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Comparisons across border cities show retail and wholesale trade employment to be more sensitive than manufacturing employment to changes in exchange rates. This result suggests that these cities can become less sensitive to future peso shocks by developing their industrial infrastructure. Consequently, adverse employment effects of exchange rate shocks, such as those following the 1982 peso devaluations, are likely to be reduced by attracting maquiladoras and other manufacturing firms to border cities.

Different approaches to time series forecasting for Texas suggest that less complicated univariate techniques often work at least as well as more sophisticated procedures. Only over longer forecast horizons do multivariate vector autoregression models predict better, and then only in some cases. Otherwise, simpler univariate methods forecast as well. Multivariate time series models for Texas variables also require more effort to construct than has sometimes been claimed for other such regional models.

Industrial Diversification, Exchange Rate Shocks, and the Texas-Mexico Border

*By Alberto E. Davila, Ronald H. Schmidt, and Gary M. Ziegler**

Unemployment surged along the Texas-Mexico border following the February and August 1982 peso devaluations. The higher unemployment rates can be attributed to other factors also—the recessions in both Mexico and the United States, falling oil prices, a glutted natural gas market, and a bad year for agriculture—but clearly the devaluations had a major impact.

Comparisons across border cities, however, demonstrate that there were significant differences in the degree to which the major border cities were affected by the devaluations. Laredo's unemployment rate increased from 9.8 percent in January 1982 to 23.7 percent in September 1982. By contrast, El Paso's rate rose from 8.8 percent to 12.2 percent in this period.

Empirical results presented in this article suggest that the unemployment impact of the peso devaluations was related to the relative share of manufacturing employment in some border cities. After controlling for nondevaluation employment effects through multiple regression analysis, manufacturing employment was found to be less sensitive than wholesale and retail trade employment to exchange rate movements. The evidence also demonstrates how the uneven impact of the devaluations on border cities was related to the different degrees of dependence on the Mexican economy. Manufacturing and trade employment in Laredo exhibited stronger ties to the Mexican economy than to the Texas economy. By contrast, Brownsville and, to some extent, McAllen and El Paso were more closely linked to the Texas economy.

The results of this study suggest that Texas-Mexico border cities can become less sensitive to future peso shocks by developing their industrial infrastructure. Cities along the border can attract labor-intensive firms that are drawn by the relatively low wages of workers there, as well as firms that use either Mexican inputs or raw materials found in

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the border region.

Texas border cities can also take advantage of the expanding number of *maquiladoras* in neighboring Mexican cities. (See the accompanying box.) Maquiladora employment results in spillover effects on twin-plant operations on the U.S. side. Furthermore, because maquiladora workers produce goods for U.S. consumption, increases in maquiladora employment can potentially reduce the sensitivity of border cities to exchange rate fluctuations.

In the past, cities along the border have not been equally successful in attracting manufacturing firms or maquiladoras. This can be seen by comparing the manufacturing bases of El Paso and Laredo. Continuation of these trends may lead, therefore, to a greater degree of heterogeneity with respect to the impact of future peso devaluations on unemployment along the border.

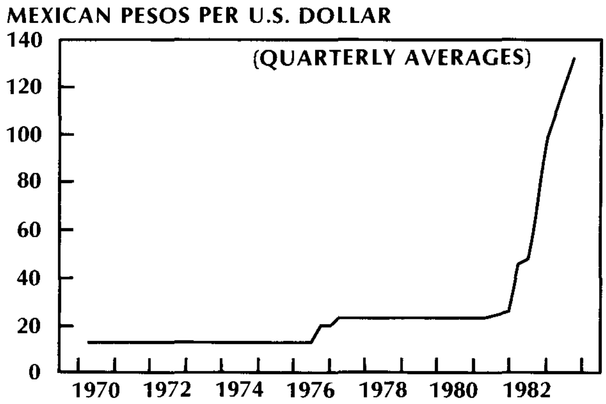
Problems with a pegged exchange rate

The peso has experienced three abrupt devaluations against the dollar over the past decade, once in 1976 and twice in 1982 (Chart 1). These large, discrete jumps reflected the inability of the Mexican government to maintain a pegged exchange rate as the peso became increasingly overvalued with respect to the dollar. A truly floating peso would have resulted in a slower, more continuous pattern of change.

Several factors are usually cited in the literature as contributing to the underlying equilibrium value of a currency, ranging from differences in current account balances to real interest rate gaps between countries. In the long run, however, the exchange rate should reflect differences in price levels between countries. This article concentrates on the overvaluation of the peso as reflected by differences in inflation rates between Mexico and the United States. These differences had a direct bearing on the allocation of resources in Texas-Mexico border cities and were, therefore, responsible for much of the impact of the peso shocks on these cities.

Inflation rates differed considerably between Mexico and the United States in the periods preceding each of the most recent peso devaluations. From 1970 through August 1976, the consumer price index for Mexico grew an average of 5.8 percent faster than the consumer price index for the United States. Between 1977 and 1981, the index grew an average of 10.3 percent faster than its U.S. counterpart.[1]

Chart 1
Peso/Dollar Exchange Rate



SOURCE OF PRIMARY DATA: Board of Governors, Federal Reserve System.

In the 1970–76 and 1977–81 periods, however, the peso/dollar exchange rate showed little change. (In fact, in the 1970–76 period, there was no change in the exchange rate.) As a result, the peso became increasingly overvalued with respect to the dollar.[2]

Because Mexican consumers were able to trade with U.S. merchants at the official exchange rate, overvaluation of the peso allowed them to purchase more U.S. goods and services than would have been possible at levels determined by freely floating exchange rates. This overvaluation "subsidy" to Mexican consumers encouraged border cities to increase their reliance on retail trade with Mexico.

1. The natural logarithm of the ratio of the Mexican consumer price index to the U.S. consumer price index was regressed against time for each of the two periods. The coefficients represent the difference between growth rates of the Mexican and U.S. price indexes.

2. A measure of purchasing power parity (PPP) was used to obtain an estimate of what the peso/dollar exchange rate would have been under floating exchange rates. The PPP takes into account changes in price levels between the United States and Mexico. Values of PPP from 1970 through August 1976 and from late 1977 through January 1982 (before the first 1982 devaluation) indicate that pressure on the peso was rising in these intervals.

Table 1
BORDER AREA EMPLOYMENT, BY SELECTED SECTORS

Standard metropolitan statistical area	Manufacturing Total	Manufacturing Durable goods	Manufacturing Nondurable goods	Contract construction	Trade Wholesale	Trade Retail	Services	Government
	Annual averages for 1982 employment							
El Paso	38,700	12,150	26,550	8,150	10,150	31,350	27,150	33,500
Percent of total . . .	20.3	6.4	13.9	4.3	5.3	16.5	14.3	17.6
Laredo	1,950	600	1,350	1,850	1,800	10,350	5,100	6,700
Percent of total . . .	4.8	1.5	3.3	4.5	4.4	25.2	12.4	16.3
McAllen[1]	9,300	1,800	7,500	5,950	9,150	17,850	10,150	20,000
Percent of total . . .	8.4	1.6	6.8	5.4	8.3	16.2	9.2	18.1
Brownsville[2]	10,700	5,350	5,350	4,050	4,200	14,150	10,400	12,300
Percent of total . . .	12.4	6.2	6.2	4.7	4.9	16.5	12.1	14.3

1. McAllen-Pharr-Edinburg.
2. Brownsville-Harlingen-San Benito.
SOURCE OF PRIMARY DATA: Texas Employment Commission.

Because of the price and income effects on the Mexican side of the border, Mexican firms and consumers drastically reduced their purchases in U.S. border city markets. This decline in sales to Mexico led to significant layoffs by border merchants.

Absence of more frequent changes in the exchange rate, therefore, exacerbated the employment effects of exchange rate changes by providing additional short-run incentives for U.S. firms in border cities to focus on retail trade with Mexico. In times of devaluation, those are the firms most affected by the loss of purchasing power on the Mexican side of the border.

Manufacturing activity in the border cities was less vulnerable to peso shocks because the linkage to the Mexican economy was not as direct. Consequently, the elimination of the subsidy by official devaluations of the peso had a much smaller impact on cities that concentrated more extensively on manufacturing than on international trade with Mexico.

Differential employment effects

The four major Texas cities along the border—El Paso, Laredo, McAllen, and Brownsville—were all affected differently by the peso devaluations (Chart 2). In particular, Laredo and McAllen experienced larger increases in unemployment than did Brownsville and El Paso.

These differential effects of exchange rate changes on the four border cities reflect fundamental differences in their underlying economic structures. As shown in Table 1, El Paso and Brownsville, the two cities least affected by the devaluations, had the largest manufacturing employment shares in 1982—20.3 percent and 12.4 percent, respectively. Laredo, which had the largest increase in unemployment following the devaluations, had only 4.8 percent of its employment in manufacturing.

