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January 1988

In 1987 a special session of the Texas Legislature was called to solve the state government's fiscal problems. The action the legislature took to solve those problems—namely, increasing taxes and cutting inflation-adjusted spending—could influence future economic growth in the state. This article examines how changes in the composition and level of taxes and state government spending will affect the ability of Texas to attract the business investment and work force that are crucial for continued economic development.

The recent volatility of the Texas economy points up the importance of accurate economic forecasting procedures that can help public and private policy makers. This article describes the construction of a multivariate time series forecasting model for the Texas economy and gives the model's 1988 forecast for seven selected Texas variables. The model developed here demonstrates generally greater out-of-sample forecast accuracy than do several other often-used forecasting approaches. This model can be used to produce statistically based forecasts, but it may also serve as the basis for an analyst's judgmental adjustments.

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The New Fiscal Environment in Texas: What It Means for State Economic Growth

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In 1987 a special session of the Texas Legislature was called to solve the fiscal problems faced by the state government. In fiscal year 1986, the state government's spending had crept above its revenue. A wider gap was projected for fiscal year 1987.

Given a requirement to balance the budget, the state's fiscal problems necessitated some combination of real spending cuts and increased taxation. And by the time the legislature left Austin in July, it had increased taxes and adopted a budget for fiscal years 1988 and 1989 that, when adjusted for prospective inflation, cut state government spending. These actions allow the State of Texas to balance its budget over the 1988-89 biennium and to retire the tax anticipation bonds that it sold to finance its 1987 deficit.[1]

The general sales tax was increased and broadened. The corporate franchise tax, which is assessed on the Texas capital of corporations doing business in the state, also was increased—as were taxes on motor fuels, motor vehicle sales, insurance, and a number of other items. Adjusted for expected inflation, spending for education, roads and highways, and some other government services was cut.

How will these changes in state fiscal policy affect economic growth as Texas looks beyond energy for future economic development?

The key to economic growth in Texas, or any state for that matter, is attracting new business investment and labor to the state while keeping the existing capital investment and work force in the state. States compete with each other to attract these mobile resources. And though climate, location, industry mix, and natural resources generally are more important determinants of state economic performance, a good fiscal policy can give a state a competitive edge in attracting and keeping business investment and able workers. These mobile resources are more attracted to the states that provide highly valued government services. On the other hand, they are less attracted to the states in which they would incur higher taxes. The most attractive fiscal policies strike a balance between the provision of government services and the taxes required to finance those services.[2]

As recently as 1984, the state and local governments in Texas had struck such a balance. From the perspective of fiscal policy, Texas was more attractive to business investment and labor than was the average state. Though Texas had a smaller government sector than the national average, the state and local government spending was advantageously concentrated in the most valued services. And revenue from oil and gas severance taxes allowed the state to provide a higher level of service than the taxation of capital and labor would otherwise have indicated.[3]

The preceding discussion suggests the three aspects of Texas fiscal policy to be addressed here. Using 1984 as a point of departure, this article examines how recent changes in state fiscal policy affect the size of the state government, the composition of its revenue, and the composition of its spending. The article also examines how these changes will affect the state's ability to attract the business investment and labor that are critical to future economic growth.

Size of the state government

As the size of the government grows relative to the taxpayers' ability to pay, the value of additional government spending declines. This is the result of three factors. As is the case for all goods, the value of an additional unit of a given government service declines relative to other goods as more of the service is provided.[4] In addition, the growth of government may be associated with the provision of less desired goods. Finally, if increases in tax progressivity are required to fund additional state government spending, the cost to economic growth of additional taxation will rise as taxes are increased.[5] Beyond a certain point, therefore, growth in the size of a state government that is greater than growth in the taxpayers' ability to pay will retard economic growth by reducing the state's attractiveness to business investment and labor.

