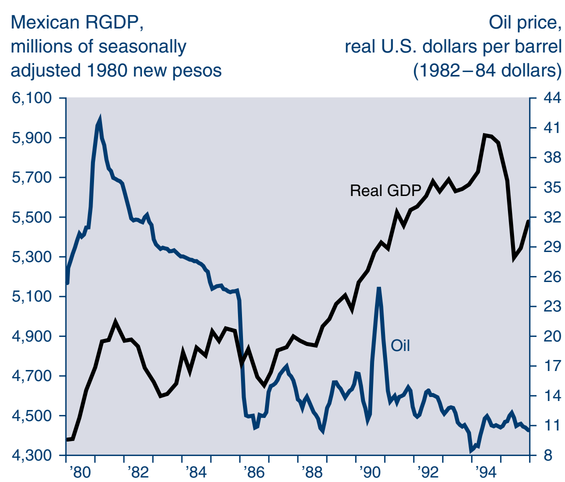
The first challenge in developing composite indexes of leading and coincident economic indicators is defining a business cycle chronology. Without first determining peaks and troughs in the business cycle, there would be no way to judge how an indicator performs at business cycle turning points. To classify indicators as leading, it is important to identify turning points on a monthly basis. The NBER dates the months of peaks and troughs in the U.S. business cycle by studying movements in a wide variety of monthly and quarterly economic indicators that measure factors such as output, employment, and income.

Business cycle turning points in the United States have historically been defined by increases and decreases in the level of economic activity. Since World War II, however, business cycles in many countries have been defined by swings in trend-adjusted activity, or growth cycles. In developing the growth cycle chronologies for the eleven countries shown in Table 1, Klein and Moore trend-adjust many coincident economic indicators by calculating and then eliminating flexible nonlinear trends in the series.[9]

Creating a Mexican index of coincident economic indicators

Data limitations severely limit the application of the Klein and Moore growth-cycle chronology to Mexico. Most monthly and quarterly economic time series for Mexico date back only to 1980. Because of the relatively short time period covered, it is difficult to define long-term trends and thus to define long-term growth patterns. Instead, we focus on the classical business

Figure 2
Large Oil Prices Swings Important to Mexico



SOURCES: INEGI and Federal Reserve Bank of Dallas.

cycle chronology, which defines periods in which the level of activity either increases or declines.

The method we choose for compiling a business cycle chronology for Mexico is first to define a monthly coincident index for Mexico and then to use peaks and troughs in this series to determine business cycle turning points. We use turning points and overall movements in the index to judge the cyclical timing and conformity of potential leading indicators. To calculate the coincident index, we first try to obtain the list of coincident indicators shown in Table 1. Since these indicators have been shown to coincide with the business cycles in many countries, it is likely that they would perform in a similar manner in Mexico. To gain some confidence that this is so, we perform several tests based on the performance measures presented above.

We are able to obtain all the Klein–Moore coincident indicators except personal income.[10] The data we obtain for RGDP, employment, and industrial production began in 1980, and the unemployment rate and real manufacturing and trade sales began in 1987. As a starting point for our analysis, we first seasonally adjust all the data using the X-11 procedure developed by the U.S. Bureau of the Census. We then analyze how well each of the other indicators conforms to movements in RGDP. Although business cycles are defined by the movement in many economic indicators, one of the most important of these is RGDP. A positive attribute of RGDP is that it is the most comprehensive economic indicator available, measuring the combined effects of the utilization of labor and capital and the productivity of these factors. A significant impediment to its use, however, is that it is quarterly, which reduces its timeliness and its precision in dating turning points.

To measure conformity to RGDP, we calculate correlation coefficients between changes in RGDP and past and future quarterly changes in the candidate series. The candidate series and RGDP are first filtered to eliminate any spurious correlation due to both series following the same autoregressive or moving average process.[11] We calculate standard errors to test if the correlation coefficients are statistically significant. A statistically significant correlation between changes in the component series and changes in RGDP at a zero lag is a good indication that the series conforms well and is coincident with changes in RGDP. Similarly, statistical significance at lead quarters provides evidence of business cycle conformity with a leading relationship. This procedure is part of the identification stage of a single-input transfer function model and is described in more detail in Vandaele (1983).[12]

Figure 3
Cross Correlations Between Mexican RGDP and Industrial Production
(Both Series Have Been Prewhitened)

As an example of the conformity analysis, Figure 3 presents evidence that industrial production conforms well with RGDP and that the relationship is coincident. Although the figure contains some evidence that a shock to RGDP leads a change in industrial production by two quarters, the large 0.66 correlation coefficient at the coincident quarter is highly significant and provides strong evidence that the overall timing of the relationship is coincident.

The results of the cross-correlation analysis are used, along with the timeliness of release and smoothness criteria, to verify the usage of the Klein–Moore coincident indicators. Timeliness of release is measured by the number of days following the reporting period that the data are released. Smoothness is measured by the months-for-cyclical dominance (MCD) criteria. If the MCD is 3, then a three-month moving average of the series must be calculated in order for the trend/cycle movements to represent a larger share of any given change than the random, or noise, component. MCD estimation is part of the decomposition and seasonal adjustment of time series computed by the Census Bureau's X-11 program.[13]

The overall results of our analysis show that the potential coincident indicators we have collected are all useful in defining cyclical swings in the Mexican economy. The cross correlations show that all the series conform coincidentally with Mexican RGDP. Timeliness of release is generally slower than that for the respective data in most industrialized countries and represents a significant impediment to timely analysis of the economy. The approximate number of days to release following the end of the reporting month is thirty-nine for employment, fifty for the unemployment rate and manufacturing and trade sales, and sixty-seven for industrial production.[14] These long delays reduce the usefulness of the series in timely analysis of business cycles. The volatility of the series also varies. The MCD is 1 for employment, 3 for industrial production, and 4 for the unemployment rate and manufacturing and trade sales.

The final variable that we use in the coincident index is a monthly estimate of RGDP. To estimate RGDP monthly, we use the method of best linear unbiased interpolation and extrapolation introduced by Chow and Lin (1971). The Chow–Lin procedure uses the monthly movements in related economic series to estimate the monthly movements of the quarterly series. A key feature of the Chow–Lin procedure is the restriction that the monthly interpolated values sum to the quarterly estimates. Since employment and industrial production extend back to 1980, and both have strong conformity to RGDP, we use these two series to interpolate RGDP. The estimated monthly measure is quite volatile, with an MCD of 3.

To construct the composite index, we calculate symmetrical monthly percent changes in each of the series by taking the monthly difference in the series and dividing by the average of the two months. The changes in each of the series are then standardized by dividing by the average absolute percent change in the series so that the most volatile series do not dominate movements in the index. Other than the standardizations, the changes in each of the series are given equal weights. The equally weighted standardized changes are summed across available indicators to create the change in the index. The index is given a base value of 100 for February 1980, and the changes are used to extend this level forward. Before 1987, movements in the index are based solely on changes in the three available series (RGDP, industrial production, and employment), while the post-1986 movements are based on the changes in all five of the indicators.

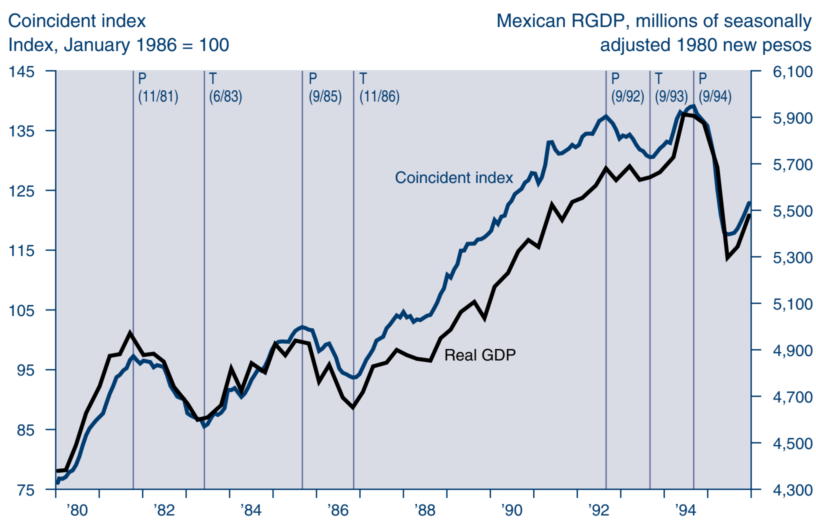
Before calculating the index, we determine the appropriate level of smoothing of the components so that the coincident index will be a useful measure of business cycle turning points. If the coincident index is highly volatile, then it would be difficult to distinguish a cyclical turn in the index from a shorter temporary change. Although taking a moving average of a series increases its smoothness, it also decreases its timeliness. For example, because a moving average best reflects the trend/cycle movements of the middle month, a three-month moving average that ends in June best reflects the trend/cycle movement only through May.

As mentioned earlier, one advantage of combining indicators into a composite index is that much of the noise in the individual series can be eliminated by offsetting shocks across indicators. To test the importance of this composite effect, we first compute a composite coincident index without smoothing any of the component series. The composite series is quite volatile, with an MCD of 3.

As a second experiment, we calculate an index with industrial production, manufacturing and trade sales, and the unemployment rate all smoothed using centered three-month moving averages. The composite index, computed with the three smoothed series, employment, and monthly RGDP, displays generally smooth movements and has an MCD of 1.[15] Although taking a centered three-month moving average of three of the components reduces the timeliness of the coincident index, the significant reduction in noise makes the index a much more useful measure of the business cycle. We therefore choose this method to calculate the coincident index.[16]

Overall movements in the coincident index track movements in RGDP, as shown in Figure 4.[17] Peaks and troughs in the index define four periods of economic recession in Mexico since the beginning of 1980. Although RGDP falls for three consecutive quarters beginning in the first quarter of 1988, its overall decline is

Figure 4
Mexican Coincident Economic Indicators



SOURCES: INEGI and Federal Reserve Bank of Dallas.

Box 1
The CIBCR Index of Coincident Indicators for Mexico

In an independent study directed by Geoffrey Moore at the CIBCR, a similar index of coincident indicators was constructed for Mexico using the same four monthly series as in the coincident index presented in this article: industrial production, real retail sales, insured employment, and the unemployment rate. In addition, Moore added a measure of real monthly earnings. Moore also treated RGDP differently; monthly values were generated by simple linear interpolation of the quarterly values. The six components were seasonally adjusted and standardized but were not smoothed.

The data covered the period from July 1982 through April 1995, just allowing the index to date the onset of the most recent Mexican recession in late 1994. The creators of the CIBCR index relied mainly on their long experience with the U.S. indicators and those for other countries guided by the U.S. model to make a quick first evaluation of the Mexican data. The resulting coincident index for Mexico, therefore, is experimental and tentative.

The index presented in this article, although somewhat more formally developed, is also experimental and will remain so until it accumulates a long, out-of-sample history. However, it is interesting to compare the two independently constructed indexes and reassuring to find that their results are very similar. As shown in Table A, there are two instances of coincident timing, three of one-month leads of the CIBCR index over our index, and two of one-month lags. On average, the two indexes have nearly coincident timing at both peaks and troughs.

Table A
Two Coincident Indexes for Mexico: A Comparison

Dallas Fed Index		CIBCR Index		Lead (–) or Lag (+) in Months CIBCR vs. Dallas Fed Index	
Peak	Trough	Peak	Trough	Peak	Trough
Nov. 1981		Nov. 1981		0	
	June 1983		July 1983		+1
Sept. 1985		Sept. 1985		0	
	Nov. 1986		Oct. 1986		–1
Sept. 1992		Oct. 1992		+1	
	Sept. 1993		Aug. 1993		–1
Oct. 1994		Sept. 1994		–1	

NOTE: See the accompanying article on the sources, methods, and composition of the two indexes.

slight and the coincident index decreased only briefly, for three months. Hence, we decided not to treat this 1988 episode as a business cycle contraction.

The dating of business cycle turning points has an important effect on the subsequent analysis of leading indicators. When and if a recession begins affects not only the timing of potential leading indicators but also the number of false signals given by the indicator. Because of this importance, we compare the turning points in our coincident index with the turning points in the coincident index for Mexico computed independently by Geoffrey Moore at the CIBCR. As described in the box titled "The CIBCR Index of Coincident Indicators for Mexico," the Moore index is consistent with ours, with at most one-month differences in turning-point dates.