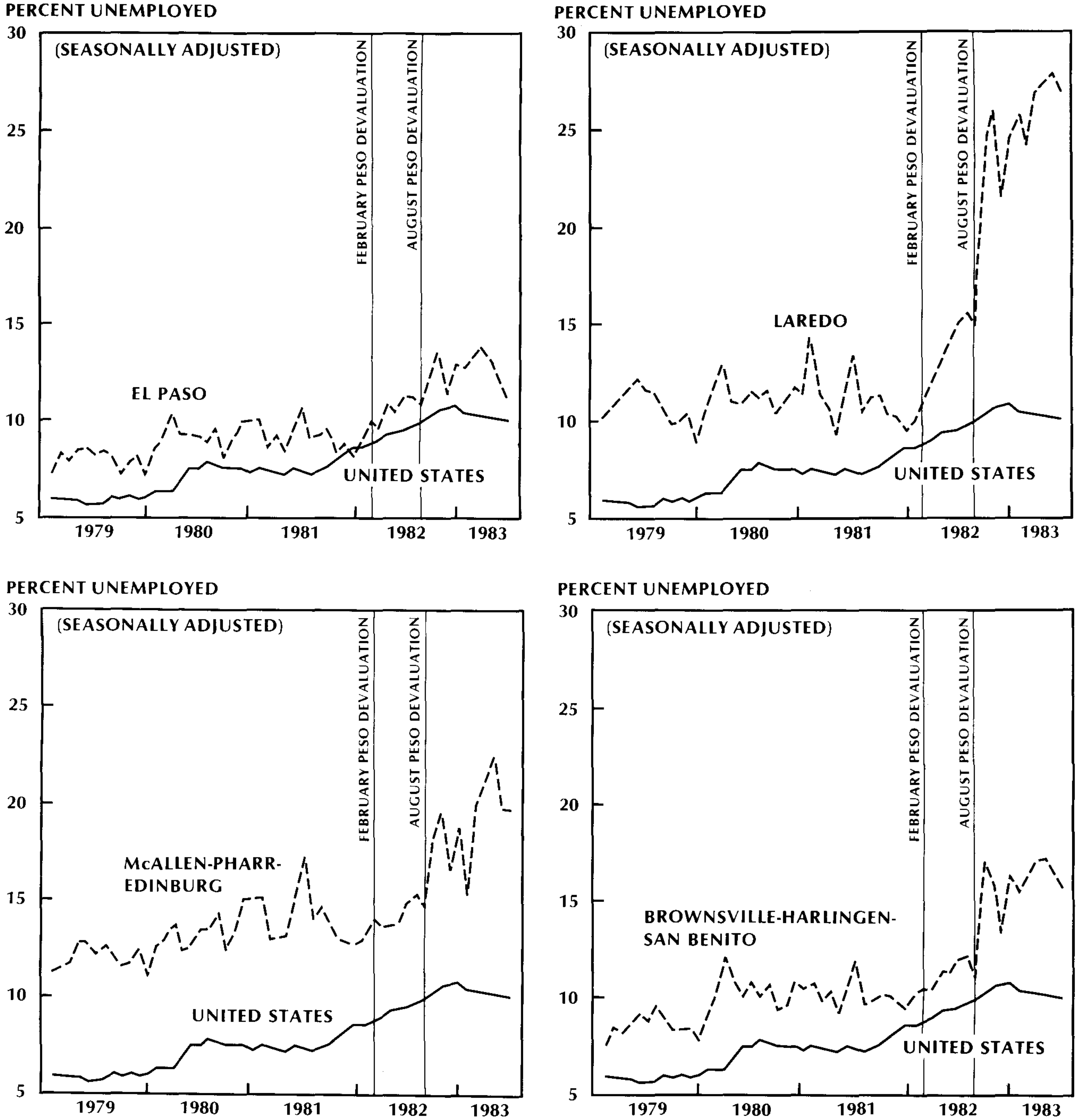
To help untangle the effects of exchange rates on different types of employment, a set of regression equations was constructed for each city. In addition to exchange rates, both of the major categories of employment—trade (wholesale and retail) and manufacturing—were also hypothesized to be influenced by industrial production in Texas and Mexico, oil and natural gas prices, and the number of maquiladora workers employed in the Mexican city adjacent to each of the four border cities.[3]

Industrial production indexes for Texas and Mexico were included in an attempt to control for the

3. Additional variables describing the economic infrastructure and capital investment in each city would provide considerable power in explaining the employment patterns more precisely. Unfortunately, monthly series on such variables are not currently available for these cities.

Chart 2

Unemployment Rates in Major Texas Border Areas and the United States



SOURCES OF PRIMARY DATA: Texas Employment Commission.
U.S. Department of Labor, Bureau of Labor Statistics.

The Maquiladora Program

Maquiladoras are assembly plants, mostly in northern Mexico, that are an outgrowth of the border industrialization program initiated in 1965.[1] Originally intended to industrialize the northern states of Mexico, the maquiladora program has also increased the manufacturing base of U.S. border cities through the creation of U.S. "twin plants." As part of the program, a U.S. firm locating a plant in Mexico also builds a plant on the U.S. side of the border. This twin plant is usually a distribution center for the Mexican maquiladora plant, although some twin plants do additional assembly work.

American firms have found the Maquiladora program attractive for several reasons. Tariff codes in both Mexico and the United States permit American firms to ship raw materials and assembled goods between the two countries at lower duties. An American firm is allowed to ship raw materials to Mexico duty-free, use them to produce a good in its maquiladora, and import the assembled product into the United States, paying duties only on the value added to the good in Mexico.

The maquiladora program provides significant cost advantages because of Mexico's proximity to U.S. distribution centers and because of the low cost of Mexican labor. Low transportation costs from Mexico make other low-wage countries in the Far East, South America, and the Caribbean relatively less attractive to U.S. firms. Furthermore, the fact that wages of Mexican workers are less than those of U.S. workers has created incentives for labor-intensive firms to locate assembly plants in Mexico rather than in the United States.

1. For discussions of the border industrialization program, see Anna-Stina Ericson, "An Analysis of Mexico's Border Industrialization Program," *Monthly Labor Review*, May 1970, 33–40, and Donald W. Baerresen, "Mexico's Assembly Program: Implications for the United States," *Texas Business Review*, November–December 1981, 253–57.

effects of cyclical changes in business conditions on employment along the border. Positive coefficients indicate that border cities tend to be influenced by the same factors that affect the overall Texas and Mexican economies. Oil and natural gas prices reflect the employment and wealth effects corresponding to changes in energy markets.[4] Higher natural gas prices, for example, increase the income of owners of gas wells and lead to increases in the drilling industry. Higher natural gas prices also increase spending in areas that have significant deposits of natural gas. The number of maquiladora workers was included to capture the effect of the growth of twin plants in the cities.

Regression results using monthly data from July 1978 to April 1983 are reported in Table 2.[5] In each of the four cities, the coefficient on the exchange rate was negative and significant for employment in the trade sector. Furthermore, looking across equations, the coefficients were larger for Laredo and McAllen and considerably smaller for El Paso and Brownsville.

Manufacturing employment was also negatively affected by devaluations in all cities except McAllen. For McAllen, this coefficient was insignificantly different from zero. The exchange rate coefficients in the manufacturing employment equations, however, were consistently smaller than those in the trade employment equations.[6] Changes in the value of the peso have an immediate impact on the

4. The regressions reported in Table 2 use nominal prices for oil and natural gas. Regressions that used real oil and natural gas prices (nominal prices deflated by the U.S. consumer price index) in place of the nominal prices had no effect on the signs, significance, or relative magnitudes of the coefficients in Table 2.

5. The results of the simple linear regressions reported in Table 2 were insensitive to alternative, more complicated formulations. The use of lag structures, nonlinearities, and multiple-equation estimation techniques had little effect on the relationship between exchange rate coefficients in the manufacturing and trade employment equations.

6. The hypothesis that the coefficients on exchange rates in the trade and manufacturing employment equations were insignificantly different from each other was tested for each city individually. The hypothesis was rejected at the 90-percent confidence level for all cities except Brownsville.

Table 2
INFLUENCES ON BORDER AREA EMPLOYMENT, JULY 1978-APRIL 1983

Area, employment sector	Regression intercept	Peso/ dollar exchange rate	Texas industrial production index	Mexican production index	Natural gas price	Oil price	Maquiladora employment	Rho	R^2
El Paso									
Manufacturing . . .	9,397.93	-16.85	38.53	21.18	1.38	5.82	.21	-.81	.74
	(2.1)*	(-1.9)	(1.8)	(1.9)	(.6)	(2.2)*	(2.1)*	(-10.4)*	
Trade	32,961.06	-18.31	-1.21	7.59	4.26	-.84	.07	-.65	.68
	(11.2)*	(-3.3)*	(-.1)	(.9)	(3.2)*	(-.5)	(1.0)	(-6.6)*	
Laredo									
Manufacturing . . .	739.52	-2.21	2.85	3.33	-.41	.63	-.03	-.75	.53
	(1.2)	(-1.8)	(1.2)	(2.3)*	(-1.4)	(2.1)*	(-.2)	(-8.5)*	
Trade	4,592.66	-30.95	7.70	19.75	3.04	1.53	-1.09	-.63	.83
	(1.7)	(-5.7)*	(.7)	(2.8)*	(2.4)*	(1.2)	(-1.6)	(-6.1)*	
McAllen[1]									
Manufacturing . . .	-22,345.96	6.12	147.18	6.43	-3.91	.82	-.38	.10	.49
	(-2.3)*	(.4)	(2.8)*	(.2)	(-.8)	(.2)	(-.9)	(.8)	
Trade	15,836.74	-30.86	3.12	-8.54	6.41	-1.90	.80	-.472	.92
	(3.9)*	(-4.5)*	(.2)	(-.8)	(2.9)*	(-1.0)	(3.8)*	(-4.1)*	
Brownsville[2]									
Manufacturing . . .	5,230.30	-18.13	18.18	13.74	-1.50	.51	.01	-.53	.85
	(2.5)*	(-5.6)*	(2.0)*	(2.5)*	(-1.9)	(.5)	(.1)	(-4.8)*	
Trade	7,288.88	-21.83	21.09	3.76	4.39	-1.02	.07	-.32	.95
	(4.3)*	(-8.6)*	(2.6)*	(.7)	(7.1)*	(-1.3)	(1.1)	(-2.7)*	