Recent growth of the state government. In 1984 the combined per capita expenditures of state and local governments in Texas were below the national average.[6] As is reflected in Chart 1, however, real state government spending in Texas grew at an annual average of 6.4 percent a year from 1984 to 1987—a rate more than twice that of state personal income, which is a rough measure of the taxpayers' ability to pay.[7] As shown in Chart 2, it was a different story for state revenue. By 1986, state spending had crept above revenue, and in 1987 a wider deficit emerged. The slow growth in state revenue from 1984 to 1987 was largely the result of declining severance tax receipts, though economic problems reduced some other tax receipts in 1987.

For fiscal years 1988 and 1989, real state government spending is projected to fall, bringing down the average rate of growth over the five-year period from 1984 to 1989 to a 2.5-percent annual rate. Nevertheless, the growth of real state spending projected over this five-year period remains higher than the growth projected for real personal income. Permanently increased tax rates will boost state tax revenue in fiscal years 1988 and 1989, pushing up the projected average rate of growth in state revenue from 1984 to 1989 to a 3.2-percent annual rate.

Future growth of the state government. Though increases in the tax rates put the state government on a sound financial footing, these increases could eventually induce excessive growth of the state government. During fiscal years 1988 and 1989, higher tax revenue will allow the state government to fund its current expenditures and retire outstanding tax anticipation bonds. Beyond fiscal year 1989, however, state funds are unlikely to be needed to retire tax anticipation bonds. And tax revenue is likely to rise further as economic conditions improve. Combined, these two factors can be expected to lead to a large budgetary surplus in future years. If Texas is like other states, the emergence of such a surplus could foster a sharp increase in state government spending, which, in turn, could discourage growth of the private sector.[8]

Moreover, a cycle of government growth could develop in which taxes are increased to stabilize state government expenditures during each succeeding economic downturn. Then, when the economy recovers, the new tax instruments would support an increase in state government expenditures. Over the business cycle and time, growth in state government could outstrip the Texas economy, slowing the overall rate of economic growth in the state.

Breaking the cycle. The establishment of an economic stabilization (or "rainy-day") fund could break the cycle that encourages rapid growth of the state government over the business cycle. If the state had established such a fund in previous years, when it had the revenue to do so, some of the state government spending in 1987 could have been supported with the fund, and at least part of the recent tax hike could have been avoided. Of course, taxes would have had to be somewhat higher and/or spending somewhat lower in previous years to provide the savings necessary for the rainy-day fund.

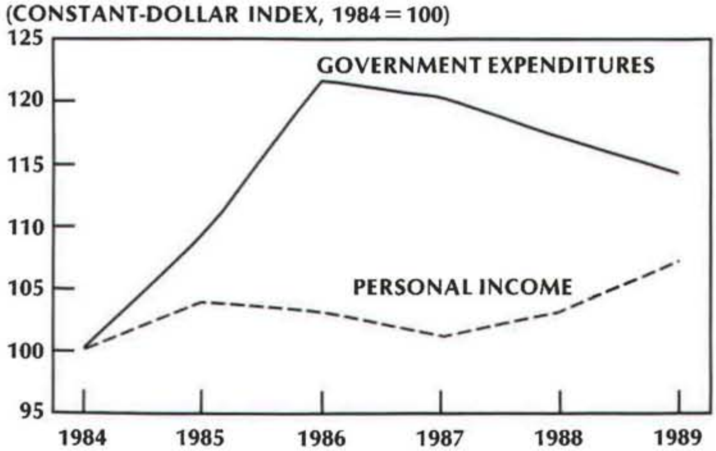
Composition of state government revenue

As shown in Chart 3, taxes contributed about 70 percent of total state revenue in fiscal year 1984; federal funding, about 20 percent; and other sources (including royalties, land rents, and interest), about 10 percent. Roughly the same percentages are expected for fiscal years 1988 and 1989.

In contrast, the composition of state tax revenue shows a dramatic change from 1984 to 1989. Severance taxes, which contributed nearly 15 percent of state revenue in 1984, are expected to contribute about 5 percent in 1988 and 1989. As shares of total revenue, all other tax revenues are increased, but the shares for the sales tax and the motor fuel and vehicle taxes are increased the most.