A leading index for Mexico

Once we have calculated the coincident index, we can use it to judge potential leading indicators. All indicators are first seasonally adjusted using the X-11 procedure. The cyclical timing of potential leading indicators is judged by simply recording how many months prior to a peak (trough) in the coincident index the indicator reaches a maximum (minimum). The measures of conformity, smoothness, and timeliness are the same as those used for the coincident index. In evaluating the potential leading series, the measures of conformity and cyclical timing are given more weight than the other two performance measures. The measures of cyclical performance for the components that we select to be in the leading index are listed in Table 2.

As shown in Table 2, we select eight components covering various sectors of the economy. Stock prices, the ratio of price to labor cost, and the average workweek in manufacturing are from the list of leading indicators in Table 1.[18] Three other components are linked to leading indicators listed in Table 1 that were not available for Mexico. The combination of the real value of construction structures and imports of capital goods is related to the combination of housing permits, and contracts and orders for plant and equipment. Net insufficient inventories relative to sales is related to the change in business inventories. Finally, the real dollar price of oil and the real value of the peso relative to the dollar reflect the two major influences on the Mexican economy over the past two decades: oil and foreign trade.

The statistics on the months for cyclical dominance show a large variance in smoothness across indicators. If a leading indicator has a large lead time, then there is little cost in smoothing the indicator. For example, the ratio of price to unit labor cost has an MCD of 6, but the cross-correlation matrix reveals that this indicator has up to a fifteen-month lead with the coincident index. Taking a six-month (noncentered) moving average of this indicator causes some timing distortion in the sense that the timing of the noncentered moving average is not the same as the original series. In terms of its leading ability, however, the noncentered moving average merely shifts the series lead time to twelve months, still plenty of warning time and closer to the lead time of most of the other indicators.[19]

We first calculate the leading index without smoothing any of the eight components. The resulting composite index is highly volatile, with an MCD of 3. We then smooth all the components by their months for cyclical dominance. The resulting index is smooth and has an average lead time of 3.7 months over all peaks and troughs. Several of the components, however, no longer lead the cyclical peaks and troughs, so the monthly moving average of these indicators is reduced. The moving average of hours worked in manufacturing is reduced from six to three, and the moving average of imports of capital goods is reduced from four to two. This allows these indicators to turn prior to the cyclical turning points and yet remain smooth enough to be able to distinguish peaks and troughs in the series. The resulting composite leading index is generally smooth, with an MCD of 1.

The leading index shows a strong relationship with the coincident index, as shown in Figure 5. A peak in the leading index is defined as the maximum value of the leading index in

Table 2
Performance Measures of the Components of the Mexican Leading Index

Indicator	Average timing at turning points (months)	Lead months with statistically significant correlation with coincident index*	Months for cyclical dominance	Release lag (days after reporting period)
Average monthly hours, manufacturing	–5.4	0,1	6	56
Real value of construction structures**	–4.2	0	4	30–90
Real stock price	–10	1	2	12
Ratio, price to labor cost	–8.6	16,17	4	56
Net insufficient inventories	–5	0,4	6	45
Real peso–dollar exchange rate	–5.1	1,6,15	2	12
Oil price/U.S. CPI***	–8.3	1,3,5,7,9	1	12
Imports of capital goods	–.4	0,1,2,3,4,5,6,7,9	4	37

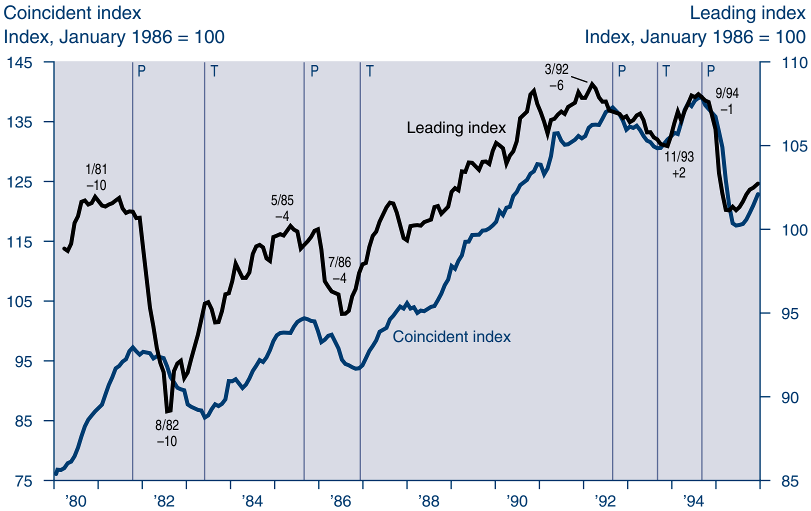
* A zero in this column indicates that there is a statistically significant correlation between changes in the variable and changes in the coincident index at the coincident month, while a 1 indicates there is a one-month lead between changes in the variable and changes in the coincident index. See the accompanying article for further details on the computation of this variable.

** Released every three months.

*** Consumer price index.

NOTE: Variables tested but not chosen were raw materials price index, capital goods production, production of machinery and equipment, real M1–M4, the growth rates of M1–M4 net decrease in manufacturing inventories.

Figure 5
Mexican Composite Indexes of Economic Activity



the expansion period prior to the recession, and a trough in the leading index is defined as the minimum value of the series in the recession period prior to the expansion. The cyclical timing of the leading index has generally been good, with an average lead time of about five months at peaks and four months at troughs. The index, however, lags by two months at the September 1993 trough and has several false signals of recession, particularly in the 1987–88 period and the period from 1990 to 1991. A cross-correlation analysis between changes in the leading index and changes in the coincident index shows significant positive leads at months one, three, five, and six, and a joint significance test of the first six months is strongly significant.[20]

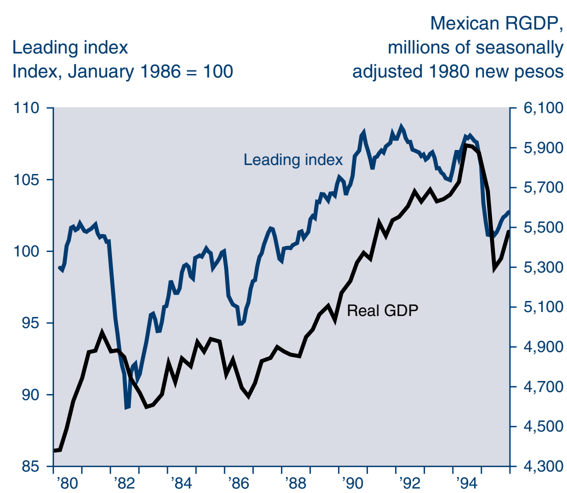
Although the MCD for the leading index is 1, Figure 5 indicates that, as previously noted, the leading index often declines for brief periods, and several times for extended periods, without an ensuing recession. As shown in Figures 5 and 6, however, most of these declines are followed by at least a weakening of the coincident index or at least a one-quarter decline in RGDP. The sharp decline in the leading index from June 1987 to January 1988 is followed by a three-quarter decline in RGDP beginning in the first quarter of 1988 and a brief three-month decline in the coincident index beginning in February 1988. The brief but sharp decline in the leading index from November 1990 to March 1991 is followed by flatness in the coincident index from June 1991 to January of 1992 and a one-quarter decline in RGDP in the third quarter of 1991.

The periods of sluggish economic activity in 1988 and 1991 would likely have been classified as growth recessions (*i.e.,* significant cyclical slowdowns in economic activity) if a growth-cycle chronology had been used. The fact that the leading index declined prior to these periods of weak growth is consistent with the U.S. leading index, which is, on the whole, better at signaling growth-cycle turns than business cycle turns as a result of its high sensitivity.

In contrast to the corresponding U.S. time series, it is not uncommon for the Mexican coincident index or RGDP to decline for a quarter during economic expansions. This volatility in the coincident indicators makes it difficult to develop a leading index that is sensitive only to business cycle turns and not to brief periods of decline within expansion phases. The instability of the coincident index and Mexican RGDP likely is an accurate reflection of the inherent instability of this developing economy.

While, ex post, it is easy to determine the peaks and troughs in the leading index, the volatility of the index makes this more difficult on a month-to-month basis. A popular rule used with the U.S. leading index is that three consecutive declines in the index is a strong signal that a recession is ahead, although it is important to note that this rule has never been endorsed by the NBER, CIBCR, or other serious students of business cycles. One weakness of this method is that it does not take into account the magnitude of the decline in the leading index. Diebold and Rudebusch (1989) show that a sequential probability method has a better forecasting record. The sequential probability method uses past data on changes in the leading index to estimate the probability that the leading index is in a contractionary (expansionary)

Figure 6
Mexican Economic Indicators



phase and thus is signaling a contraction (expansion) in the economy.

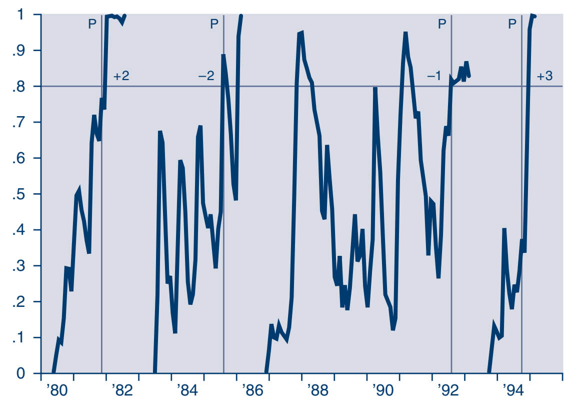
The probability of recession estimates the probability that the leading index has changed signaling regimes. For example, if the economy is in an expansion with the leading index persistently increasing and then the leading index declines for one month, the probability of recession estimates the likelihood that the leading index has begun a cyclical downturn and not just a brief decline. To further the example, if the leading index increases 1 percent and in the past this occurred fifteen times during expansions and only once during contractions, then the resulting probability would be high that the current change is signaling expansion. The method also allows the previous period's probability of recession or expansion to affect the current period's probability. For example, if the leading index is rising and then declines 1 percent, the probability of recession is less than if the 1-percent decline in the leading index is preceded by several months of decline. For more detailed information on the sequential probability method, see the box titled "Calculating the Probability of Recession and Expansion."

The probability of recession based on changes in the leading index shows that the index gives little early warning of upcoming recessions. As shown in Figure 7, the probability of recession reaches above 80 percent with a two-month lag, a two-month lead, a one-month lead, and a three-month lag. Thus, on average, the probability of recession is higher than 80 percent at 0.5 months following the beginning of the recession. The probability of recession also increases above 80 percent in two periods that are not followed by recession, although these signals are followed by declines in RGDP and the coincident index.

These results suggest that once a peak in the leading index has been reached, on average, it is not apparent that it is a cyclical peak until 0.5 months after the recession has begun. However, if the leading index is persistently increasing with no localized peaks, then it is correct to estimate that, on average, the expansion should continue for at least five more months. Thus, the timing ability of the leading index differs if it has recently changed direction.

While the performance of the leading index in predicting recessions seems poor, it is important to note that, in view of the volatility of the coincident indicators, the signal from the leading indicators may lead well in advance of any sign of recession given by changes in RGDP or the coincident index. As a test of the relative

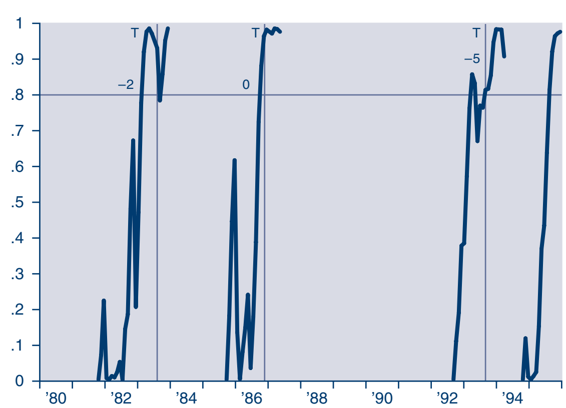
Figure 7
Probability of Recession in Mexico



signaling ability of the leading index, we apply the same recursive probability methodology that we use with the leading index to changes in the coincident index and to changes in RGDP. The recessionary signals from both series lag those of the leading index. Using the coincident index, the probability of recession increases above 80 percent with a one-month lead, a five-month lag, a three-month lag, and a zero lag with four peaks in the time period. Thus, the average signal occurs 1.75 months following the start of the recession, compared with the 0.5 months timing of the leading index. There is also one more false signal given by the coincident index. Counting the last month of the quarter as the signaling month, the average signal given by movements in RGDP lags the peak by 1.5 months with two more false signals than the leading index.