1. McAllen-Pharr-Edinburg.
2. Brownsville-Harlingen-San Benito.
NOTE: Trade employment covers both wholesale and retail trade.
Figures in parentheses are *t* statistics; * indicates significance of the independent variable at the 5-percent level.
All estimates except those for manufacturing employment in the McAllen area were corrected for first-order autocorrelation.
Rho is the estimated autocorrelation coefficient.
SOURCES OF PRIMARY DATA: Banco de México.
Board of Governors, Federal Reserve System.
Federal Reserve Bank of Dallas.
Secretaría de Programación y Presupuesto.
Texas Employment Commission.
U.S. Department of Labor, Bureau of Labor Statistics.

retail trade portion of a city's economy because of the reduction in purchasing power on the Mexican side of the border.

Aside from the exchange rate results, the other coefficients in Table 2 help to explain the differential employment effects of the devaluations across cities. One of the more interesting results is the relative effect of the Texas industrial production index (TIPI) and the Mexican production index (MPI) on the different cities. Both trade and manufacturing employment in Laredo demonstrated greater responsiveness to MPI than to TIPI. By contrast, the coefficients on TIPI and MPI for the other cities generally indicate a closer link to the Texas economy.

This result reflects the long-term development patterns and geography of the different cities. McAllen is located a few miles from the border, with one of its major products being citrus fruit targeted toward the U.S. market. El Paso, with its copper smelters and garment manufacturing, and Brownsville, with its seafood processing, both produce commodities bound for the U.S. market. Laredo, on the other hand, developed on one of the major rail lines connecting Mexico and the United States. The stronger impact of devaluations on Laredo, therefore, is to a large extent a result of its historical role as a trade center between the two countries.

To say that Texas cities with closer ties to Mexico are more affected by peso devaluations is almost tautological, of course. It could be argued that if the border cities were to cease trading with Mexico, they would not be affected by fluctuations in the peso. Such an argument, however, ignores the fact that cities typically develop along the border to take advantage of foreign trade with Mexico. Consequently, although the cities would be less influenced by changes in the peso if they were to turn away from the Mexican market toward the U.S. market, they would probably be worse off. Trade, especially trade with factor mobility, can be shown to lead to greater production for both countries involved.

Factors influencing the growth of manufacturing along the border

The evidence in Table 2 suggests a link between the share of manufacturing employment and the effect of an exchange rate shock on unemployment rates along the border. The extent to which cities alter the composition of their industrial structures over time, therefore, may change the relative sensitivity of their economies to future devaluations. Results from this study suggest border cities that develop their manufacturing base tend to be less vulnerable to devaluations.

Several factors have influenced and continue to influence the pattern of industrial development in border cities.[7] One important factor is the low wage paid to border workers relative to the U.S. average. According to the 1980 Census, workers along the border earned 39 percent less than their counterparts in the interior of Texas.[8] Consequently, labor-intensive firms have incentives to relocate to the border. For example, a large number of apparel manufacturing plants have moved to the border cities, especially to El Paso.

Region-specific natural resources can also affect the pattern of manufacturing along the Texas-Mexico border. Because of its proximity to the Gulf of Mexico, Brownsville has a large proportion of manufacturing employment in seafood processing. McAllen has a considerable number of frozen fruit and vegetable plants, reflecting Hidalgo County's leading role in citrus production, and El Paso has several copper smelters and mines.

In all these cases, firms have sought to combine the advantages of proximity to natural resources with the lower-than-average wages to establish labor-intensive manufacturing plants. The existing wage gap between Texas border cities and the U.S. interior, in particular, could be used by border cities to encourage further movement of capital to the border.

Contribution of maquiladoras

The newest and potentially most dynamic development influencing diversification patterns across border cities is the maquiladora program. The maquiladora program has grown rapidly in recent years. Between July 1978 and April 1983, total employment in maquiladora plants in Ciudad Juárez, Nuevo Laredo, Reynosa, and Matamoros rose 48.3 percent, from 50,066 workers to 74,239. As shown in Table 3, Reynosa (across from McAllen) has had the fastest maquiladora employment growth rate over the past five years, while Matamoros (across from Brownsville) has had the slowest growth rate.

This program can be hypothesized to have two effects on decreasing the sensitivity of the border cities to exchange rate shocks. First, the twin-plant concept is targeted toward labor-intensive manufacturing industries that can best take advantage of the low wages on the Mexican side of the border. As a result, the maquiladora program can be expected to increase the manufacturing base of the border cities. The creation of an assembly plant on the

7. For some discussions of the manufacturing characteristics of Texas-Mexico border cities, see the following articles in the *Texas Business Review*: Charles P. Zlatkovich and Carol T. F. Bennett, "El Paso Economic Profile," January 1977, 4–7; Charles P. Zlatkovich and Carol T. F. Bennett, "The Lower Rio Grande Valley: An Area of Rapid Growth," September 1977, 204–9; and Niles Hansen, "Development of the Southwest Borderlands," November–December 1981, 247–52.

8. This estimate is based on annual wages and salaries of householders as defined by the Public Use Sample of the 1980 Census. For more on the border-interior wage differential, see Alberto E. Davila, "Sources of Depressed Earnings Along the Texas-Mexico Border," *Economic Review*, Federal Reserve Bank of Dallas, November 1982, 13–19.

Mexican side is likely to generate incentives for firms to move other divisions of their manufacturing firms to the border, especially given the relatively low wages that also exist on the U.S. side of the border.

Second, even in cases where the U.S. firm chooses to establish a distribution center, rather than a manufacturing center, on the U.S. side of the border, sensitivity to peso devaluations is reduced. In such cases, output of the maquiladora firms tends to be targeted toward the general U.S. market. As a result, the maquiladora-related portion of the trade sector on the U.S. side and the maquiladora portion on the Mexican side are less influenced by changes in the Mexican economy than by changes in the U.S. economy. This aspect of the maquiladora program is especially attractive because the economies of both the U.S. border city and the Mexican twin city have less dependence of employment on the value of the peso.

Some evidence of the influence of maquiladoras on employment in the border cities can be seen in the regression results reported in Table 2. In both the manufacturing employment equation for El Paso and the trade employment equation for McAllen, the coefficient on maquiladora employment was positive and significant. Coefficients in the other equations, however, turned up insignificant at the 5-percent level.

The significance of the coefficients for El Paso and McAllen, as well as the lack of significance for the other cities, may be the result of the uneven implementation of the maquiladora program across cities. El Paso and McAllen had the fastest growth rates of the four border cities in maquiladora employment on the Mexican side of the border (Table 3). Furthermore, Ciudad Juárez, which is across from El Paso, is the city along the border with the most maquiladora workers.

The difference in employment effects between El Paso and McAllen, with the positive effect on manufacturing employment in El Paso and on trade employment in McAllen, may be the result of differences in existing economic infrastructures. As shown in Table 1, El Paso has a larger manufacturing sector than McAllen. Proximity to existing manufacturing is often an added incentive for firms to move manufacturing facilities to the border, rather than setting up a distribution center.

Table 3
MAQUILADORA EMPLOYMENT IN BORDER CITIES

Mexican city (Texas city)	April 1983 level	Annual growth rate, July 1978–April 1983 (Percent)
Ciudad Juárez (El Paso)	48,039	8.4
Nuevo Laredo (Laredo)	2,383	3.6
Reynosa (McAllen)	9,277	22.8
Matamoros (Brownsville)	14,540	.4

SOURCE OF PRIMARY DATA:
Secretaría de Programación y Presupuesto.

The effects of maquiladora employment demonstrated in Table 2 tend to support the hypothesis that border cities are better insulated from exchange rate shocks through the program. The results, however, are far from conclusive. Several problems warranting further study should be pointed out in interpreting the effects of the maquiladora program.

First, the data used in this article, which have not been used previously, do not allow inference about a direct link for either the trade sector or the manufacturing sector of employment in the border cities. No data are currently available that would make it possible to determine directly the type of employment created in U.S. border cities by the establishment of a maquiladora plant on the Mexican side of the border. The positive effects that emerge for the trade sector in McAllen and the manufacturing sector in El Paso reflect a "spillover" from income gains in Mexico from maquiladora employment. This income effect, of course, is also an insulating factor for the border cities, because jobs in maquiladora plants are not as responsive as jobs in other firms in Mexico to changes in the Mexican economy.