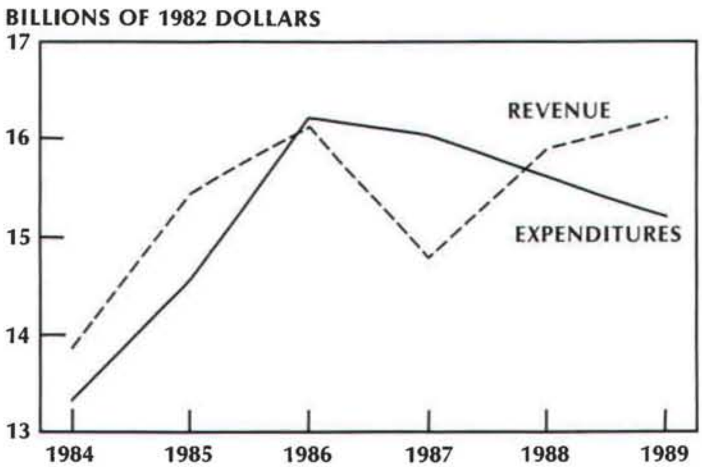
Severance taxes. From the perspective of economic growth, severance taxes are a very attractive source of state government revenue. The severance tax falls primarily on oil and gas resources that cannot move to avoid the tax. Very little of it seems to fall on the capital and labor used to develop and produce the oil and natural gas. In the past, severance tax revenue allowed the State of Texas to provide a higher level of government services than the relatively low

Chart 1
Texas Personal Income and State Government Expenditures



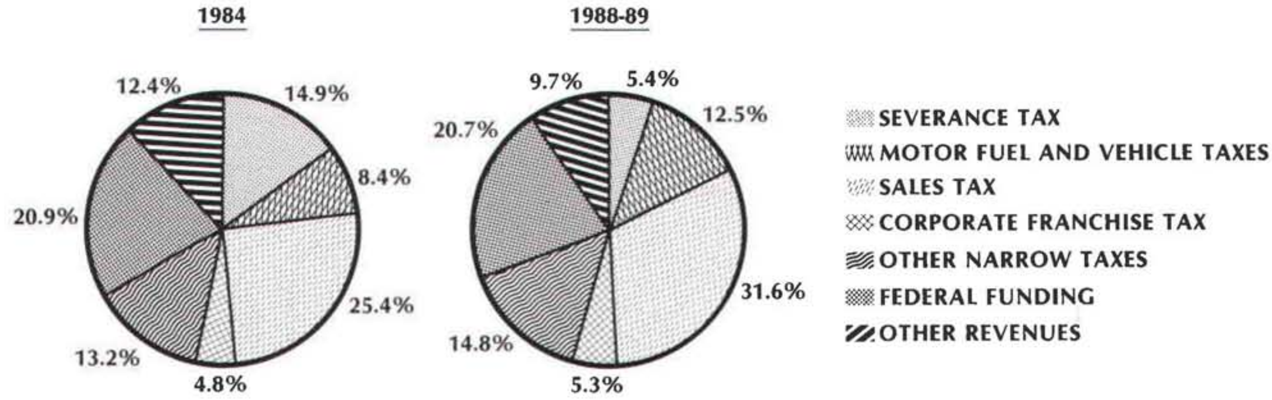
SOURCES OF PRIMARY DATA: Texas Association of Taxpayers.
Texas Comptroller of Public Accounts.
U.S. Department of Commerce.
Author's projections.

Chart 2
State of Texas Expenditures and Revenue



SOURCES OF PRIMARY DATA: Texas Association of Taxpayers.
Texas Comptroller of Public Accounts.
U.S. Department of Commerce.
Author's projections.

Chart 3
Sources of State of Texas Revenue



SOURCES OF PRIMARY DATA: Texas Comptroller of Public Accounts.
Author's projections.

level of other taxes would suggest. Declining severance tax revenue is eroding that advantage.