The ability of the leading index to signal upcoming expansions appears to be stronger. As shown in Figure 8, the probability of expansion rises above 80 percent with a two-month

Figure 8
Probability of Expansion in Mexico



Box 2
Calculating the Probability of Recession and Expansion

To calculate the probability of recession and expansion, we use a modified Bayesian updating formula due to Neftci (1982) and Diebold and Rudebusch (1989). The recursive probability is defined as

$$P_t = ((P_{t-1} + PL(1 - P_{t-1}))Fd_t)/((P_{t-1} + PL(1 - P_{t-1}))Fd_t + (1 - P_{t-1})(1 - PL)Fu_t),$$

where P_t is the probability of recession in period t and P_{t-1} is the probability of recession in the previous period. PL is the a priori probability that the leading index has entered a contraction phase, given that a month earlier it was in an expansion phase. Initially, Neftci (1982) postulates that the probability of recession may be affected by the length of the expansion: the longer the current expansion the more likely it is that a recession would occur in the next period. However, Diebold and Rudebusch (1991) find that, for the United States, the probability of recession is not dependent on the length of the current expansion. We assume that the time-independence results Diebold and Rudebusch find also hold for Mexico, and, thus, we set PL equal to a constant.

Given that the value of PL is time-independent, the fixed value of PL is somewhat arbitrary. Initially, PL was set equal to the number of past contraction phases divided by the cumulative length of past expansion phases as put forth in Diebold and Rudebusch. This value, which was equal to 0.032, resulted in a very low probability of recession throughout most of the expansion period, with the probability increasing above 30 percent prior to recessions. Increasing PL to 0.15 resulted in an upward shift of the probability distribution, so that the probability of recession was higher throughout the expansion and increased above 80 percent prior to recessions. By increasing PL to 0.15, the number of false signals given by the index did not change nor did the timing of the signal created by the index; the sole change was a shift in the signaling rule from a probability greater than 30 percent to a probability greater than 80 percent. Since the 80-percent signaling rule was more intuitive, we set PL equal to 0.15.

Fd_t and Fu_t in the above equation denote the likelihoods that the latest change in the leading index came from the contraction phase of the index and the expansion phase of the index, respectively. That is, Fd_t measures how probable the latest leading index change would be if the leading index were currently in its contractionary phase, and Fu_t measures the probability of the current change if the leading index were in its expansionary phase. The larger the current decline in the leading index, the larger is Fd_t relative to Fu_t. Following Diebold and Rudebusch, we assume that changes in the leading index are normally distributed. Furthermore, if P_t is greater than 0.95 we restrict P_{t-1} in the next period to equal 0.95. This prevents the probability of recession estimate from getting stuck at a value of 1.

In the month that the leading index reaches a cyclical trough, the probability that the leading index is in its contractionary phase is set equal to zero and the recursive probability of recession in subsequent months is calculated using the equation above. Once the leading index reaches a cyclical peak, the probability that the leading index is in its expansionary phase is set to zero and a modified version of the above equation calculates the recursive probability of an upcoming recession. The modification switches Fd_t and Fu_t and replaces PL with the a priori probability that the leading index has entered its expansion phase, given that in the prior month it was in its contractionary phase.

lead, a coincident change, and a five-month lead. Once again, the lead times are representative of the lead of the actual start of the expansion, not the realization that the expansion has started based on changes in aggregate indicators such as output and employment. Applying the recursive probability of expansion to changes in the coincident index and RGDP results in signals given well past the actual trough in the business cycle. The average signal of expansion occurs three months following the start of the expansion when changes in the coincident index are used and six months when changes in RGDP are used.

While the leading index appears to have some predictive content, its usefulness is sharply hampered by reporting lags in the data. The lead times discussed above do not account for timeliness of release of the indicators. Long reporting lags delay the calculation of the leading and coincident indexes as much as ninety days following the end of the reporting month.[21] This reduces the actual lead (increases the lag) in the realization of turning points. The timing of the signals given by the leading index relative to those given by RGDP and the coincident index, however, remains the same since the reporting lags are similar across the two indexes and RGDP.

Overall, our findings indicate that the leading index has some usefulness in predicting changes in the Mexican business cycle, although data volatility and long reporting lags limit the amount of advance warning the index can give. As an example, for the most recent recession, movements in the leading index did not signal an 80-percent probability of recession until December 1994, three months after the recession began (although the recession was somewhat mild in the fourth quarter of 1994 and intensified in the first half of 1995). The timing of the signal was weakened further by reporting lags that delayed the calculation of the December leading index until the latter half of March. Although a strong recession signal from the leading index did not occur until six months after the recession began, similar signals did not appear from movements in RGDP until the second week in May. A strong signal of recession from the coincident index occurs about the same time as the signal from the leading index, although in the past, changes in the coincident index have signaled a high probability of recession later than the leading index.

As shown in Figure 7, the probability of recession is quite volatile, reflecting much uncertainty about the economic outlook. While this volatility can be the result of a poor selection of indicators or poor computational techniques, it likely reflects, at least in part, the general volatility and uncertainty that actually exists in this dynamic economy. Much of the uncertainty likely rests in social and political factors that often change rapidly and are difficult to predict. For example, 1994 alone brought an armed uprising, the assassination of a presidential candidate, an assortment of kidnappings, presidential elections, and a dramatic currency devaluation. One area of future research would be to try to include indicators that are more sensitive to the important political and social factors that affect the Mexican economy.

Summary

Over the past decade, the Mexican economy underwent significant economic reforms that set the stage for improved economic growth in the late 1980s and early 1990s. While the country seemed on track for another year of economic growth in 1995, a sudden, unexpected peso devaluation sent the economy into the depths of recession. This sudden shock and past shocks to the Mexican economy have increased the demand for timely economic indicators to help monitor where the economy is and where it is headed.

In this article, we develop indexes of leading and coincident indicators that are similar to those the NBER developed for the United States and other countries. The coincident index comprises five series that have been shown to track the business cycle movements in many countries. The leading index comprises eight series that tend to lead movements in the Mexican economy. The components represent a wide variety of economic sectors and processes.

An evaluation of the composite leading index shows that, while the index peaks prior to recessions, strong signals of recession usually are not given until right at, or slightly after, the cyclical turning point. Also, volatility in the index led to several false signals over the time period since 1980. Nonetheless, the signals of recession given by the leading index generally result in fewer false signals of recession and have a greater lead time (shorter lag time) than the signals given by changes in RGDP and the coincident index. The leading index performs somewhat better in signaling upcoming expansions, with an average lead time of 2.3 months and no false signals. Using changes in the coincident index or RGDP, the signal of economic expansion does not occur for several months after the trough.

To judge the usefulness of the computed indexes or their components more completely, the real-time performance of the series must be studied over long periods of time and across many business cycles. To this extent, the Center for International Business Cycle Research will be producing and monitoring a corresponding set of Mexican composite economic indexes, along with their components. The finalization of the indexes and their monthly production are still in their early stages.[22]

Notes

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1 For a detailed discussion of Mexico's economic past, the events leading up to the 1995 economic crash, and the long-run outlook, see Gould (1995).

2 The need for timely, accurate data on Mexico was thought to be so important that the group of countries that provided a $50 billion loan to Mexico in 1995 stipulated as a part of the agreement that Mexico commit to economic and financial transparency. In response, Mexico began producing and publishing some economic and financial information on a more

timely basis. International reserve data, for example, which until 1994 had been released only three times per year, are now published on a weekly basis.

[3] The index originated in a 1938 study conducted for the NBER by Wesley Mitchell and Arthur Burns and has been further developed in work by Geoffrey Moore and others at the NBER and the Center for International Business Cycle Research (CIBCR), Columbia University. The Conference Board is a private, business-sponsored research organization. Before December 1995, the U.S. Department of Commerce, Bureau of Economic Analysis (BEA) produced the composite indexes of leading, coincident, and lagging economic indicators. It should be noted that the indexes developed and maintained by CIBCR differ from those of the Commerce Department and Conference Board.

[4] For recent criticism of the leading ability of the U.S. leading index, see Koenig and Emery (1994). For research that supports the use of the leading index, see Auerbach (1982) and Koch and Rasche (1988).

[5] For a more detailed explanation of the reasons for combining indicators into composite indexes, see Zarnowitz (1992, 316–17).

[6] The results in Table 1 were derived from data currently available. Because these data are revised often, the results do not reflect real-time data and are thus subject to the criticism presented in Koenig and Emery (1994).

[7] For a more detailed discussion on the role of oil prices and exchange rates on the Mexican economy, see Gould (1995).

[8] In general, all the potential series studied are highly economically significant. Statistical adequacy is hard to determine without a detailed study of the process by which each series is calculated. We have left these criteria for further research.

[9] They first compute deviations from seventy-five-month moving averages. These deviations are then divided into business cycle phases, and a three-phase moving average is calculated and defined as the trend. Turning-point selection criteria developed in Bry and Boschan (1971) are then used to date turning points in the trend-adjusted series. For more information on this process, see Klein and Moore (1985, 29–41).

[10] The series obtained for Mexico are sometimes different from the respective series calculated in the United States. For example, the employment series for Mexico is the number of workers who are covered by social insurance and represents a much smaller fraction of the total employed than the employment series for the United States. We obtain the monthly inventory-in-relation-to-sales series and the raw materials price index from Banco de México. The U.S. refiners' acquisition cost of crude oil published by the U.S. Department of Energy is used as a measure of the nominal oil price. The nominal peso/U.S. dollar exchange rate and the U.S. and Mexican CPIs are from International Monetary Fund, International Financial Statistics. The rest of the series is from INEGI.

[11] Each of the candidate series is first made into a random (white noise) process by an appropriate ARIMA model, and this model is then used to filter RGDP. Because the time series process of each series is unique to the series, different ARIMA models are used for different candidate series. The appropriateness of the ARIMA model is judged by the lack of statistical significance between changes in the error term from the model and lag changes in the error term.

[12] The procedure, described in Vandaele (1983, 267–99), is easily performed with statistical packages such as SAS.

[13] The statistical computer package SAS reports an MCD in its PROC X-11 procedure.

[14] We estimate the timeliness of release using data through June 1995. Actual release dates may vary. Over the past year and continuing into 1996, Mexican government agencies have increased their efforts to release economic data on a more timely basis. Thus, the release lags in this study are tentative.

[15] Because industrial production is released later than the other series, we also have tried an index with only the unemployment rate and manufacturing and trade sales smoothed. This index, which has an MCD of 2, is erratic, with peaks and troughs that are sometimes hard to distinguish.

[16] One way to increase the timeliness of the coincident index is to estimate the most recent month's change in the three smoothed series by calculating a two-month moving average in each of the series and using its most recent change to estimate the current month's change in the smoothed series. This process will increase the timeliness but will also lead to increased revisions.

[17] Calculating the coincident index without monthly RGDP results in essentially the same relationship between the index and quarterly RGDP as that shown in Figure 4.

[18] In our index, we look at real stock prices. Inflation in Mexico has been significantly higher (and more variable) than in the countries shown in Table 1, so that deflating the stock price index is necessary to reduce inflation distortions.

[19] It is important to center moving averages in the components of the coincident index, since this index is used to designate the actual month a recession starts or ends. The same is not true of the leading index. The turning points in the leading index have no particular interpretation other than as a signaling device of upcoming changes in the economy.

[20] Changes in the leading index are first converted to a white noise process with an appropriate ARIMA model and then the coincident index is prefiltered with the same model.

[21] See note 14.

[22] For more information of the availability of the indexes and their components, call the CIBCR at (212) 688-2222.

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Forecasting M2 Growth: An Exploration In Real Time

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The focus of earlier work was on developing an empirical model capable of reproducing the recent pattern of money growth. This article examines whether by substituting real-time forecasts of spending growth and interest rates into the model, it can be successfully used to predict changes in money growth.