Second, the use of maquiladora employment data for the city directly across from the U.S. city as a proxy for U.S. twin-plant development has some limitations. Maquiladoras have begun to move from the border into the interior of Mexico.[9] Although these plants have twin plants in U.S. border cities, it is difficult to identify the location of a twin plant's maquiladora from available maquiladora data.[10]

Establishing a clear relationship between the maquiladora program and the insulation of the border cities from future peso devaluations, therefore, cannot be accomplished without further study. Nonetheless, the results of this preliminary research provide some support for the hypothesis that maquiladoras, through developing the manufacturing industry on both sides of the border and through increasing the share of the trade sector dedicated to a wider U.S. market, could lead to less dependence of U.S. border employment on the value of the peso.

Implications

If the peso becomes seriously misaligned again, future abrupt movements in the exchange rate are a possibility. The Mexican government has made recent attempts to change the official exchange rate between the peso and the dollar more systematically, but there is no guarantee that a significant misalignment of the exchange rate will not occur.[11]

The results of this study suggest that border cities can reduce the impact of future peso shocks on their economies by expanding the manufacturing base on the U.S. side of the border and encouraging the development of maquiladora industries on the Mexican side. They can do so by aggressively attracting industries well suited to take advantage of region-specific characteristics and the low wages along the border.

Preliminary empirical evidence reported in this article also supports the hypothesis that further development of maquiladora plants could aid in reducing employment effects from devaluations. Further research is required to untangle the relationships between existing maquiladora development and employment diversification along the Texas border. Such studies are important because the maquiladora program is likely to continue its rapid growth and the Mexican government has continued to promote maquiladora investment.[12]

An additional aspect of this study relates to the heterogeneous nature of the impact of peso devaluations on Texas border cities. Unless the least-diversified border cities, like Laredo, keep pace with the industrial expansion of El Paso, the response of border cities to exchange rate shocks may widen in the future.

9. In January 1980, employment in maquiladora plants reported in Ciudad Juárez, Nuevo Laredo, Reynosa, and Matamoros accounted for 85 percent of total employment in the states of Chihuahua and Tamaulipas. Between January 1980 and April 1983, however, growth in maquiladora employment in the four cities grew 25.2 percent, while maquiladora employment outside the cities grew 39.6 percent.

10. To see if including interior data led to stronger results for the maquiladora variable, state maquiladora data were substituted for the city data used in the regressions in Table 2. The results were mixed, with Brownsville showing a stronger and significant effect in the maquiladora variable but with the other cities showing no effect.

11. The Mexican government has been adjusting the exchange rate by 13 centavos per day since September 1983 and has announced plans to continue the adjustment through 1984.

12. In the *Official Gazette* for August 15, 1983, the Mexican government announced a decree for the promotion of the maquiladora industry. This decree made several changes easing restrictions on maquiladora operations. For example, maquiladora plants are no longer required to export quality-control rejects; they need not export goods through the same port where they import raw materials; and they are authorized to sell 20 percent of production, as long as they are not in direct competition with Mexican industries. For additional changes and a more detailed version of the contents of this decree, see American Chamber of Commerce of Mexico, *Maquiladora Newsletter*, September 1983, 3–14.

Time Series Forecasting Models of the Texas Economy: A Comparison

By James G. Hoehn, William C. Gruben, and Thomas B. Fomby*

This article compares time series models for forecasting the Texas economy, ranging from extremely simple specifications to some rather complex methods. Movements in seven major Texas economic variables were forecast using these various techniques. The models were used to examine the forecasting power embedded in a variable's own past movements, in the past movements of other Texas variables, in the past movements of a set of national variables, and in combinations of these classes of variables.

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As a group, the time series models utilized have three noteworthy characteristics. First, they are relatively simple, compared with the large, multi-equation structural forecasting models that often receive considerable attention. Second, also unlike structural models, these time series models are designed only to forecast, not to explain economic interrelationships. For example, it is unwise to use time series models to estimate the economic impact of a change in governmental programs or to calculate the likely economic effect of some shock in the private sector. Third, the time series models all forecast movement of one variable on the basis of past movements in that variable. Some models also incorporate information based on past movements of other variables, but only to the extent that these other variables are useful in predicting later behavior, without regard to causal linkages.

The out-of-sample forecast results of the models showed that no single time series approach was consistently superior in predicting the values of all seven Texas variables. In addition, the more mathematically complicated approaches to forecasting did not always prove superior to less sophisticated methods. In fact, results suggest that great care must be taken in constructing the relatively complicated and much-praised vector autoregression models if they are to prove even the forecasting equals of simple univariate time series models.

For example, a type of vector autoregression model reported as valuable in a regional model of the Ninth Federal Reserve District proved for the seven Texas variables to be the poorest forecaster of all models constructed.[1] However, it was also found that the accuracy of univariate time series models diminished more rapidly with the length of the forecast horizon than did that of some of the multivariate models.

Time series approaches used

The differences between various time series models lie in the ways each incorporates information about the own past movements of a dependent variable and about the past movements of other variables in the forecasting process. These differences involve dissimilarities not only in the explanatory variables used but in the functional forms applied to the variables.

One of the simplest approaches to forecasting on the basis of a variable's own past behavior is the assumption of a "random walk" with drift. The random walk with drift implies that a variable's growth can be characterized as unrelated deviations from some average growth rate. This article illustrates that the behavior of some Texas variables can as well be characterized as a random walk as by the alternatives examined.

The autoregressive integrated moving average (ARIMA) approach to forecasting incorporates a variable's past movements to forecast its future changes. For this univariate single-equation method of forecasting, George Box and Gwilym Jenkins have developed an approach for choosing which patterns of behavior to incorporate and which to ignore.[2]

Box-Jenkins ARIMA models were examined as part of this research, but another ARIMA model specification was also applied for the Texas economy, the ARIMA (2, 1, 0). In the (2, 1, 0) configuration, there are two lags in an equation (the 2 in the 2, 1, 0), the data are expressed in first differences (the 1 in the 2, 1, 0), and there are no moving-average parameters in the equation (the 0 in the 2, 1, 0), unlike the configurations in some other ARIMA equations.

Transfer functions represent a level of sophistication only slightly higher than the ARIMAs. Transfer function models used in this study included regression of a variable's growth rate on two lags of its growth rate plus two lags of the growth rate of one or possibly more variables.

Two other types of transfer function models were also examined. One, the "closed-region" model, included seven equations. In each equation the growth rate of one of the seven Texas variables was regressed on two own lags plus two lags of the growth rates of each of the other six Texas variables.

To examine the usefulness of national information in forecasting the Texas economy, a seven-equation "trickle-down" model was also constructed. In each of these equations, the growth rate of one of the seven Texas variables was regressed on two own lags plus two lags of five national variables.

The information thus acquired with regard to the relative forecasting power of different individual variables, different sets of variables, and different functional forms in forecasting each of the seven Texas variables was then applied in the construction of three alternative vector autoregression (VAR) models. In a VAR model, all variables in a system of equations are used to forecast movements in every variable in that system.

The closed-region model described above can be

1. See Paul A. Anderson, "Help for the Regional Economic Forecaster: Vector Autoregression," *Federal Reserve Bank of Minneapolis Quarterly Review*, Summer 1979, 2-7. The author compares his VAR model's *ex ante*, out-of-sample results with *ex post*, within-sample errors of an annual structural model of the Philadelphia region and with the same errors for an average of structural model forecasts for seven regions. He does not compare the forecast errors of his VAR model with those of other types of time series models, such as univariate models. Such a comparison would be useful because univariate models often outperform large structural models. See, for example, the remarks of C. W. J. Granger and Paul Newbold in *Forecasting Economic Time Series* (New York: Academic Press, 1977), 289-300.

2. A common reference source for discussions of this procedure is George E. P. Box and Gwilym M. Jenkins, *Time Series Analysis, Forecasting and Control* (San Francisco: Holden-Day, 1970). A more rudimentary explanation is found in Charles R. Nelson, *Applied Time Series Analysis for Managerial Forecasting* (San Francisco: Holden-Day, 1973).

Table 1
GLOSSARY OF VARIABLES

Regional variables

TIPI	=	Texas industrial production index.
CPIDFW	=	consumer price index for Dallas–Fort Worth metropolitan area (quarterly averages from interpolation of available monthly figures; deseasonalized using the X-11 procedure).
PAYROLL	=	nonagricultural wage and salary employment in Texas.
TEMP	=	total civilian employment in Texas.
RTPY	=	Texas personal income, deflated by the *CPIDFW* (seasonally adjusted using the X-11 procedure).
RTRET	=	Texas retail sales, deflated by the *CPIDFW* (seasonally adjusted using the X-11 procedure).
TLF	=	Texas civilian labor force.

National variables

LEAD	=	index of 12 leading economic indicators.
COINC	=	index of four roughly coincident economic indicators.
IPI	=	industrial production index.
NEMP	=	total nonagricultural civilian employment (persons 16 years of age and over).
FYAVG	=	Moody's all-industry average corporate bond yield.