Apparently, little can be done to reverse or prevent falling severance tax revenue. Lower energy prices and reduced production of oil and natural gas account for the decline in this tax revenue. Over the period from 1984 to 1989, real severance tax revenue is expected to decline nearly 60 percent, as is reflected in Chart 4. Still further declines should be expected after that.

Increased taxes. To make up for declining severance tax revenue and to fund the growth in state government spending, the legislature increased nearly all other taxes. Real state government tax revenue from sources other than the severance tax is projected to grow 45 percent from 1984 to 1989. That is more than six times the growth in state personal income projected for the same period.

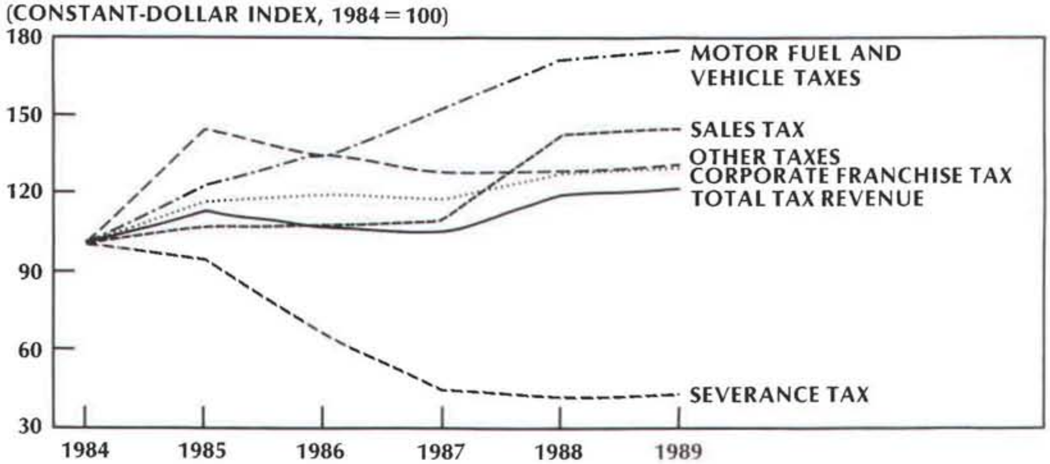
Given that the legislature has confined itself to raising already-existing taxes, it did a remarkable job in minimizing the harm that could have been done to economic growth. Motor fuel and vehicle taxes—taxes that are like user fees—are the most rapidly increasing sources of state revenue. The broad-based sales tax is the second most rapidly growing source of revenue. The narrow corporate franchise tax and other narrow taxes are the slowest growing sources of tax revenue.

Increased revenue from motor fuel and vehicle taxes put road and highway funding closer to a user-fee basis. Those who are using the roads and highways will be paying for a larger share of the costs. User fees—or taxes like user fees—are among the best ways to raise a given dollar amount of government revenue. This method of funding assures that individuals who do not use and value a particular government service will not have to pay for it. In addition, user fees provide a method for monitoring public demand for the government service so that the government can better supply the most desired quantities of it.

Though less conducive to economic growth than user fees or taxes like user fees, broad-based taxes (such as the sales tax) are less harmful to economic growth in raising a given amount of revenue than are narrow taxes like the corporate franchise tax. In comparison to a narrow tax, a broad-based tax falls less heavily on any one resource or activity. For the given amount of revenue that it raises, therefore, a broad-based tax has less effect on private decisions and, thus, on economic growth.[9]

Alternatives. The legislature need not have confined itself to already-existing taxes. There are several alternatives. User fees and taxes like user fees could be extended to more state government services, such as natural resource management and parks. A corporate income (or profits) tax could be substituted for the corporate franchise tax. And a personal income tax might be substituted for the sales tax.