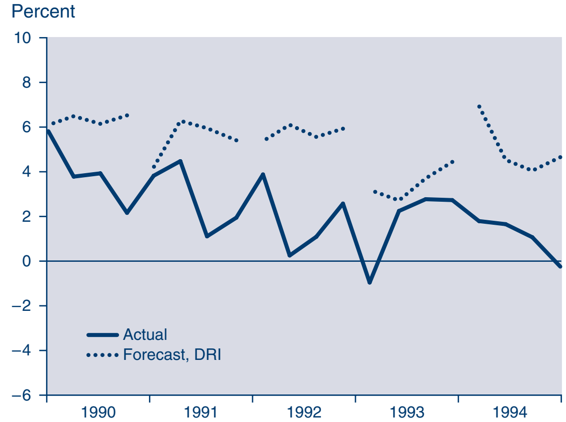
For several reasons, it is important that Federal Reserve policymakers have a good understanding of the relationship between money growth, interest rates, and spending. For example, the Federal Reserve is legally obligated to provide Congress with annual money growth projections. Federal Reserve officials must be prepared to explain the basis for these projections and to interpret deviations of actual money growth from past forecasts. Moreover, several studies have suggested that there is information on future spending and future inflation in the difference between the current money supply and the long-run demand for money (Hallman, Porter, and Small 1991; Feldstein and Stock 1993; Koenig 1994; Duca 1994). Successful extraction of this information requires that the long-run demand for money be accurately estimated.

Unfortunately, many models have systematically overpredicted money growth during the 1990s—often by very large amounts. The forecasting record of DRI/McGraw-Hill (DRI) is typical. Figure 1 shows actual annualized M2 growth from 1990 through 1994, along with the M2 growth forecasts published by DRI each January. In every quarter over this five-year period, DRI overpredicted M2 growth. The average error was over 3 percentage points.

The M2 model developed in the late 1980s by the staff of the Federal Reserve Board also overpredicted money growth.[1] In 1993, citing increased uncertainty in the relationship between M2 and spending, the Federal Open Market Committee announced that it would de-emphasize M2 in the policy-making process (Greenspan 1993).

Recent efforts to explain the unexpectedly weak M2 growth of the early 1990s have fo-

Figure 1
Actual M2 Growth and DRI Forecasts



SOURCES: DRI/McGraw-Hill; Federal Reserve Board.

cused on two fundamental underlying causes: (1) a deterioration in the competitiveness of banks and savings and loans resulting from tighter regulation, higher deposit insurance premiums, and more stringent capital standards and (2) financial innovations that have made nonbank assets like stocks and bonds increasingly attractive to households.[2] Koenig (1996) argues that insofar as banks have become less competitive, their higher costs ought to be reflected in an increase in the spread between the yield on stocks and bonds and the yield on bank deposits. If existing measures of money's opportunity cost fail to show an increase in this spread, it may be necessary to revise those measures. In particular, empirical results suggest that one should allow long-term bond rates to play a role in determining money's opportunity cost. Moreover, Koenig argues that whereas many of the important financial innovations of the early 1980s (such as the introduction of money market deposit accounts) were a result of sudden, discrete changes in the law, recent financial innovation can best be modeled as a continuous, ongoing process. Consistent with this point of view, Koenig reports evidence—even in early sample periods—of a gradual acceleration in M2's velocity growth. An M2 model that allows long-term bond rates to affect M2's opportunity cost and that allows a gradual acceleration in M2's velocity growth does not exhibit a statistically significant money-growth shortfall in the early 1990s. The recent performance of the model is somewhat further improved if the definition of money is expanded to include household bond market mutual funds, as advocated by Duca (1994, 1995).

The focus of my earlier work was on developing an empirical model capable of *reproducing* the recent pattern of money growth. This article examines whether by substituting real-time forecasts of spending growth and interest rates into the model, it can be successfully used to *predict* changes in money growth.[3] The spending and interest rate forecasts in question are obtained from DRI reports published each January. Results of the exercise have generally been encouraging. However, in 1995 a sharp flattening of the yield curve led to a more pronounced than expected acceleration of money growth. Consequently, the future usefulness of the model remains an open question.

This article begins with a review of the M2 growth model developed in my earlier article. Next, I examine the accuracy of DRI forecasts of spending and interest rates. Finally, I use DRI spending and interest rate predictions from January of each year to obtain ex ante forecasts of M2 growth. A similar exercise is undertaken for M2 expanded to include household bond funds. Results for the latter monetary aggregate are generally similar to those for conventional M2. Although the expanded aggregate is somewhat easier to predict through 1994, preliminary data suggest that 1995 errors are even larger than those recorded using conventional M2.

The model

This section makes two points.[4] First, even in early sample periods, there is evidence both that long-term interest rates help explain the pattern of money growth and that money growth has been gradually decelerating relative to spending growth. Second, a model that incorporates these effects does a satisfactory job of reproducing the pattern of M2 growth observed during the first half of the 1990s.

Description. The M2 growth model used in this article has two main components—a long-run equilibrium condition and short-run dynamics. The long-run equilibrium condition is a money-demand relationship of the form

$$(1) \qquad m^*_t = \tau_t - a_3 oc_t + x_t,$$

where m^* denotes the logarithm of the long-run equilibrium demand for nominal M2 balances, x is the logarithm of nominal nondurables and services consumption expenditures, oc is the logarithm of M2's opportunity cost (defined below), and a_3 is a non-negative parameter. A deterministic time trend, τ, is included as a right-hand-side variable in equation 1, as a proxy for the effects of financial innovation on the long-run demand for money. Specifically, it is assumed that

$$(2) \qquad \tau_t = a_0 + a_0' DMMDA_t - a_1 t - a_2 t^2,$$

where *DMMDA* is a dummy variable that equals 1 after the introduction of money market deposit accounts (MMDAs) and zero otherwise.[5] If financial innovation has been accelerating, one would expect to find $a_2 > 0$.

In the short run, money growth is assumed to be greater the greater the gap is between the long-run demand for money balances and the current level of money balances. Money growth also depends upon lagged values of itself, current and lagged values of consumption spending, and current and lagged changes in money's opportunity cost:

Table 1
Estimates of an Error-Correction Model of M2 Growth

	Sample period	
	1964:1–89:4	1964:1–94:4
a_0	6.107**	5.991**
	(.167)	(.134)
a_0'	.0363*	.0539**
	(.0162)	(.0134)
a_1	–.00907**	–.01099**
	(.00202)	(.00150)
a_2	$.417 \times 10^{-4}$**	$.501 \times 10^{-4}$**
	$(.080 \times 10^{-4})$	$(.055 \times 10^{-4})$
a_3	.111**	.115**
	(.016)	(.014)
θ	.359**	.431**
	(.078)	(.061)
c_1	.0269**	.0284**
	(.0041)	(.0038)
c_2	–.00738	–.00996*
	(.00477)	(.00444)
c_3	–.00708*	–.00611*
	(.00318)	(.00292)
c_4	.144**	.128**
	(.028)	(.024)
c_5	–.00830**	–.00770**
	(.00251)	(.00238)
c_{5A}	–.00340	–.00594*
	(.00278)	(.00263)
c_6	.184	.228*
	(.105)	(.089)
c_{6A}	–.227*	–.299**
	(.108)	(.090)
c_{6B}	.114	.147
	(.097)	(.084)
c_7	.362**	.415**
	(.073)	(.065)
Q (4)	6.43	5.05
Q (12)	16.81	13.83
Q (20)	25.36	25.81
SSE	.00127	.00142
SEE	.00380	.00363
Adjusted R^2	.782	.849

* Significant at 5-percent level.
** Significant at 1-percent level.

$$(3) \quad \Delta m_t = \phi_t + c_1 D83Q1 + c_2 D83Q2 + c_3 DCON + c_4 (m^* - m)_{t-1} + c_5 \Delta oc_t + c_{5A} \Delta oc_{t-1} + c_6 \Delta x_t + c_{6A} \Delta x_{t-1} + c_{6B} \Delta x_{t-2} + c_7 \Delta m_{t-1}.$$

Here, ϕ_t is a time trend and

$D83Q1 \equiv$ dummy equal to 1 in 1983:1 to control for MMDAs,
$D83Q2 \equiv$ dummy equal to 1 in 1983:2 to control for MMDAs, and
$DCON \equiv$ 1 in 1980:2 when credit controls were imposed and –1 in 1980:3 after credit controls were lifted.

The (logarithm of the) long-run demand for money, m^*, is given by equation 1.

The opportunity cost of holding money is defined to be a weighted average of long-term and short-term bond rates less the average return on M2 deposits. Thus,

$$(4) \quad oc_t = \ln[\theta R10Y_t + (1 - \theta) R3M_t - RM2_t],$$

where $R10Y_t$, $R3M_t$, and $RM2_t$ are the rates of return on ten-year Treasury bonds, three-month Treasury bills, and M2 deposits, respectively, and where the weighting coefficient, θ, is estimated along with the other parameters of the model. Including a long-term bond rate in the opportunity cost formula allows for the possibility that households regard long-term nonintermediated securities as substitutes for some monetary assets. Theoretical arguments favoring this approach are developed by Orr (1970), Friedman (1977), and Poole (1988). Empirical support has come from Hamburger (1966, 1977, 1983) and, more recently, Feinman and Porter (1992).

As shown in the appendix, the time trends in equations 1 and 3 are not independent. If actual money growth is to have the same unconditional mean as growth in the long-run demand for money, then the time trend in equation 3 must take the form

$$(5) \quad \phi_t = c_0 - 2a_2[t - c_7(t-1)],$$

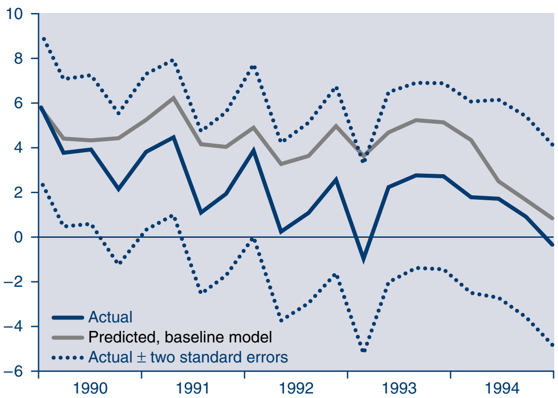
where c_0 is a fixed parameter. Hence, equation 3 can be rewritten as

$$(3') \quad \Delta m_t = c_0 - 2a_2 t + c_1 D83Q1 + c_2 D83Q2 + c_3 DCON + c_4 (m^* - m)_{t-1} + c_5 \Delta oc_t + c_{5A} \Delta oc_{t-1} + c_6 \Delta x_t + c_{6A} \Delta x_{t-1} + c_{6B} \Delta x_{t-2} + c_7 [\Delta m_{t-1} + 2a_2 (t-1)].$$

Intuitively, insofar as a_2 is greater than zero, equations 1 and 2 imply that long-run trend growth in desired money balances will gradually fall relative to growth in spending. If actual money growth is, on average, to equal desired money growth, then actual money growth must also gradually slow for any given rate of spending growth.

Estimation results. Equations 1, 2, and 4 were substituted into 3′, and the resultant equation was estimated using nonlinear least squares.[6] Results are presented in Table 1. Column 1 of the table reports results for a sample

Figure 2
Actual and Predicted M2 Growth



SOURCES: Federal Reserve Board; author's calculations.

period ending in the fourth quarter of 1989, when M2 was near the height of its popularity as an indicator of the stance of monetary policy and the future direction of the economy. Column 2 extends the sample period through 1994:4, by which time the breakdown of the Federal Reserve Board's money-growth model was evident.

Note, first, that the weight attached to the long-term bond rate in the opportunity cost formula (θ in equation 4) is statistically and economically significant even in the sample ending prior to the recent period of "missing money." There is also evidence of an acceleration in velocity growth in the early sample: the estimate of the parameter a_2 in column 1 of Table 1 implies that annualized money growth falls by about 13 hundredths of a percentage point per year relative to spending growth, all else constant.[7]

Note, second, that the model developed above exhibits relatively few symptoms of instability. Thus, parameter drift is limited: the estimates in columns 1 and 2 of Table 1 are generally within one standard error of each other, and in no case does the difference exceed two standard errors.[8] Moreover, the adjusted R^2 of the model rises from 0.78 to 0.85 as the sample is extended, and the model's standard error falls from about 1.52 percentage points (annualized) in the early sample to 1.45 percentage points (annualized) in the later sample.