NOTE: All series were seasonally adjusted by the publishing agency except the three regional series that were adjusted by the authors, using the X-11 computer procedure of the Commerce Department. The national series were taken from the CITIBASE data bank; most of the national variable names are the same as those in that file.
Seasonally adjusted data were used in this initial exploration in order to render more transparent the resulting models and their relative success in exploiting economic relationships as opposed to their ability to deal with seasonality. Time series that include (seasonal) moving-average parameters are generally best when seasonal factors are not strictly deterministic.

SOURCES OF PRIMARY DATA: Board of Governors, Federal Reserve System.
Business Week.
Federal Reserve Bank of Dallas.
MoodyRs Investors Service.
U.S. Department of Commerce, Bureau of Economic Analysis.
U.S. Department of Commerce, Bureau of the Census.
U.S. Department of Labor, Bureau of Labor Statistics.

considered a form of VAR model because every variable that is a left-hand-side variable in any equation is also a right-hand-side variable in all equations. The closed-region model is a simple VAR model, however, in the sense that prior restrictions on the values of the coefficients and on the standard deviations of these variables are not imposed. It should be distinguished from so-called Bayesian VAR models, in which such prior restrictions are imposed.

The nature of prior restrictions as they are often applied to Bayesian VAR models, along with the rationales for including them, will be discussed in later sections. Indeed, an important purpose of this article is to present the first published comparison of alternative approaches to prior specifications for regional VAR modeling. The article also contrasts the forecasting ability of models having different prior specifications with results derived from univariate time series procedures.

Another function of this article is that, with respect to vector autoregression modeling, it offers some new methodology for the selection of prior restrictions. These selection procedures, based on information gained from some of the other time series forecasting models constructed in this study, improved the forecasting power for a VAR model of the Texas economy. Even with these improved procedures for deciding on the prior restrictions to impose, however, Bayesian VAR modeling does not seem to offer consistently better results than ARIMA forecasts.

The forecasting problem

The purpose of all the forecasting procedures outlined is to predict the following seasonally adjusted Texas quarterly variables: (1) the Texas industrial production index (*TIPI*); (2) the consumer price index for the Dallas-Fort Worth metropolitan area (*CPIDFW*); (3) nonagricultural wage and salary employment (*PAYROLL*); (4) total employment (*TEMP*); (5) Texas personal income, deflated by the *CPIDFW* (*RTPY*); (6) Texas retail sales, deflated by the *CPIDFW* (*RTRET*); and (7) the Texas labor force (*TLF*). More information about the variables appears in Table 1.

Estimations were generally performed on growth rates, rather than on raw data. All variables were first placed in natural logarithmic form. Except in the VAR models, estimations were performed on first differences of the logarithms, which are essentially the growth rates of the original data.

The objective of the alternative forecasting procedures used in this study was to minimize the root mean square error (RMSE) of out-of-sample forecasts. To achieve this goal, various specifications were examined with regard to the within-sample and out-of-sample error reductions they offered compared with a set of benchmark equations.

For the within-sample examinations, amendments to various equations were considered in light of their power to reduce standard error of equation. Such power was measured by the statistic

$$I_{BA} = [(SEE_A - SEE_B)/SEE_A] \times 100,$$

where SEE_A is the standard error of some equation, A, used to forecast a given variable and SEE_B is the standard error of another equation, B, used to forecast the same variable. If the value for I_{BA} is positive, B represents an improvement over A in terms of standard error of equation because a positive value for I signifies a lower SEE value for B than for A. Conversely, a negative value for I_{BA} means that equation B has poorer within-sample forecasting characteristics than A.

Univariate ARIMA models

ARIMA models treat each Texas variable in isolation in estimation and in forecasting. Such a model takes the form, denoted ARIMA (p, d, q), of

$$(1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p)(1 - L)^d y_t$$
$$= \mu + (1 - \theta_1 L - \theta_2 L^2 - \ldots - \theta_q L^q) a_t,$$

where y_t is the natural logarithm of the series and a_t is a normally distributed unobservable random variable with zero mean, finite and constant variance, and zero autocorrelation at all lags.[3] The expression L is a lag, or backward shift, operator. There are p autoregressive terms (lagged y's) and q moving-average terms (lagged a's). Typically, economic time series that exhibit growth must be transformed to natural logarithms and differenced once (making d equal 1, to signify first differences) in order to make assumptions about the disturbance term plausible for any p and q. That practice was followed in the study described in this article.

ARIMA models can be identified using methods established by Box and Jenkins. These methods first infer plausible candidate equation forms from sample autocorrelations, subsequently subject them to diagnostic tests, and repeat this process (if necessary) until an adequate model is found. The Box-Jenkins approach seeks a simple representation adequate to characterize the behavior of the series.

It is useful to ask statistically if a given ARIMA equation forecasts any better than a model that assumes a variable behaves as a random walk with drift—that is, any discrepancy from a long-term average growth rate does not persist. The (p, d, q) form of the ARIMA would be expressed as (0, 1, 0). This random walk specification means that recent past movement in a variable, as well as recent lagged disturbances in that movement from some long-term stable rate of change, gives no extra information about future movement.

Four of the seven Texas variables proved to be nothing more than such random walks. For total employment, the Texas labor force, Texas personal income, and Texas retail sales, each quarter's data are new draws from the same hat. If the growth rate of one of the variables deviates significantly from its long-term average, that information should not motivate revision of the forecast of the next quarter's growth rate.

Growth rates of the Texas industrial production index, the Dallas-Fort Worth consumer price index, and nonagricultural employment, on the other hand, deviate from a long-term average growth rate in a

3. Box and Jenkins, *Time Series Analysis*, 74, 87–93.

Table 2
UNIVARIATE ARIMA MODELS

(1) Texas industrial production index

$$(1 - L)\ln(TIPI_t) = .01783 + (1 + .63L)e_t.$$

SEE = .01538; I = 11.1.

To lag	Chi-square	Significance
6	6.2	.19
12	15.1	.13
18	19.4	.25
24	24.3	.33

(2) Consumer price index, Dallas-Fort Worth

$$(1 - .89L)(1 - L)\ln(CPIDFW_t) = .02051 + (1 - .38L)e_t.$$

SEE = .00769; I = 29.7.

To lag	Chi-square	Significance
6	1.7	.67
12	6.5	.69
18	9.1	.87
24	17.0	.71

(3) Payroll employment

$$(1 - .73L)(1 - L)\ln(PAYROLL_t) = .01145 + e_t.$$

SEE = .00432; I = 30.1.

To lag	Chi-square	Significance
6	.8	.94
12	7.2	.70
18	9.1	.91
24	19.0	.65

The other four series (*TEMP, RTPY, RTRET,* and *TLF*) are modeled in natural logs as random walks with drift: $(1 - L)\ln(TEMP_t) = .00884 + e_t$, and so on.

systematic way. The patterns of deviation imply that very recent past growth rates of these series can be used meaningfully to project future growth rates. Table 2 presents the ARIMA equations for these three variables. Compared with estimates assuming a simple random walk with drift, the Box-Jenkins ARIMA models reduced standard error of equation for nonagricultural employment by 30.1 percent, for the Dallas-Fort Worth consumer price index by 29.7 percent, and for the Texas industrial production index by 11.1 percent.

Table 3
UNIVARIATE ARIMA (2, 1, 0) MODELS

$$(1 - \phi_1 L - \phi_2 L^2)(1 - L)\ln(y_t) = a_t$$

Variable (y)	SEE	$\bar{R}^2$	$I(B, A)$[1]
TIPI	.01579	.19	9.0
CPIDFW	.00768	.51	29.7
PAYROLL	.00443	.59	28.4
TEMP	.00825	−.03	−2.9
RTPY	.01364	−.01	−.1
RTRET	.02175	.02	1.3
TLF	.00641	.04	.6

1. $I(B, A) = \left[1 - \frac{\text{standard error of ARIMA (2, 1, 0)}}{\text{standard deviation of } (1 - L)\ln(y)}\right] \times 100.$

NOTE: $\bar{R}^2$ is the coefficient of determination adjusted for degrees of freedom.

It was also useful to compare the forecasts of the ARIMA (2, 1, 0) equations with those of a random walk with drift. Recall that simple ARIMA (2, 1, 0) models were different from the Box-Jenkins ARIMA models, since the latter were given whatever form seemed to be adequate. Nevertheless, as Table 3 shows, the ARIMA (2, 1, 0) functions improved standard error of equation, compared with forecasts based on the assumption of a random walk with drift, by almost as much as the Box-Jenkins equations did. Like the Box-Jenkins ARIMAs, the ARIMA (2, 1, 0) functions offered considerable improvement for the Dallas-Fort Worth consumer price index, nonagricultural employment, and the Texas industrial production index. Also like the Box-Jenkins ARIMAs, however, the ARIMA (2, 1, 0) equations were unable to improve standard error of equation greatly for any of the other four variables, relative to a random walk with drift.