Chart 4
State of Texas Tax Revenue, by Source



SOURCES OF PRIMARY DATA: Texas Comptroller of Public Accounts.
U.S. Department of Commerce.
Author's projections.

A corporate income (or profits) tax would be less harmful to economic growth than is the corporate franchise tax. For a given amount of tax revenue, the corporate franchise tax discourages business investment more than would a corporate income tax. A corporate franchise tax is assessed directly on the capital that business investment builds, regardless of the firm's profits. In contrast, the corporate income tax falls more broadly across the productive assets of the firm, with less discouraging effect on business investment.[10]

A flat tax rate of 2.5 percent on total gross personal income would raise about the same revenue as does the current Texas general sales tax of 6 percent.[11] A higher tax rate would be required if deductions, such as those on the federal income tax return, were permitted in the calculation of taxable income.

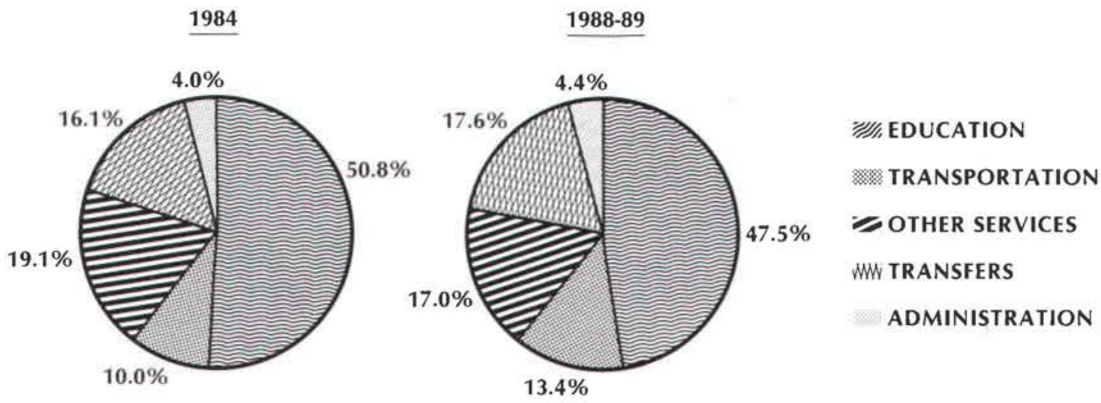
As a substitute for general sales taxes, a state personal income tax has a principal advantage; it currently remains deductible against the federal income tax. Because sales taxes are no longer deductible, revenue raised through an income tax would cost roughly 10 percent less for the average taxpayer in Texas than the same amount of revenue raised through the sales tax. The figure would be about 30 percent less for the average itemizer in the state.[12] Of course, this advantage could be eliminated with future changes in U.S. tax laws.

Texas also may be nearing the practical limits for sales taxation. As state sales tax rates climb, residents will find it increasingly worthwhile to buy goods outside Texas to avoid sales taxation.[13] A state income tax is much more difficult to avoid.

A state income tax is not without drawbacks, however. Nearly all high-tax states rely heavily on income taxation. Income taxes are easily made progressive, and progressivity seems to discourage economic growth by pushing taxable resources from the state.[14] Furthermore, adoption of an income tax could lead to a growth-hindering tyranny of the majority, in which excessive growth in the size of the state government is funded by increasingly progressive income taxes.[15]

The composition of revenue: a summary. In short, the composition of state tax revenue in Texas has become less conducive to economic growth than it was in 1984. This deterioration is largely the result of unavoidable reductions in state severance tax receipts. Given that the legislature confined itself to existing tax instruments to offset declining severance tax revenue and increase state government funding, it did a fine job of minimizing the harm to economic growth. Some of the alternatives that the legislature did not choose—such as greater reliance on user fees and taxes like user fees and the substitution of a corporate income tax for the corporate franchise tax—might have

Chart 5
Composition of State of Texas Spending



SOURCES OF PRIMARY DATA: Texas Comptroller of Public Accounts.
Author's projections.

further reduced the harm to economic growth.