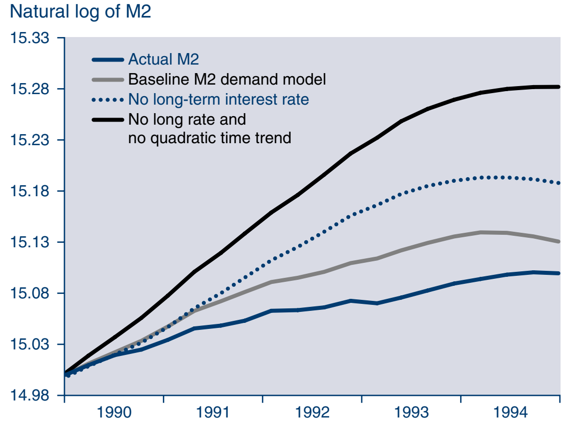
Figures 2 and 3 provide perspective. To construct Figure 2, parameter estimates from column 1 of Table 1 were combined with actual values of right-hand-side variables (including actual lagged money and actual lagged money growth) to generate simulated values of money growth from 1990 through 1994. These simulated values are plotted along with actual money growth and two-standard-error bands. The figure shows that although the model consistently predicts more rapid money growth than was actually observed, with but one exception (1993:1), the errors are not statistically significant.

Figure 3 presents results from several *dynamic* simulation exercises. To generate the plot labeled *baseline M2 demand model*, parameter estimates were taken from column 1 of Table 1. Actual values of nonmonetary right-hand-side variables were substituted into the estimated equations, along with lagged predicted (not actual) values of money and money growth. In fourth-quarter 1994, five years after the beginning of the simulation, the gap between the actual and predicted levels of M2 is only 3.1 percent.

Two other simulated paths are also presented in Figure 3. To generate these paths, the baseline model was reestimated with, first, the long-term bond rate and, second, with both the long-term bond rate and the quadratic trend excluded. Note how poorly the restricted models do in comparison with the baseline model: in the model without the long-term bond rate, the gap between the actual and predicted levels of M2 is nearly 9 percent at the end of the simulation period; in the model without both the long-term bond rate and the quadratic time trend, the corresponding gap is over 18 percent!

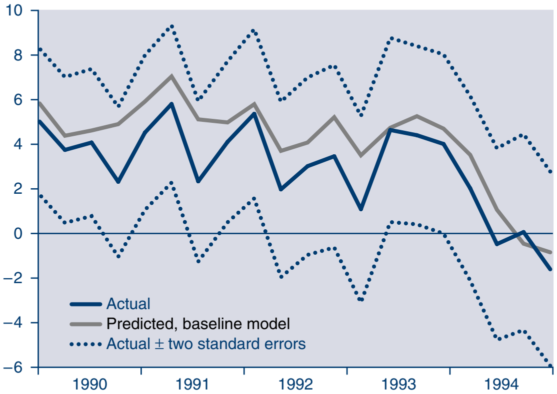
Bond-fund-adjusted M2. The weakness in M2 growth during the early 1990s was associated with large flows out of certificates of deposit (CDs) and large flows into bond market mutual funds (BMMFs). Duca (1995, 1994) has suggested that the definition of money be ex-

Figure 3
Actual and Predicted M2 from Three Dynamic Forecasting Exercises



SOURCES: Federal Reserve Board; author's calculations.

Figure 4
Actual and Predicted M2B Growth



SOURCES: Federal Reserve Board; author's calculations.

panded to include household bond market mutual fund balances, thus internalizing substitution between CDs and BMMFs. Despite this internalization, when the model developed above is reestimated using Duca's bond-fund-adjusted M2 (M2B) in place of conventional M2, the point estimates of the weight attached to the long-term bond rate in equation 4 and of the coefficient of time squared in equation 2 are virtually unchanged (Koenig 1996). As illustrated in Figures 4 and 5 (which are the M2B analogs of Figures 2 and 3), the out-of-sample stability of the model is somewhat better using M2B than using M2.[9] However, the choice of monetary aggregate is of second-order importance compared with the choice of whether to allow long-term interest rates to affect money's opportunity cost and whether to allow for a gradual slowing of trend money growth relative to trend spending growth. In Figure 5, for example, including long-term interest rates and a quadratic time trend in the M2B model reduces the end-of-1994 gap between the actual and predicted levels of money by 14.6 percentage points—from 16.2 percent to 1.6 percent. By comparison, using M2B in place of M2 in the forecasting model causes the end-of-1994 gap between the actual and predicted levels of money to decline by only 1.5 percentage points.

Real-time forecasting

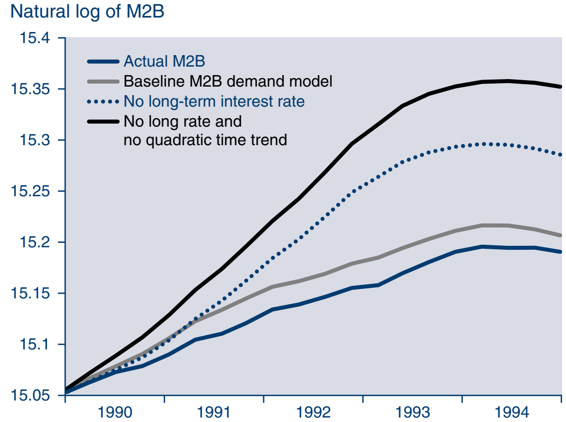
In this section, I take spending and interest rate forecasts published by DRI each January from 1990 through 1995 and find the implied time paths of M2 and M2B, as predicted by the money-growth model described above. The aim is to find out how accurately the model would have predicted money growth in each of the past six years, given DRI's spending and interest rate forecasts. The model does a good job of predicting M2 growth through 1994, provided coefficients are periodically reestimated. However, large underpredictions in 1995 raise questions about the model's future forecasting performance. Results using M2B are less sensitive to periodic reestimation of the model's coefficients. On the other hand, preliminary data suggest that 1995 M2B growth is underpredicted even more dramatically than is 1995 M2 growth.

Real-time forecasts of consumption and money's opportunity cost. Successful real-time forecasts of money growth depend on successful real-time forecasts of spending and interest rates. Therefore, the first step in the forecasting analysis must be an examination of how accurate DRI has been in its consumer spending and interest rate predictions.

Figure 6 shows actual annualized growth in nominal consumer spending on nondurables and services (the solid line), along with a series of DRI forecasts of the same variable (dotted lines). Each year's forecasted values are taken from the DRI *Review of the U.S. Economy* published in January of that year. In particular quarters, the DRI forecast has been off by as much as 2 percentage points. However, the errors are not consistently positive or consistently negative. Nor are the errors persistent: an overestimate is as likely to be followed by an underestimate as another overestimate.

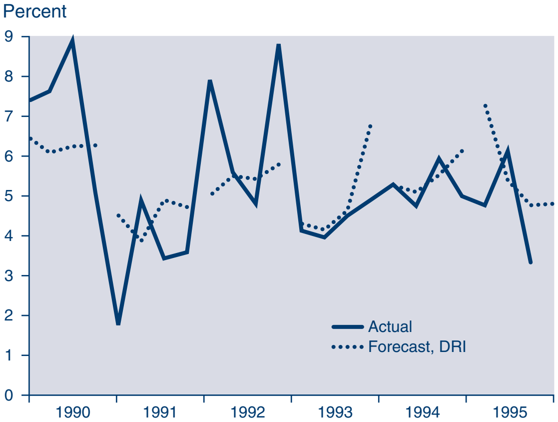
DRI does not publish a forecast of M2's opportunity cost, but a forecast can be constructed by regressing historical opportunity cost data on interest rate series that DRI *does* predict. I started with a sample period extending from 1964 through 1989 and regressed the opportunity cost on a constant, three own lags, the

Figure 5
Actual and Predicted M2B from Three Dynamic Forecasting Exercises



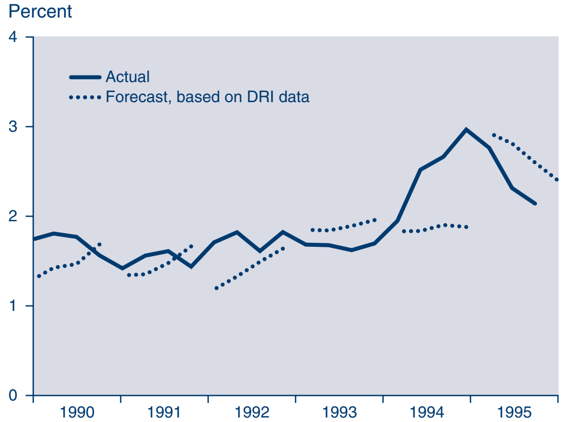
SOURCES: Federal Reserve Board; author's calculations.

Figure 6
Actual and DRI Forecasts of Consumer Spending Growth



SOURCES: U.S. Department of Commerce; DRI/McGraw-Hill.

Figure 7
Actual and Forecasted M2 Opportunity Cost



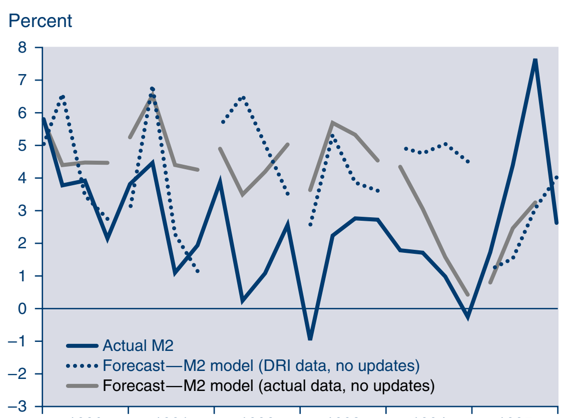
SOURCES: Federal Reserve Board; DRI/McGraw-Hill; author's calculations.

three-month CD rate, the federal funds rate, current and three lagged values of the three-month T-bill rate, and current and four lagged values of the ten-year Treasury bond rate.[10] The regression has an $\bar{R}^2$ of 0.96, and there is no evidence of serial correlation of the residuals.[11] January 1990 DRI forecasts of the three-month CD rate, the federal funds rate, the three-month T-bill rate, and the ten-year T-bond rate were substituted into the fitted equation to obtain a predicted opportunity cost for each quarter of 1990. The whole process was repeated—using a 1964–90 sample and January 1991 DRI interest rate forecasts—to obtain opportunity cost predictions for 1991. Similar predictions were obtained for 1992, 1993, 1994, and 1995.[12] Actual and forecasted opportunity costs are plotted in Figure 7.

As shown in the figure, although they are generally small, deviations of forecasted opportunity costs from actual opportunity costs exhibit considerable intrayear persistence. Thus, DRI's interest rate forecasts would have led one to underpredict M2's opportunity cost during most of 1990 and all of 1992 and to slightly overpredict M2's opportunity cost during 1993. The sharp increase in the opportunity cost during 1994 was entirely unanticipated by DRI. In January 1995, DRI's interest rate forecasts implied that M2 deposit rates would begin to catch up with Treasury bill and bond rates, resulting in a gradual decline in M2's opportunity cost. The actual decline was considerably more rapid.

Real-time forecasts of M2 growth. Given DRI's spending and interest rate forecasts, how accurately would the money-demand model described above have predicted M2 growth in each of the past six years? Figure 8 provides some insight. The figure plots actual M2 growth along with M2 growth predictions based on DRI spending and interest rate forecasts. In addition, to provide a feel for how sensitive the model's predictive performance is to the accuracy of DRI's spending and interest rate forecasts, Figure 8 includes M2 growth predictions based on *actual* spending and interest rate data. In generating both sets of M2 predictions, model coefficients are held fixed at values obtained in an estimation that ends in fourth-quarter 1989 (prior to the recent episode of "missing money"). The forecaster is assumed to observe actual money and money growth for the quarter preceding each forecast year. However, *within* each forecast year, lagged *predicted* values of money and money growth—rather than lagged *actual* values—are substi-

Figure 8
Actual and Forecasted M2 Growth



SOURCES: Federal Reserve Board; author's calculations.

Table 2
Forecasted Four-Quarter M2 Growth Rates

		No Coefficient Updating		Coefficient Updating		
	Actual	Actual RHS	DRI RHS	Actual RHS	DRI RHS	DRI Model
1990	3.91	4.77	4.45	4.77	4.45	6.51
1991	2.83	5.11	3.32	4.67	3.12	5.60
1992	1.94	4.40	5.17	2.63	3.35	5.90
1993	1.69	4.80	3.83	2.40	1.08	3.57
1994	1.06	2.35	4.82	–.72	1.57	5.17
1995	4.08	—	2.45	—	–.28	4.12
Mean*	2.29	4.29	4.32	2.75	2.71	5.35
RMSE*	—	2.16	2.44	1.29	.77	3.18
Mean**	2.58	—	4.01	—	2.22	5.14
RMSE**	—	—	2.32	—	1.91	2.90

* 1990–94.
** 1990–95.