Multivariate closed-region and trickle-down models

Multivariate time series models to forecast the Texas variables included two general types: the closed-region model, incorporating only Texas data, and the trickle-down model, incorporating only national variables plus own lags. These were used

Table 4
IMPROVEMENT IN STANDARD ERROR OF EQUATION FROM ADDITION OF REGIONAL VARIABLES

Dependent variable	*TIPI*	*CPIDFW*	*PAYROLL*	*TEMP*	*RTPY*	*RTRET*	*TLF*	Row sum
	Independent variables — Reduction in standard error, relative to standard error of ARIMA (2, 1, 0) model, that results from including two lagged growth rates of the column variable (Percent)							
TIPI		-1.6	6.7*	10.1*	3.7	4.7	5.9*	29.5
CPIDFW	-2.1		6.3*	8.3*	4.5	4.7	5.4*	27.1
PAYROLL	1.7	-.9		3.2	1.9	-1.1	.1	4.9
TEMP	2.4	.0	5.0*		-1.8	-.4	-1.1	7.7
RTPY	-1.1	3.4	-2.3	.3		.5	1.1	1.9
RTRET	-2.2	7.3*	-1.4	-1.1	-2.0		-2.2	2.4
TLF	.3	3.6	-.8	-2.2	-1.8	.5		-.4
Column sum	-1.0	11.8	13.5	18.6	12.1	8.9	9.2	
Less *CPIDFW* and *TLF* rows	.8	8.2	8.0	12.5	9.4	3.7	3.8	

* Significant at the .05 level (two-tailed test), using an *F* statistic with 2 numerator degrees of freedom and 40 denominator degrees of freedom.

to supplement own lags of the variable to be explained. In both cases, each Texas variable was initially regressed on two own lags and two lags of other variables.

Since all regression equations in these two classes of multivariate models contained two lags of each variable, a useful standard by which to compare their performance is the set of ARIMA (2, 1, 0) equations. In fact, the ARIMA (2, 1, 0) equations were constructed for such comparisons.

To begin tests of the forecasting power tied to within-region interactions, regression equations involving only regional variables were constructed. Each of the seven Texas variables was regressed on two own lags plus two lags of one of the other six variables. For example, the Texas industrial production index was regressed on two own lags plus two lags of nonagricultural employment. Likewise, the Texas industrial production index was regressed on two own lags plus two lags of the Dallas–Fort Worth consumer price index. Forty-two regression equations were required to produce all possible combinations of two own lags plus two lags of another Texas variable.

Table 4 shows the information gain from an equation with two own lags plus two lags of one other Texas variable compared with the ARIMA (2, 1, 0) for the same regressor. For example, an equation regressing the Texas industrial production index on two own lags plus two lags of nonagricultural employment reduces the standard error of equation (SEE) by 6.7 percent compared with the SEE of the Texas industrial production index ARIMA (2, 1, 0). Inclusion of some variables actually increased the SEE. These cases are recognized by the negative signs on their *I* values. For example, the equation regressing Texas personal income on two own lags plus two lags of nonagricultural employment resulted in a 2.3-percent increase in error.

These results suggest that regional interaction variables alone could significantly aid forecasts of industrial production and consumer prices with information from the three labor series. Predictions of household employment and deflated retail sales appear to gain some information from consumer prices. The Texas industrial production index has little value in aiding predictions of other variables, but predictions of it benefit from consideration of other series. Overall, the employment series provide the most information about future Texas economic events, at least when considered within sample.

As a final attempt to examine the predictive power that regional variables have on one another, a comprehensive closed-region model was con-

Table 5
IMPROVEMENT IN STANDARD ERROR OF EQUATION FOR COMPREHENSIVE CLOSED-REGION AND TRICKLE-DOWN MODELS

Dependent variable	Closed-region model				Trickle-down model			
	SEE	$\bar{R}^2$	I[1]	F[2]	SEE	$\bar{R}^2$	I[1]	F[3]
TIPI	.01466	.30	7.2	1.56	.01441	.32	8.7	1.84
CPIDFW	.00672	.63	12.5	2.07	.00584	.72	23.9	4.06
PAYROLL	.00440	.51	.7	1.04	.00443	.51	-.1	.99
TEMP	.00749	.16	9.2	1.75	.00792	.06	4.0	1.36
RTPY	.01378	-.01	-1.0	.93	.01265	.15	7.3	1.69
RTRET	.02293	-.09	-5.4	.76	.01842	.30	15.3	2.85
TLF	.00626	.08	2.3	1.16	.00644	.03	-.5	.96

1. Information gain, measured by percentage reduction in standard error relative to standard error of ARIMA (2, 1, 0) model.
2. F (12, 30); the critical values are 1.77 at the .10 level, 2.09 at the .05 level, and 2.84 at the .01 level.
3. F (10, 32); the critical values are 1.82 at the .10 level, 2.16 at the .05 level, and 2.98 at the .01 level.
NOTE: $\bar{R}^2$ is the coefficient of determination adjusted for degrees of freedom.

structed. This model was composed of seven regression equations, one with each of the seven Texas variables on the left-hand side. The right-hand side included two own lags plus two lags of each of the other six Texas variables. The *F* and *I* statistics presented in Table 5 suggest that regional interactions aid prediction of industrial production but fail to confirm the large gain for consumer prices that might be expected from the results of Table 4. The closed-region model provides a 12.5-percent reduction in the SEE of the consumer price growth rate, a 9.2-percent standard error reduction for the total employment within-sample forecasts, and a 7.2-percent reduction for the Texas industrial production forecasts.

However, as it stands, the closed-region model appears very much "overparameterized." Each equation in the closed-region model has so many right-hand-side variables that multicollinearity and loss of degrees of freedom interfere with forecast accuracy. Further analysis could possibly uncover a more efficient closed-region model using exclusion restrictions. Variables with parameters not statistically different from zero, for example, could be deleted.

Because economic conditions in Texas are affected by the same events as in the nation as a whole, it is also appropriate to search among national economic indicators for information about future conditions in Texas. The following key national variables were chosen as those most likely to improve time series forecasts of the Texas economy:[4] (1) the composite index of leading indicators (*LEAD*); (2) the index of roughly coincident indicators (*COINC*); (3) the U.S. industrial production index (*IPI*); (4) U.S. nonagricultural employment (*NEMP*); and (5) Moody's all-industry average corporate bond yield (*FYAVG*). Fuller descriptions of these variables appear in Table 1.

In order to examine the improvement over the ARIMA (2, 1, 0) that these national variables give to forecasts of the seven Texas variables, the following procedures were used. Growth rates of each of the seven regional variables were regressed on (1) two own lags plus two lagged growth rates of the index of leading economic indicators and (2) these variables plus two lagged growth rates of one of the other four variables. This design reflects the prior notion that the leading index is the single most powerful source of information for forecasting.

4. The 5 national variables were chosen from a set of 14 by procedures described in James G. Hoehn and William C. Gruben with Thomas B. Fomby, "Some Time Series Methods of Forecasting the Texas Economy," Federal Reserve Bank of Dallas Research Paper no. 8402 (Dallas, 1984).

Table 6
IMPROVEMENT IN STANDARD ERROR OF EQUATION FROM ADDITION OF NATIONAL VARIABLES

Dependent variable	*TIPI*	*CPIDFW*	*PAYROLL*	*TEMP*	*RTPY*	*RTRET*	*TLF*
	Reduction in standard error, relative to standard error of ARIMA (2, 1, 0) model, that results from including two lags of *LEAD* with two own lags of the column variable (Percent)						
LEAD	12.2*	5.9*	2.0	0.0	-1.0	1.5	-1.5
	Reduction in standard error, relative to standard error of an equation with two own lags of the column variable plus two lags of *LEAD*, that results from adding to the same equation two lags of the row variable (Percent)						
COINC ...	-1.2	9.9*	1.9	-1.0	-7.9*	10.6**	-.2
IPI	-2.5	10.0*	3.5	.6	12.2*	17.4*	4.5
NEMP	.9	9.7*	-2.3	-1.0	6.2*	6.8*	-2.0
FYAVG ...	-.1	15.4*	-.2	2.7	7.3*	7.0*	1.7

* Significant at the .05 level when equation is compared with the benchmark equation.
** Significant at the .01 level when equation is compared with the benchmark equation.

Table 6, with the *I* values pertinent to each equation, reveals that the index of leading economic indicators by itself was able to effect a 12.2-percent improvement in SEE over the ARIMA (2, 1, 0) for the Texas industrial production index equation and a 5.9-percent improvement for the Dallas-Fort Worth CPI equation. The addition of the coincident index to the leading index in the equations reduced the within-sample forecasting power for the Texas industrial production index but improved this power for deflated Texas personal income and retail sales, as well as for the Dallas-Fort Worth consumer price index. Regressions containing two own lags, two lags of the leading index, and two lags of U.S. industrial production had greater power in within-sample predictions of the Dallas-Fort Worth consumer price index, Texas personal income, and Texas retail sales but had poor results in equations predicting the other variables. Generally, national variables showed little success in forecasting the Texas labor series, just as the closed-region model had fared poorly on this score.

Finally, a trickle-down model was constructed relating growth rates in each of the seven Texas variables to two own lags and two lags of each of the five key national variables. Table 5 shows the standard errors of the equations and the information gains relative to the ARIMA (2, 1, 0) models. Not surprisingly, considering the results in Table 6, this trickle-down model achieved considerable within-sample success for consumer prices and deflated retail sales. The *F* statistics are highly significant for consumer prices and significant for deflated retail sales. The trickle-down model outperforms the closed-region model for four of the seven variables.