Composition of state government spending

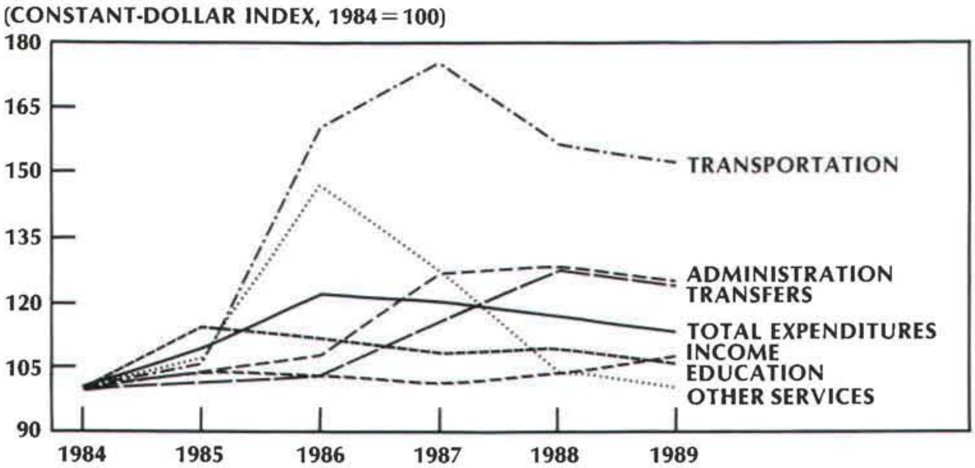
In comparison to state government revenue, the composition of state government spending shows smaller changes since 1984. The changes have been significant, nonetheless. As shown in Chart 5, state expenditures for transportation, transfers, and administration have increased as shares of total state government spending from 1984 to 1989, while expenditures for education and other government services have decreased as shares of total state spending.

But it is spending on government services that attracts business investment and able workers to a state. When provided efficiently, education is one of the most highly valued services state and local governments can provide. Good transportation facilities, primarily roads and highways, are also quite valuable in attracting business investment and labor. Efficient spending in the category of "other services"—which includes such items as public safety, health and hospitals, and natural resource management—also attracts business investment and labor to a state but less strongly than do expenditures for education and transportation. On the other hand, administrative expenditures and transfer spending, which includes welfare, do not attract business investment and labor. They also have the negative effect of diverting state revenue from expenditures that do attract these mobile resources. In comparison to 1984, a smaller portion of total state government spending in the 1988-89 budget will be devoted to services that attract investment and able workers.

Spending on growth-enhancing services. In 1984, state and local governments in Texas spent slightly more per capita on education than did those in the average state.[16] Though real state educational spending was increased sharply in 1985, it declined in the following two years, as shown in Chart 6. Under the most recently adopted budget, educational spending is projected for further declines through 1989. On average, real state spending on education is projected to grow at an annual rate of only about 1 percent over the five-year period from 1984 to 1989. That figure is less than the projected growth of state income and, also, much less than the projected growth of total state government expenditures.

State and local governments in Texas spent slightly less per capita on transportation facilities and the category of other services than was the case for the respective national averages in 1984.[17] Real state spending for roads and highways has grown at an annual rate of more than 20 percent since 1984, however. And though the 1988-89 budget contains sharp cuts in real state expenditures for transportation, the projected growth of spending in this category is more than three times that of real total state expenditures in the five years from 1984 to 1989. The projected growth in real

Chart 6
Texas Personal Income and State of Texas Expenditures, by Type



SOURCES OF PRIMARY DATA: Texas Association of Taxpayers.
Texas Comptroller of Public Accounts.
U.S. Department of Commerce.
Author's projections.

state spending in the category of other services over the period from 1984 to 1989 is just one-tenth of 1 percent.