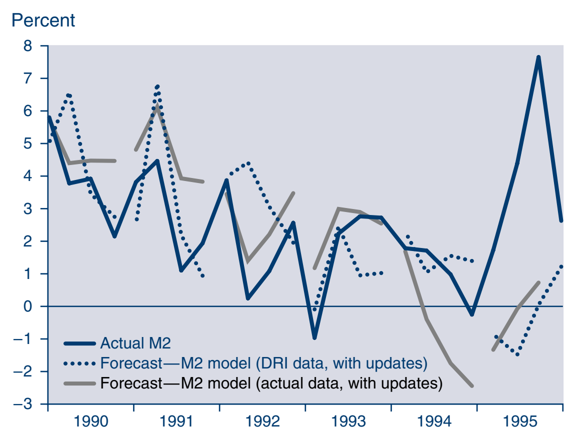
tuted into equation 3′ to generate the current quarter's predicted change in M2. In other words, within each year the M2 growth forecasts are dynamic.

As might be expected, given the results displayed in Figure 2, the model systematically overpredicts M2 growth over most of the forecast horizon. For the M2 growth forecasts based on actual spending and interest rate data, overpredictions are most serious over the two-year period running from 1992:2 through 1994:1. For the real-time M2 growth predictions based on DRI spending and interest rate forecasts, errors are largest in 1992 and 1994. For both sets of M2 growth predictions, preliminary data suggest that the model *under*predicted money growth during most of 1995, especially in the second and third quarters.

Over the forecast period as a whole, an analyst would have done about as well basing his M2 growth predictions on DRI spending and interest rate forecasts as on actual spending and interest rate data. This point is documented in Table 2. The first column gives actual fourth-quarter over fourth-quarter M2 growth rates for each of the years from 1990 through 1995. The second and third columns give fourth-quarter over fourth-quarter growth predictions that correspond to the forecasts plotted in Figure 8. Thus, predictions in column 2 are calculated using actual right-hand-side (RHS) spending and interest rate data. Predictions in column 3 are calculated using right-hand-side spending and interest rate forecasts taken from DRI. Note that the mean growth rates and root-mean-square errors reported in these columns are fairly similar. In both cases, the mean error over the 1990–94 period is about 2 percentage points, and the root-mean-square error is a bit over 2 percentage points. The corresponding figures for DRI's own M2 growth predictions over this period are 3.1 percentage points and 3.2 percentage points, respectively. (See Table 2, column 6.) Thus, although the forecasting performance of the model developed above is hardly an unqualified success, it is substantially better than that of at least one major private forecasting firm.

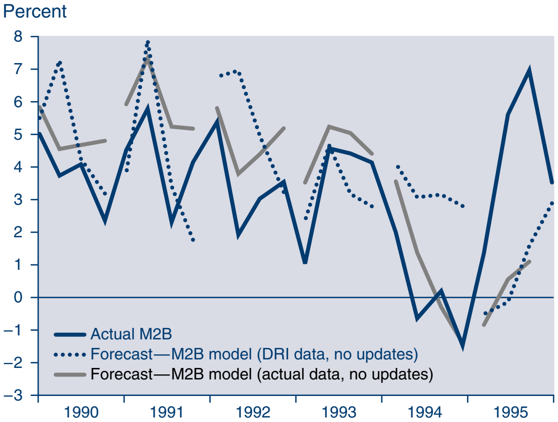
The 1990–94 predictive performance of the baseline model can be improved by allowing reestimation of the model at the beginning of each year, to obtain updated coefficient esti-

Figure 9
Actual and Forecasted M2 Growth



SOURCES: Federal Reserve Board; author's calculations.

Figure 10
Actual and Forecasted M2B Growth



SOURCES: Federal Reserve Board; author's calculations.

mates. Results for this case are plotted in Figure 9. As in Figure 8, during 1992 and 1994, when DRI interest rate forecasts would have led one to underestimate M2's opportunity cost, M2 growth forecasts based on DRI data are noticeably stronger than those based on actual data. Nevertheless, for the forecast period as a whole, the M2 growth forecasts based on DRI estimates of spending and interest rates are no worse than those based on actual spending and interest rate data. The mean forecast error is about one-half percentage point in either case, and the root-mean-square error is about 1 percentage point. (See columns 4 and 5 of Table 2.) Unfortunately, the model with updated coefficients underpredicts 1995 M2 growth by almost 4.4 percentage points. For comparison, without coefficient updating the model underpredicts 1995 M2 growth by about 1.6 percentage points.

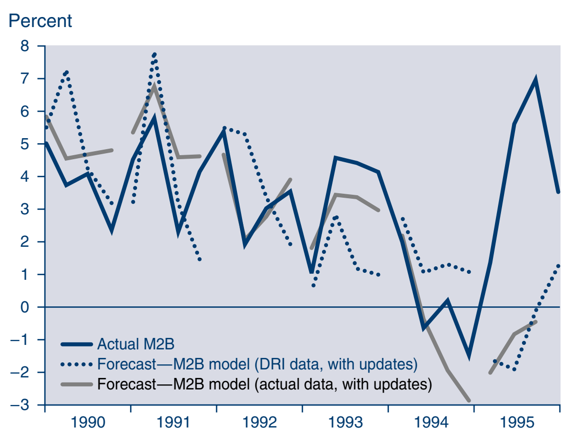
In summary, the biggest constraint on the real-time predictive performance of the M2 demand model developed here comes not from the need to forecast spending and interest rates but from instability in the coefficients of the model. This instability—although not statistically significant—limits the usefulness of the model for forecasting purposes. On the other hand, the results displayed in Figure 8 raise the possibility that coefficient instability may have been largely confined to the two-year period from 1992:2 through 1994:1. Only time will tell whether this conjecture is correct. In the meantime, the M2 growth forecasts generated by the model described in this article must be used with a good deal of caution.

Real-time forecasts of M2B growth. Finally, consider how easy it would have been for an analyst to predict M2B growth, year by year, using the model developed here and spending and interest rate forecasts published by DRI. As shown in Figure 10, even without coefficient updates the model does a good job of predicting the pattern of M2B growth through 1994. Using *actual* spending and interest rate data, the model overpredicts money growth over much of the forecast horizon. However, the errors are noticeably smaller than those plotted in Figure 8. Using real-time *DRI* forecasts of spending and interest rates, the largest M2B growth overpredictions occur during 1992 and 1994—years in which DRI's interest rate forecasts would have led one to underpredict M2B's opportunity cost.[13] According to results displayed in columns 2 and 3 of Table 3, using DRI spending and interest rate forecasts would not have resulted in any significant additional bias in predicted M2B growth but would have increased the model's root-mean-square error by almost 50 percent (from 1.25 percentage points to 1.82 percentage points).

Figure 11 shows the effects of allowing the coefficients of the M2B model to be reestimated at the start of each year. From 1990 through 1994, bias is virtually eliminated and the model accurately traces the quarterly movements in M2B growth—especially when actual spending and interest rate data are used as right-hand-side variables. As shown in columns 4 and 5 of Table 2, it remains the case that using real-time DRI forecasts of spending and interest rates increases the model's 1990–94 root-mean-square error by about 50 percent relative to what it would have been had accurate spending and interest rate forecasts been available.

Unfortunately, available data suggest that the model described in this article underpredicts 1995 M2B growth even more dramatically than it underpredicts 1995 M2 growth.[14] This

Figure 11
Actual and Forecasted M2B Growth



SOURCES: Federal Reserve Board; author's calculations.

Table 3
Predicted Four-Quarter M2B Growth Rates

		No Coefficient Updating		Coefficient Updating	
	Actual	Actual RHS	RHS from DRI	Actual RHS	RHS from DRI
1990	3.79	4.97	5.05	4.97	5.05
1991	4.19	5.92	4.22	5.32	3.91
1992	3.46	4.79	5.48	3.35	4.02
1993	3.54	4.55	3.25	2.89	1.36
1994	.00	.81	3.29	–.76	1.54
1995	4.36	—	.95	—	–.61
Mean*	3.00	4.21	4.26	3.15	3.18
RMSE*	—	1.25	1.82	.86	1.35
Mean**	3.22	—	3.71	—	2.54
RMSE**	—	—	2.17	—	2.37

* 1990–94.
** 1990–95.

result is obtained regardless of whether model coefficients are updated each year. Thus, without coefficient updating the real-time 1995 M2 forecast error is 1.6 percentage points, while the corresponding M2B forecast error is 3.4 percentage points. With coefficient updates, the 1995 M2 and M2B forecast errors are 4.4 percent and 5 percent, respectively. For the 1990–95 forecast period as a whole, M2B is no easier to predict than is conventional M2.

Concluding remarks

Understanding the relationship between money growth, interest rates, and spending is important to Federal Reserve policymakers. Movements in money, properly interpreted, are potentially valuable as indicators of current and future spending and future inflation. Moreover, the Federal Reserve is required by law to announce growth projections for the monetary aggregates, and Federal Reserve officials are expected to explain deviations of actual money growth from those projections.

Results presented here suggest that it is important to control for movements in long-term interest rates when explaining M2 growth and that the pace of financial innovation has been gradually accelerating. A money-growth model that takes these influences into account reproduces much (though not all) of the observed weakness in M2 growth in the early 1990s, a period during which several other M2 models have broken down. Evidence that long-term interest rates affect M2 growth and that the pace of financial innovation is accelerating emerges even in samples that end prior to the recent period of M2 weakness. Nearly identical results are obtained for an M2 aggregate expanded to include household bond funds.

The money-growth model estimated in this article can be combined with DRI forecasts of spending and interest rates to yield real-time money-growth predictions. Results are not entirely satisfactory. When its coefficients are held fixed at 1989 levels, the model substantially overpredicts M2 growth during 1992 and 1993. When its coefficients are updated each year, the model does well for 1990 through 1994 but badly underpredicts 1995 M2 growth. If one confines one's attention to the 1990–94 period, coefficient instability appears to be less of a problem when predicting the growth rate of an M2 aggregate expanded to include bond funds than it is when predicting conventional M2. However, preliminary data indicate that 1995 underpredictions are even more serious for the expanded aggregate than they are for M2.

Notes

Anne King and Whitney Andrew provided patient research assistance. Nathan Balke, John Duca, Ken Emery, Joe Haslag, and Yash Mehra offered helpful comments.

1 For a description of the Board model, see Moore, Porter, and Small (1990). Feinman and Porter (1992) document the breakdown of the Board model.

2 For elaboration, see Feinman and Porter (1992) and the articles contained in the November/December 1994 issue of the Federal Reserve Bank of St. Louis'

Review. The earliest attempts to explain the M2 growth slowdown focused on the impact of the savings and loan crisis (Carlson and Parrott 1991, Duca 1993). This line of attack was largely abandoned, however, when slow M2 growth continued well after the thrift crisis had wound down.

3 Recall that the Federal Reserve is legally obligated to provide Congress with money-growth projections.

4 For a more complete discussion, see Koenig (1996).

5 A similar time trend, but with $a_2 = 0$, is included in the M2 growth model developed by Moore, Porter, and Small (1990). Clearly, a time trend may adequately proxy for financial change over one sample period and not over others.

6 Embedding the long-run equilibrium condition within the short-run dynamics of money growth prior to estimation reduces finite-sample bias (Banerjee, Dolado, Hendry, and Smith 1986).

7 Together, equations 1 and 2 imply that

$$\Delta m^*_t = \Delta x_t + (a_2 - a_1) - 2a_2 t,$$

assuming a constant opportunity cost. Thus, the quarterly growth rate of m^* falls by $2a_2$ each quarter. It follows that the annualized growth rate of m^* falls by $8a_2$ each quarter, or $32a_2$ each year.

8 One of the largest changes—relative to its reported standard error—is in the coefficient (a_2) of time squared in the long-run money-demand equation. However, the size of this change may be more apparent than real. It is well known that the estimated coefficients of nonstationary variables have nonstandard distributions. The reported errors for such coefficients are biased downward.

9 However, the model significantly underpredicts M2B growth during the late 1980s. See Koenig (1996) for details.

10 In calculating the opportunity cost, I used the value of the weighting parameter, θ, obtained from estimation of the money-demand model over a 1964–89 sample period.

11 The test statistic is $Q(26) = 26.075$, with p-value 0.459.

12 The weighting parameter, θ, was revised with each new forecast.

13 The pattern of M2B opportunity cost forecasts is similar to the pattern of M2 opportunity cost forecasts shown in Figure 7.