Out-of-sample performance of ARIMA, closed-region, and trickle-down models

The usefulness of the closed-region and trickle-down models can be assessed by constructing forecasts outside the sample and comparing their accuracy with that of the univariate forecasting equations. The out-of-sample forecasting period chosen was the first quarter of 1981 through the second quarter of 1983. Each model's parameters were reestimated each quarter to reflect new data, but the general form of the model was left unchanged.

For each of the seven variables, a sample of 10 one-period-ahead forecasts, 9 two-period-ahead forecasts, and so on, to 5 six-period-ahead forecasts, was obtained for each of the four models. The *j*-step forecast error is the actual log of the variable less

Table 7
OUT-OF-SAMPLE FORECAST PERFORMANCE OF SELECTED UNIVARIATE MODELS AND MULTIVARIATE MODELS

Variable, forecast horizon (quarters ahead)	Univariate models		Multivariate models	
	Box-Jenkins	ARIMA (2, 1, 0)	Closed-region	Trickle-down
	Root mean square errors			
TIPI: 1 . . .	.0240	.0234	.0218	.0239
2 . . .	.0446	.0446	.0439	.0417
3 . . .	.0626	.0584	.0615	.0509
4 . . .	.0842	.0808	.0827	.0629
5 . . .	.1075	.1049	.1090	.0805
6 . . .	.1260	.1259	.1309	.1022
CPIDFW: 1 . . .	.0078	.0078	.0074	.0052
2 . . .	.0156	.0148	.0146	.0111
3 . . .	.0250	.0231	.0260	.0181
4 . . .	.0357	.0325	.0416	.0280
5 . . .	.0501	.0455	.0613	.0421
6 . . .	.0679	.0621	.0831	.0587
PAYROLL: 1 . . .	.0072	.0074	.0083	.0081
2 . . .	.0150	.0148	.0152	.0168
3 . . .	.0267	.0270	.0263	.0280
4 . . .	.0411	.0415	.0406	.0410
5 . . .	.0567	.0572	.0551	.0539
6 . . .	.0658	.0657	.0631	.0629
TEMP: 1 . . .	.0068	.0072	.0096	.0096
2 . . .	.0101	.0105	.0104	.0139
3 . . .	.0129	.0133	.0118	.0131
4 . . .	.0169	.0172	.0159	.0146
5 . . .	.0202	.0201	.0218	.0144
6 . . .	.0220	.0215	.0241	.0159
RTPY: 1 . . .	.0127	.0140	.0124	.0185
2 . . .	.0164	.0172	.0181	.0241
3 . . .	.0229	.0238	.0219	.0240
4 . . .	.0296	.0310	.0296	.0255
5 . . .	.0343	.0345	.0280	.0262
6 . . .	.0414	.0425	.0295	.0357
RTRET: 1 . . .	.0235	.0233	.0255	.0270
2 . . .	.0379	.0394	.0449	.0372
3 . . .	.0477	.0509	.0562	.0418
4 . . .	.0581	.0628	.0596	.0456
5 . . .	.0686	.0749	.0596	.0618
6 . . .	.0790	.0866	.0516	.0798
TLF: 1 . . .	.0067	.0061	.0084	.0071
2 . . .	.0071	.0064	.0077	.0101
3 . . .	.0040	.0039	.0060	.0074
4 . . .	.0048	.0057	.0057	.0185
5 . . .	.0079	.0080	.0082	.0102
6 . . .	.0084	.0083	.0081	.0107

the forecast log of the variable, conditional on information available *j* quarters ago and earlier. The root mean square errors of univariate models serve as appropriate benchmarks for evaluating multivariate alternatives because if more complex models cannot forecast better, univariate forecasting models are probably the most useful bases for judgmental forecasts.

Table 7 presents the RMSEs for each of the four models. There was little difference in forecast accuracy between the Box-Jenkins and ARIMA (2, 1, 0) models. This suggests that autoregression models of low order, such as the ARIMA (2, 1, 0), may forecast nearly as well as ARIMAs built using Box-Jenkins identification procedures, at least for the seasonally adjusted series studied here.

While the overparameterized closed-region model achieved few successes relative to the univariate equations, it did perform as well or better for all but one of the six out-of-sample personal income forecast horizons and for the last four steps ahead in the case of nonagricultural employment. However, the promising aspect of within-sample performance of this model in predicting the Texas employment series bore relatively little fruit in out-of-sample forecasts. Taken as a whole, the closed-region model is an unattractive alternative to univariate equations. Even in the more distant nonagricultural employment forecasts, where the closed-region model proved better than the univariate models, the superiority was very slight.

The trickle-down model suffers from somewhat less overparameterization than the closed-region model and outperformed any other model in this study in out-of-sample forecasts of the Dallas–Fort Worth consumer price index. The trickle-down model had mixed success compared with the univariate equations for all other Texas variables except the labor force, where it failed. However, the trickle-down model forecast a little better than the closed-region model.

The univariate models tend to lose their superiority to the multivariate models at the longer forecast horizons. For a one-quarter-ahead forecast for the seven Texas variables, ARIMA (2, 1, 0) functions are superior to the trickle-down model in six out of seven cases, while the Box-Jenkins ARIMAs are superior to the trickle-down model in five out of seven cases. Conversely, for a six-quarter-ahead forecast, the trickle-down model is superior to the

ARIMA (2, 1, 0) in six out of seven cases and superior to the Box-Jenkins ARIMA in five out of seven cases. This tendency is far less pronounced for the closed-region model.

The forecasting superiority of the trickle-down model compared with the closed-region model is also a function of the length of the forecast period. One quarter ahead, the forecasting quality of the two models is about even. By the sixth quarter ahead, the trickle-down model exhibits marked superiority. Generally, this study suggests that the relative attractiveness of a given time series modeling procedure over others is a function of the forecast horizon.

Vector autoregression

Given the prior notion that information about the future course of each Texas series ought to be present in both U.S. and Texas variables, it is tempting to build a model that uses both. While Texas and U.S. variables could be included together in a forecasting equation, the problem of too many right-hand-side variables discourages the procedure of including all of them. To do so spends precious degrees of freedom and can lead to serious multicollinearity. Consequently, parameter estimates become inaccurate. As a result, parsimonious models generally forecast better than those that are not.

Nevertheless, the preceding results make it clear that information useful in forecasting Texas variables is widely diffused. A multivariate forecasting approach would be highly desirable if there were a method of capturing the information embedded in both Texas and U.S. data while avoiding the problems of overparameterization. Under such circumstances, vector autoregression may offer possibilities for capturing information in an attractively eclectic format.

In recent years, vector autoregression has been used by some economists as a medium for summarizing the relationships at various lags among groups of variables. Vector autoregression is simply a set of regressions, with the current value of each variable being regressed on the lagged values of all the variables in the system. Since all variables in the system are used to forecast movements in every variable in the system, there are no exogenous variables in a vector autoregression model. Thus, the closed-region model described in this article can be considered a very simple VAR model because every variable that is a left-hand-side variable in any equation is also a right-hand-side variable in all equations. The trickle-down model is not a VAR model because, with the exception of own lags, every right-hand-side variable is exogenous to the model.

While the closed-region model can be considered a VAR model and the trickle-down model cannot be, neither forecast consistently better than the univariate models. Clearly, vector autoregression does not automatically solve forecasting problems. Both equations had too many parameters.

Much of the problem of overparameterization, however, involves excessive coefficient variance and consequent imprecision in coefficient estimation, primarily as a result of multicollinearity. More generally, the number of observations typically available for vector autoregression is inadequate for obtaining precise estimates of the large number of free parameters in a VAR model. One way of addressing these problems in vector autoregression is by imposing restrictions on the values and variances of a model's coefficients. In the case of the VAR models of the Texas economy, these Bayesian procedures were carried out by means of the RATS (Regression Analysis of Time Series) modeling package, which greatly facilitated the creation of VAR models and the imposition of restrictions on them.[5]

The prior distribution generally used in the

5. Thomas A. Doan and Robert B. Litterman, in *User's Manual, RATS Version 4.1* (Minneapolis: VAR Econometrics, 1981), demonstrate clearly how to impose alternative prior specifications. Thomas Doan, Robert Litterman, and Christopher A. Sims ("Forecasting and Conditional Projection Using Realistic Prior Distributions," NBER Working Paper Series, no. 1202 [Cambridge, Mass.: National Bureau of Economic Research, 1983]) provide some evidence that vector autoregressions with well-chosen prior distributions can improve national economic forecasts relative to univariate autoregressions, even in a system of 10 variables. However, this result is subject to several caveats. The improvement over univariate equations is slight, the univariate benchmarks are arbitrarily specified rather than identified by Box-Jenkins methods, and the prior distributions are selected *ex post facto*. Nevertheless, the result is interesting, in that apparently no other forecasting method has yet been shown to deliver a systematic improvement over univariate methods in a national model with as many variables and over as long a period. Possibly other time series methods employing more parsimony could do so.

Table 8
OUT-OF-SAMPLE FORECAST PERFORMANCE OF VECTOR AUTOREGRESSION MODELS

Variable, forecast horizon (quarters ahead)	VAR I	VAR II	VAR III
	Root mean square errors		
TIPI: 1 ...	.0256	.0229	.0199
2 ...	.0478	.0414	.0346
3 ...	.0699	.0620	.0504
4 ...	.0935	.0831	.0668
5 ...	.1156	.1054	.0854
6 ...	.1364	.1316	.1061
CPIDFW: 1 ...	.0112	.0073	.0067
2 ...	.0248	.0139	.0126
3 ...	.0411	.0244	.0223
4 ...	.0601	.0387	.0357
5 ...	.0830	.0570	.0535
6 ...	.1093	.0802	.0753
PAYROLL: 1 ...	.0110	.0088	.0081
2 ...	.0224	.0174	.0156
3 ...	.0361	.0298	.0271
4 ...	.0485	.0427	.0400
5 ...	.0578	.0529	.0506
6 ...	.0642	.0611	.0593
TEMP: 1 ...	.0078	.0069	.0067
2 ...	.0120	.0096	.0090
3 ...	.0163	.0131	.0115
4 ...	.0211	.0189	.0169
5 ...	.0251	.0237	.0200
6 ...	.0281	.0292	.0230
RTPY: 1 ...	.0139	.0173	.0168
2 ...	.0187	.0252	.0249
3 ...	.0262	.0324	.0320
4 ...	.0331	.0371	.0357
5 ...	.0376	.0396	.0354
6 ...	.0440	.0406	.0330
RTRET: 1 ...	.0231	.0278	.0267
2 ...	.0384	.0426	.0429
3 ...	.0480	.0532	.0533
4 ...	.0574	.0600	.0568
5 ...	.0658	.0640	.0549
6 ...	.0742	.0686	.0485
TLF: 1 ...	.0066	.0059	.0054
2 ...	.0068	.0056	.0052
3 ...	.0047	.0056	.0030
4 ...	.0058	.0074	.0040
5 ...	.0082	.0094	.0055
6 ...	.0088	.0122	.0057

literature to restrict the characteristics is the random walk. In this approach the analyst imposes prior values of unity on the coefficient of the first own lag and zero on all other coefficients. Parameters are allowed to deviate from the prior values to a degree determined by both the data and the tightness of the priors. The degree of tightness is controlled by the standard deviations imposed on the priors. For example, as the standard deviations are increased, the parameters will tend to be closer to prior values; hence, we say that the priors have been tightened.

Some believe that efficient estimation of VAR models requires little theoretical knowledge or feel for regional data and that a simple random walk prior distribution can be imposed, with little effort at diagnosing the relative usefulness of alternative levels of restrictiveness.[6] Experience in construction of the Texas VAR models suggests that these claims are not universally applicable. Considerable time and care are required to produce a model that forecasts even as accurately as ARIMA models. In the Texas study, this nondiagnostic approach (noted as VAR I) to imposing prior restrictions produced the most inaccurate forecasts of all models considered, as a comparison of the RMSEs in the VAR I column of Table 8 with any other RMSEs in Tables 7 and 8 will show.

In constructing a VAR model of the Texas economy, three alternative specifications of prior restrictions were imposed. The choice of prior distributions of coefficient values had a substantial effect on the forecast performance of the estimated model. (Although different prior specifications were imposed in each of the three models, an unconstrained constant and a linear time trend were included in all.[7])

One approach to VAR model construction involved setting priors based on judgment derived from previous analyses undertaken in this study. Each of the seven Texas series was treated separately. The within-sample results of univariate,

6. See Anderson, "Help for the Regional Economic Forecaster." The VAR I model's priors were patterned after those of Anderson's model.

7. See Hoehn, Gruben, and Fomby, "Some Time Series Methods of Forecasting the Texas Economy," for further information on prior specifications imposed on the three VAR models.

closed-region, and trickle-down models were used to form rough notions about the extent to which the behavior of a given Texas variable reflected its own past, movements of other Texas variables as a block, and the performance of national variables as a block. The priors then were set along these dimensions. Even this approach is crude, but it does take advantage of the feel for the data that can be derived from examination of the univariate, closed-region, and trickle-down models.

For example, the growth rate of the Dallas-Fort Worth consumer price index displayed considerable autocorrelation, so the own-lag coefficients in a VAR model were given wide prior distributions. The own-lag coefficients were not restricted to values very close to 1 or 0; narrow restrictions were not imposed on their variances. Conversely, the closed-region model was of some help within sample but performed poorly out of sample. Hence, priors were tightened on lags of other regional variables. The national variable coefficients were given more freedom to seek their own levels in light of the relatively good performance of the trickle-down model.

Although the performance of this second model, VAR II in Table 8, generally falls a bit short of the univariate benchmarks, the model represents a substantial improvement over VAR I. Compared with the Box-Jenkins ARIMA for the 42 RMSEs reported per model (including an RMSE for each of the seven variables for each of six quarter-ahead forecasts), VAR I has a lower RMSE in only 6 cases, while VAR II has a lower RMSE in 15 cases.

Unlike the trickle-down model, however, there is no consistency of forecast-horizon results for the cases in which the VAR II proves more accurate than the univariate models. VAR II sometimes beats the univariate models in short-horizon forecasts, as for the Texas industrial production index and Dallas-Fort Worth consumer price index, and sometimes is superior in longer-horizon forecasts, as for Texas nonagricultural employment and retail sales. However, VAR II is never consistently superior to the univariate forecasts for any of the variables, nor is it superior for most forecasts over a given horizon.

Ex post analysis of the effect of alternative priors suggests that those of the VAR II model were generally too restrictive. In light of this analysis, the overall tightness priors were raised twofold, implying a looser prior distribution, although the personal income and labor force equations were subjected to tighter priors.

The result of these changes was the VAR III model. VAR III performs better than either of the univariate models, but its relative success is not spectacular. In the 42 comparisons of RMSEs (six different steps ahead for each of seven Texas variables), VAR III beats the Box-Jenkins ARIMAs 26 times, loses 14 times, and ties twice. VAR III beats the ARIMA (2, 1, 0) 27 times and loses 15 of the matches. The VAR III model outperforms all other time series models, univariate or multivariate, in forecasting the Texas labor force. It also provides the best or second-best forecasts for the Texas industrial production index, depending on the forecast horizon, but always beats the univariate models for this variable. VAR III does not consistently beat the univariate models on any other forecasts, and for the other variables and forecast horizons where it is superior, VAR III does not often beat the univariate models by very much. The forecast horizons in which VAR III beats the univariate models show a pattern similar to that of the trickle-down model, which had its greatest relative success in forecasts for more distant time horizons. For VAR III the pattern is not highly pronounced, but the model does have more success against the Box-Jenkins ARIMA—74 percent—and the ARIMA (2, 1, 0)—71 percent—in the more distant half of the forecast horizons (four, five, and six quarters ahead) than in the earlier half, where it beat both univariate models 57 percent of the time.

In spite of the unspectacular performance of even the most accurate of the three VAR models vis-a-vis the univariate models, the results may have implications for other regional VAR modeling. The relative success (compared with VAR I) of the VAR II model, which incorporates prior information derived from the earlier analysis, suggests that a strong feel for the data and their interrelationships can aid in the construction of a more accurate Bayesian VAR model. A second method of potentially improving forecast accuracy is to fine-tune the priors on the basis of out-of-sample experience with the VAR model. This Texas time series study included experiments with both of these methods of bettering the model. The superiority of VAR III to VAR II and VAR I demonstrates that these approaches ameliorated forecast accuracy. Given time and resources, further improvements could probably be realized along these lines, but effort was required to achieve even relatively moderate improvement over the univariate models.

It should also be noted that the fine-tuning of the priors, which resulted in the improvement of VAR III over VAR II, was performed *ex post facto*. Prior restrictions were altered in VAR III in light of the RMSEs estimated from VAR II. Because such RMSEs cannot be known except in retrospect (the difference between a forecast value and an actual value cannot be calculated unless the actual value is known), the improvements VAR III showed over VAR II would be difficult to make in a real, *ex ante* forecast.

Summary and conclusion

The preceding discussions outline steps toward developing efficient time series forecasting models of the Texas economy. Intraregional interactions are not easy to exploit for forecasting purposes. Among the seven Texas series studied, the two employment series seem the most important for the regional forecaster to watch as indicators of future changes in other series. National-regional interactions showed themselves a little easier to exploit, and they appear to aid in forecasting Texas industrial production, consumer prices, and deflated retail sales.

For the period, region, and variables under study, it was evident that vector autoregression was not as clearly superior a forecast procedure as some analysts of other regions have believed it to be for their areas. Indeed, for the overall out-of-sample forecast period of the models employed for Texas, univariate models generally performed about as well as any of the multivariate models studied. For forecast periods of less than one year, there was no evidence that any multivariate model was superior to the univariate models. A highly polished VAR model, VAR III, gave moderately better forecasts for more distant time horizons.

Experience in building time series forecasting models of Texas suggests that effective forecasting through vector autoregression can be a considerably complicated procedure. Care in imposing prior restrictions on coefficients is important.

A more promising approach for further research would exploit only the relationships found to be significant here. Recent explorations suggest that this parsimonious approach can yield systematic improvements over single-variable ARIMAs.

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