14 The 1995 M2B data displayed in Figures 10 and 11 and summarized in Table 3 are preliminary. In particular, they are not adjusted to exclude IRA and Keogh bond-fund balances, as advocated by Duca (1995, 1994). Data required to make the adjustment are not yet available. However, inflows into IRA and Keogh accounts would have to have been unrealistically large (exceeding total household bond-fund inflows) to have a material impact on the conclusions of this article.

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Appendix
Connecting the Time Trends in the Long-Run and Short-Run Money Equations

This appendix documents why the time trend in equation 3′ takes the form it does. I focus on a version of the M2 growth model that, for simplicity, has been stripped of dummy variables. In the stripped-down model, equation 3 takes the form

$$\text{(A.1)} \quad \Delta m_t = \phi_t + c_4(m^* - m)_{t-1} + c_5 \Delta oc_t + c_{5A}\Delta oc_{t-1} + c_6 \Delta x_t + c_{6A}\Delta x_{t-1} + c_{6B}\Delta x_{t-2} + c_7 \Delta m_{t-1},$$

while equations 1 and 2 can be combined to yield

$$\text{(A.2)} \quad m^*_t = a_0 - a_1 t - a_2 t^2 - a_3 oc_t + x_t .$$

What form must ϕ_t take to have $E(\Delta m_t) = E(\Delta m^*_t)$ for all t? Empirically, oc_t is stationary. Hence, $E(\Delta oc_t) = 0$. Similarly, the stationarity of Δx_t implies that $E(\Delta x_t) = E(\Delta x_{t-1}) = E(\Delta x_{t-2}) \equiv E(\Delta x)$. Taking the expectation of equation A.1 and the expectation of the first difference of A.2 yields

$$\text{(A.3)} \quad E(\Delta m_t) = \phi_t + (c_6 + c_{6A} + c_{6B})E(\Delta x) + c_7 E(\Delta m_{t-1}),$$

and

$$\text{(A.4)} \quad E(\Delta m^*_t) = (a_2 - a_1) - 2a_2 t + E(\Delta x).$$

It follows that $E(\Delta m_t) = E(\Delta m^*_t)$ for all t only if

$$\text{(A.5)} \quad \phi_t = c_0 - 2a_2[t - c_7(t-1)],$$

where

$$\text{(A.6)} \quad c_0 = (a_2 - a_1)(1 - c_7) + (1 - c_6 - c_{6A} - c_{6B} - c_7)E(\Delta x).$$

Equation A.5 has the same form as equation 5 in the text.

The Interest Rate Sensitivity of Texas Industry

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Our analysis suggests that interest rate movements affect the composition of Texas employment rather than its level.

A key factor in forecasting a region's growth is anticipating how the region will respond to changes in national policy. One important way that national policy affects a region is through real interest rates. Our analysis shows that changes in real interest rates can influence the Texas economy.

The linkage between changes in federal policy and real interest rates has been the subject of much economic research. Many fiscal policies have been shown to have considerable influence on effective real interest rates. For example, Robert Hall and Alvin Rabushka estimate that scrapping corporate and individual income taxes and replacing them with a flat tax on consumption would cut U.S. interest rates by more than 20 percent (Hall and Rabushka 1995). On the other side of the policy equation, many economists believe shifts in monetary policy can temporarily alter real short-term interest rates.[1]

Forecasting the regional consequences of such policy changes, therefore, requires good estimates of the interest rate sensitivity of regional industries. If most Texas industries are highly sensitive to interest rate changes, interest rates may be a primary channel through which policy affects the region. On the other hand, if Texas industries are insensitive to interest rate changes, the interest rate effects of policy are relatively unimportant to regional analysis. Furthermore, if some Texas industries are sensitive to interest rate changes while other industries are not, the pattern of interest rate sensitivity among industries may shed light on the compositional effects of policy change.

There is a modest literature on the extent to which industries respond to interest rate changes. Ceglowski (1989) finds that most U.S. industries are not sensitive to changes in interest rates, but that construction and some construction-related manufacturing (lumber and wood products and furniture and fixtures) are highly sensitive. Ceglowski finds evidence of moderate interest sensitivity for industries that produce transportation equipment, chemicals, textiles, and rubber and plastics. A casual analysis of industry sensitivity in the United Kingdom also indicates above-average interest sensitivity in the transportation equipment, chemicals, and textiles industries (Lonie et al. 1990). Given the central role of employment data in regional analysis, it is unfortunate that neither of these studies estimates employment responses.

We contribute to this literature by examining the sensitivity of Texas industry employment to changes in real short-term interest rates. We find that most Texas industries are insensitive to changes in real interest rates, but that a few industries, notably construction, apparel, nonelectrical machinery, and primary metals are sensitive to interest rate movements. Moreover, we find that Texas total nonagricultural employment is not sensitive to changes in real interest rates. As such, our analysis suggests that real interest rate movements influence the composition of Texas employment rather than its level.[2]

Analytical framework and estimation

We use a vector autoregressive (VAR) model to assess interest rate sensitivity. A VAR model is a system of reduced-form equations wherein the interaction among several variables is used to forecast each individual variable. Each endogenous variable is represented as a function of past values of itself and past values of all the other variables in the system.

Our system consists of five endogenous variables that were chosen to represent the major influences on Texas industry employment. The five variables are the real price of oil (which reflects the influence of the prominent energy industry), the real short-term interest rate, aggregate U.S. employment (which reflects the influence of national business cycles), aggregate Texas employment (which reflects the influence of regional business cycles), and Texas employment in the industry under evaluation.[3] We estimate this system for each industry for which employment data are available.

The VAR approach is particularly well-suited to an analysis of interest rate sensitivity for a number of reasons. First, the VAR approach allows us to examine the timing as well as the magnitude of a variable's response to a systemic shock. Therefore, we can be more precise in our estimates of the regional effects of interest rate changes. Second, the VAR approach imposes no a priori restrictions on the system's structure; rather, the approach allows the data to determine the results. Such a nonstructural approach is preferable whenever economic theory provides little guidance as to the exact nature of the relationship among variables in the system. Although the nonstructural approach prevents the inference of causality, it generates reliable estimates of the response of sectoral employment to changes in interest rates. Furthermore, because the VAR approach estimates reduced-form relationships, the channels through which interest rates affect sectoral employment need not be explicitly modeled. Finally, estimating the interest rate sensitivity of employment in a VAR system with a Choleski decomposition for the errors allows us to trace movements in employment that arise either directly from interest rate changes or indirectly through the influence of interest rates on the other included variables.

The data

The monthly data for this analysis come from a variety of sources and span the period from January 1980 to November 1995. We use refiners' acquisition cost to measure the oil price and the interest paid on three-month U.S. Treasury bills to measure the interest rate. In both cases, we adjust for inflation using the consumer price index. Employment data for the United States and Texas come from the Bureau of Labor Statistics and are seasonally adjusted using the Berger–Phillips two-step method.[4] Our measures of sectoral employment include each of the nine industry divisions—mining, construction, manufacturing, TCPU (transportation, communications, and public utilities), wholesale trade, retail trade, FIRE (finance, insurance, and real estate), services, and government—as well as the thirty-nine major industry groups within those divisions for which complete employment data are available.

Because a VAR system can be sensitive to the stationarity of the data series, we test for stationarity using augmented Dickey–Fuller tests. The first difference of the natural log is stationary for all but three of the data series (employment in chemicals manufacturing, FIRE, and depository institutions), and the second difference of the natural log is stationary for those three series.[5] Therefore, we transform the employment and price series accordingly.[6] Following convention, we did not transform the real interest rate variable.

The appropriate specification of the VAR system also critically depends on the number of lags. If the system has too few lags, the researcher has omitted valuable information and the estimation may be biased. If the system has too many lags, the researcher has included avoidable noise, and the estimation will be inefficient (but should be unbiased). We use the Akaike information criterion (AIC) and the Schwarz criterion (SC) to suggest the appropriate lag length.[7] The AIC indicates that the appropriate specification would include at least twelve lags of the variables in the system; the SC indicates that no more than two lags would be necessary. Unfortunately, a likelihood ratio test does not systematically favor the two-lag specification over the twelve-lag specification (or vice versa).[8] Therefore, in the interest of comparability, we choose to err on the side of unbiased but possibly inefficient estimation. All variables in the system are estimated as a function of twelve lags of themselves and twelve lags of each of the other variables.[9]

Assessment strategies

We use two strategies to assess the relationship between interest rate innovations and industry employment. The first strategy is to test for a direct relationship between employment changes and lagged movements in the interest rate variable using Granger-causality tests. In this context, a Granger-causality test examines the hypothesis that the interest rate coefficients in the industry employment equation are jointly zero. If we can reject the hypothesis that all of the coefficients are jointly zero, movements in interest rates are said to Granger-cause movements in employment.[10] The second strategy uses impulse response functions to capture the direct and indirect relationship between employment and interest rates. Impulse response functions trace over time how an independent and unexpected shock to one variable in the VAR system affects another.

We use a Choleski decomposition to trace the effects of a one-time shock to interest rates on employment in each of the sectors. The Choleski technique decomposes the residual (μ_i) from each equation in the VAR system into a linear combination of residuals from the other equations (μ_j) and an orthogonal element (ν_i). We specified a decomposition that allows a one-way contemporaneous relationship between interest rates and the Texas sectoral employment variables.[11] The structure is as follows:

(1) $\mu_{oil} = \nu_{oil}$,

(2) $\mu_r = c_{21}\mu_{oil} + \nu_r$,

(3) $\mu_{US} = c_{31}\mu_{oil} + c_{32}\mu_r + \nu_{US}$,

(4) $\mu_{TX} = c_{41}\mu_{oil} + c_{42}\mu_r + c_{43}\mu_{US} + \nu_{TX}$,

(5) $\mu_{ind} = c_{51}\mu_{oil} + c_{52}\mu_r + c_{53}\mu_{US} + c_{54}\mu_{TX} + \nu_{ind}$,

where μ_{oil} represents the residual from the real oil price equation, μ_r represents the residual from the real interest rate equation, μ_{US} represents the residual from the aggregate U.S. employment equation, μ_{TX} represents the residual from the aggregate Texas employment equation, and μ_{ind} represents the residual from the Texas industry employment equation.

The above structure implies that unexpected changes in oil prices (μ_{oil}) do not contemporaneously arise from any of our specified variables. Similarly, unexpected changes in real interest rates (μ_r) do not contemporaneously arise from any of the employment variables but can be contemporaneously affected by innovations in oil prices (μ_{oil}). Unexpected changes in oil prices and interest rates contemporaneously affect unexpected changes in aggregate U.S. employment (μ_{US}), but μ_{US} affects oil prices and interest rates only in subsequent periods. Similarly, current innovations in total Texas nonagricultural employment (μ_{TX}) are affected by current innovations in oil prices, interest rates, and U.S. employment but not by current innovations in the sectoral employment variables (μ_{ind}). Although innovations in sectoral employment affect Texas total employment, they are not contemporaneous—they work their effects through the system over time.

We used the estimated coefficients of the VAR system of equations and Monte Carlo integration with 1,000 replications to compute confidence bands for the impulse response functions. The methodology follows Kloek and Van Dijk (1978) with the coefficient draws taken directly from the estimated posterior distribution of the coefficients. This methodology yields one-standard-deviation confidence bands for the impulse response functions of the variables in the model.[12]

These confidence bands can be used to distinguish where the impulse response functions differ significantly from zero. Whenever the lower bound on the impulse response function is positive, we consider the impulse to be significantly positive. Whenever the upper bound on the impulse response is negative, we consider the impulse to be significantly negative. Rather than show the confidence bands directly, for simplicity we report only significant impulse responses.

Results

Our assessment strategies offer two ways to look at the interest sensitivity of Texas industry. Tables 1 and 2 present both the Granger-causality tests and the cumulative impulse responses. In all cases, the impulse responses represent the cumulative percentage change in industry employment associated with a one-percentage-point increase in the real interest rate at the beginning of the time period. Table 1 presents results for aggregate Texas employment and the nine broad industry divisions,

Table 1
The Cumulative Employment Response of Industry Divisions to an Increase of 100 Basis Points in the Real Interest Rate
(Percent change in employment)

Industry division	3-month response	6-month response	12-month response	24-month response	36-month response	60-month response
Total	.	.	.	.	.	.
Mining	.	.	.	.	.	.
* Construction	–.26	–.37	–.53	–.64	–.65	.
** Manufacturing	.	.	–.11	–.30	–.29	–.31
** TCPU	.	.	.	–.19	–.24	–.24
* Wholesale trade	.	.	.	–.18	–.24	–.25
Retail trade	.	.	.	.	.	.
FIRE	.	.	.	.	.	.
Services[a]	.	.	.	.	.	.
* Government	–.06	–.00	–.07	–.08	–.09	–.10

NOTE: A missing value indicates that the interest rate sensitivity is indistinguishable from zero. The symbols on the left indicate that innovations in the real interest rate Granger-cause innovations in employment at the 5-percent level (**) or 10-percent level (*). The symbol "a" indicates an industry that we evaluate using two-standard-deviation confidence bands for the impulse responses.

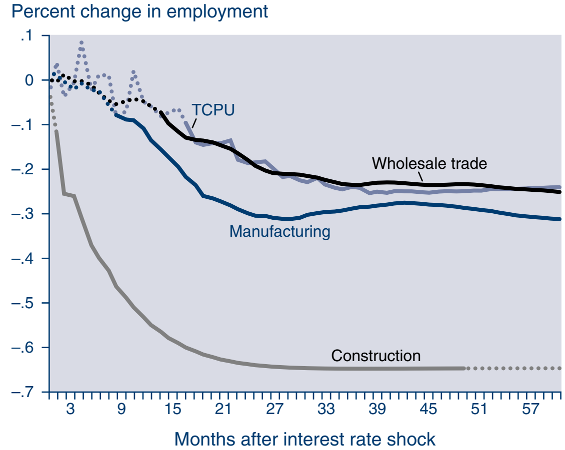
while Table 2 presents results for major industry groups within those divisions.

The data in Table 1 support three general conclusions about interest rate sensitivity. First, the Granger-causality tests and impulse responses both indicate aggregate Texas employment is not systematically influenced by changes in real short-term interest rates.[13] Second, both approaches also suggest that individual industries can be influenced by interest rate movements. We find that changes in real short-term interest rates Granger-cause employment changes in construction, manufacturing, government, and the service-producing industries that distribute goods (TCPU and wholesale trade). The impulse responses also indicate significant effects on employment in these industries. Finally, the relatively modest impulse responses suggest that no Texas industries are highly sensitive to movements in real short-term interest rates.

Consistent with conventional wisdom, the construction industry shows the quickest and strongest initial response to an interest rate shock. Within three months after an unanticipated, one-percentage-point increase in real short-term interest rates, construction employment in Texas decreases by 0.26 percent. Over the next three quarters, construction employment declines by another 0.26 percent. The peak cumulative effect of a 0.65-percent decline in construction employment is reached thirty-seven months after the initial shock.

As Figure 1 illustrates, an interest rate shock elicites a slower and weaker employment response from the manufacturing sector than from the construction sector. It takes nine months for an interest rate shock to affect manufacturing employment, and when it does, the reaction

Figure 1
Employment Response Of Private Industry Divisions



NOTE: Dotted line indicates that the impulse response is not significant.

Table 2

Cumulative Employment Response of Major Industry Groups to an Increase of 100 Basis Points in the Real Interest Rate

(Percent change in employment)

Major Industry Groups

Industry	3-month response	6-month response	12-month response	24-month response	36-month response	60-month response
Manufacturing						
** Nonelectrical machinery	.	.	–.31	–.92	–1.05	–1.17
* Primary metals	.	.	–.60	–.93	–1.04	–1.16
Apparel	–.13	–.16	–.37	–.70	–.77	–.95
** Fabricated metals	.	.	–.28	–.64	–.60	–.70
Lumber and wood	.	.	.	.	.	–.64
** Rubber	.	.	.	–.32	–.37	–.32
* Petroleum and coal[a]	.	.	.	.	.	.
** Printing[a]	.	.	.	.	.	.
Miscellaneous manufacturing[a]	.	.	.	–.37	.	.
Leather[a]	.	.	.	–.85	.	.
Textiles	.	.	.	–.31	.	.
Chemicals	.	.	.	.	.	.03
Transportation equipment	.	.11	.25	.40	.67	1.08
TCPU						
* Communications	.	.	.	–.40	–.44	–.54
Railroads	.	.	.	–.48	–.62	–.63
Air transportation[a]	.31	.34	.38	.	.	.
FIRE						
Depository institutions	.	.	.	–.03	–.04	.
Services						
** Health	–.02	–.05	–.08	–.11	–.13	.
Educational services	.	.	.	.20	.33	.47
** Personal	.	.	.12	.18	.21	.23
** Hotels	.14	.18	.28	.38	.46	.55
Government						
** Federal	.	.	.21	.30	.42	.55
* State	–.12	–.11	–.17	–.22	–.21	.
Local	.	.	–.09	–.12	–.14	.

NOTE: Only those industries for which we could detect significant interest rate sensitivity at the indicated intervals are reported. The symbols on the left indicate that innovations in the real interest rate Granger-cause innovations in employment at the 5-percent level (**) or 10-percent level (*). The symbol "a" indicates an industry that we evaluate using two-standard-deviation confidence bands for the impulse responses.

is comparatively modest. According to the impulse response functions, the manufacturing sector's peak cumulative response to an interest rate shock is less than half that of the construction sector.

In turn, the employment response of the distribution industries is weaker and slower than that of the manufacturing sector. Wholesale trade responds in fifteen months and TCPU in eighteen months. In both cases, the magnitude of the response is weaker than in manufacturing.

While the data in Table 1 are informative, there is still substantial variation within the industry divisions. Table 2 presents the estimates for major industry groups wherein we could detect systematic interest rate effects.[14] We could detect Granger causality in twelve of the thirty-nine industries for which we had complete data. We could detect significant impulse responses in twenty-two of the thirty-nine industries. Significant impulse responses in the absence of Granger causality imply either that the relationship between interest rates and industry employment is contemporaneous or that the relationship is indirect and works through the influence of interest rate movements on other variables in the VAR system.

The manufacturing industry varies dramatically with respect to both the timing and intensity of the employment response. For example, although manufacturing as a whole responds to an interest rate shock much more slowly and weakly than the construction industry, the apparel manufacturing industry responds as rapidly and builds over time to a peak response that greatly exceeds the construction industry response. Furthermore, the peak response of nonelectrical machinery, primary metals, fabricated metals, and transportation equipment manufacturing is stronger than the peak response of the construction industry.[15]

Somewhat surprisingly, only half of the manufacturing industries that are commonly related to construction activity demonstrate significant interest rate sensitivity. We cannot detect a systematic relationship between interest rate movements and changes in employment for furniture and fixtures, or stone, clay, and glass products. However, fabricated metals, and lumber and wood products demonstrate comparatively strong interest rate sensitivity. In both cases, the peak employment response is at least as strong as that of the construction industry, but appears only after a substantial lag. Lumber and wood products employment takes nearly four years to respond to an interest rate shock.

Our analysis of TCPU suggests that the industry division's sensitivity to interest rate shocks comes from the transportation and communications components: utilities are not interest sensitive by either assessment strategy. We find that communications and railroad transportation are particularly sensitive to interest rate movements. The impulse responses indicate these industries are more than twice as sensitive to interest rate movements as is aggregate TCPU, although the timing of the response is very similar.

Interestingly, although we could not detect interest rate sensitivity in the FIRE or services divisions, we find that five of their component industries are sensitive to movements in interest rates. Increases in real short-term interest rates have a negative impact on employment in depository institutions and health services but a positive impact on employment in personal services, hotels, and educational services. The positive interest rate response for personal services and hotels is consistent with Ceglowski (1989). Because most interest-sensitive industries seem to respond to an interest rate increase by decreasing employment, apparent gains for the educational services industry may reflect an increased demand for education by workers displaced from those industries.

Finally, our analysis of the government sector reveals mixed results. Higher real interest rates precede increases in federal government employment but decreases in state and local government employment. The negative effect on state government is immediate and Granger causal: the negative effect on local government is lagged and not Granger causal. Interestingly, the employment effects are strongest at the federal level and decline in intensity with the level of government.

Conclusions

Our analysis suggests that interest rate movements affect the composition of Texas employment rather than its level. We find that changes in real short-term interest rates do not predict changes in aggregate Texas employment, but do predict changes in sectoral Texas employment. In particular, we find that unanticipated increases in real short-term interest rates lead moderate employment decreases in construction, manufacturing, and the service-producing industries that distribute goods.

As such, our analysis suggests that real short-term interest rates are not a primary channel through which national policy affects Texas employment. However, our analysis does suggest that interest rate movements can be important to regional analysis because they can have compositional effects on employment.

Notes

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1 Movements in nominal interest rates need not imply similar movements in real interest rates.

2 Our finding that employment is insensitive to changes in real short-term interest rates need not imply that

output is also insensitive. If firms substitute labor for capital, rising interest rates could lower output without necessarily reducing employment.

[3] In exploratory analysis for Texas as a whole, we also incorporated a real long-term interest rate (the ten-year Treasury bond rate deflated by the Federal Reserve Bank of Philadelphia's Index of ten-year inflation expectations). A block-exogeneity test indicated that the long-term interest rate did not add any information not already captured by the short-term interest rate. Therefore, we did not include real long-term interest rates as a variable in our analysis.

[4] For a description of the Berger–Phillips method, see Berger and Phillips (1994). The real interest rate and real oil price series had no significant seasonal pattern and, therefore, were not seasonally adjusted.

[5] The construction employment series was not stationary for any plausible degree of differencing, either with or without the logarithmic transformation. However, when we restrict the sample to the period after 1985, the logarithmic series was first-difference stationary. Given the dramatic effects on the construction industry of the Tax Reform Act of 1986, it seems plausible to so restrict the sample. Therefore, the sample used for analysis of the construction industry spans the period from January 1986 to November 1995.

[6] Differencing the data makes the series stationary but reduces the information used to estimate the VAR. One might recover some of this information in an error-correction model by exploiting a long-run cointegrating relationship among the regressors. However, reliable long-run relationships are difficult to detect in short time series (Campbell and Perron 1991). Therefore, we did not employ an error-correction model.

[7] For a further discussion of the model-selection criteria, see Mills (1990) or Kennedy (1992).

[8] For twenty-three of the forty-eight industries or major industry groups, we can reject the hypothesis that the coefficients on lags three through twelve are jointly zero across all five variables and all five equations in the system. For all of the systems, we cannot reject the hypothesis that the coefficients on a thirteenth lag would be jointly zero across all five variables in all five equations. We also cannot reject the hypothesis that the coefficients on lags thirteen through twenty-four are jointly zero across all five variables and all five equations in each system.

[9] Because the construction industry is evaluated over a shorter time period, it may require a different lag structure than the rest of the analysis. The AIC indicates that three lags would be appropriate for analysis of the construction industry; the SC indicates that only one lag is necessary. Because a likelihood ratio test favors three lags, we estimate construction industry employment as a function of three lags of itself and three lags of each of the other variables.

[10] We should note that the relationship is causal only in a temporal sense. Rejecting the hypothesis implies that movements in interest rates systematically precede movements in employment and can be used to predict movements in employment. However, this need not imply that movements in interest rates induce movements in employment.

[11] If the covariance among the residuals is sufficiently high, the ordering of the dependent variables can affect the results. In our opinion, the ordering employed here reflects the most plausible transmission relationship among the variables. Furthermore, exploratory analysis suggests that variations in ordering have little qualitative impact on the results.

[12] However, because it increases our uncertainty about the estimation, we use a two-standard-deviation confidence band for the impulse response whenever we cannot reject at the 10-percent level of significance the hypothesis that the coefficients on all of the variables in the industry employment equation are jointly zero.

[13] Texas' employment insensitivity is consistent with work by Carlino and DeFina (1996) that finds that personal income is less sensitive to changes in short-term interest rates in the Southwest census region (which includes Texas) than in the nation as a whole.

[14] Complete data were not available for a number of Texas industries. Data were available but the interest rate sensitivity was indistinguishable from zero for the following industries: oil and gas extraction; nonmetallic minerals extraction; furniture and fixtures; food and kindred products; paper and allied products; stone, clay, and glass; electronics and electrical equipment; instruments; utilities; apparel stores; auto dealers; food stores; general-merchandise stores; building-materials stores; and amusements.

[15] The positive employment effect on transportation equipment manufacturing seems anomalous, but it is consistent with previous work by Peter Kretzmer (1985), which finds a similar short-term effect from unanticipated money shocks.

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