Spending on transfers and administration. In 1984, per capita expenditures for transfers and administration in Texas were much lower than the national averages.[18] Real transfer spending increased gradually from 1984 to 1986 and then accelerated in 1987 as the state economy weakened. An increase in transfer spending is projected for 1988, with a probable decline to follow in 1989. Real spending on state government administration increased sharply in 1987 and is basically maintained in the new state budget. From 1984 to 1989, spending on state government administration is projected to grow nearly twice as fast as total state government expenditures.

Summarizing the current situation. From 1984 to 1989, growth in Texas spending on the state government services that attract capital and labor is projected to be 10 percent, with most of the growth coming in transportation. That is slightly higher than the projected growth of total state personal income over the same period but well below the projected growth of 22 percent in state tax revenue. Over this five-year period, however, spending on transfers and administration is projected to grow nearly 25 percent.

In a sense, increased spending on transfers and administration, combined with state revenue problems, has crowded out expenditures for government services that attract capital and labor. As the Texas economy begins to recover, however, state spending on transfers is likely to decrease, making it possible to devote an increased share of state government spending to the growth-enhancing services.

Alternatives. Over the next few years, it may prove difficult to boost significantly the share of state government spending devoted to growth-enhancing services. Though administrative expense is a likely area in which to cut spending, it is a relatively small portion of the state budget. Cutting it sharply would not yield much support for state government services. Action to reduce transfer spending would be undesirable under current economic conditions. As it is now, Texas provides fewer social services than most states do. The issue really is how to allocate the remaining 78 percent of the state budget until state transfer spending can be reduced.

Among the government services enhancing economic growth, the category of other services was one of the better areas of state government spending to reduce temporarily. Spending in this category is less helpful to economic growth than spending on education and transportation.[19] Because spending in the category of other services was cut sharply in the 1988-89 budget, it may be undesirable to make further cuts.

Deeper cuts in transportation spending for the purpose of temporarily buoying educational spending might be less harmful to state economic development than are current spending policies. A temporary cut in spending on either education or transportation signals the state government's willingness to make similar temporary cuts in such spending in the future. This signal weakens confidence that a given level of education or a given quality of roads and highways will be provided in the future, which reduces the value of an implicit contract that the government has with its citizens to provide education, roads, and highways in return for taxes. Given that education generally is confined to specific age groups, however, a temporary cut in educational spending falls most heavily on the children in school at the time. For each household, therefore, the variance of risk is increased, which further reduces the value of the implicit contract for education. Because a similar, variance-increasing situation does not arise from deferred maintenance and construction of roads and highways, the current reductions in educational spending have more potential for harming future economic development in Texas than would temporarily deeper cuts in state transportation spending.

Nonetheless, shifting funds from roads and highways to education could prove a difficult political feat. Apparently, state government spending projected for roads and highways in the 1988-89 budget has been cut to the funds dedicated to that purpose by law. Probably the best the state can do is to minimize the harm to future economic growth by offering evidence that the cuts in educational spending are a temporary, one-time measure. Adoption of an economic stabilization fund could provide such evidence by assuring that future state government spending would have a foundation of stable funding.

The composition of spending: a summary. In short, the composition of state government spending has become less conducive to economic growth since 1984. Budgetary problems and increased spending on transfers and administration have reduced the percentage of state government expenditures devoted to government services that attract business investment and a work force to the state. The temporary nature of increased transfer spending suggests that a larger share of state government spending will be devoted to growth-enhancing services beyond fiscal year 1989.

Summary and conclusions

Fiscal policy in Texas compared favorably with that of the average state in 1984. Since then, however, changes in state fiscal policy have generally lessened the advantages evident in that year. Deficit spending and reduced severance tax revenues in 1986 and 1987 have led to increased tax rates. Consequently, tax revenues from sources other than the severance tax are projected to grow 45 percent from 1984 to 1989. In addition, the composition of state government spending has become less conducive to economic growth. State spending for government services that attract the capital and labor necessary for economic growth is projected to increase only 10 percent from 1984 to 1989, while spending on transfers and administration is projected to rise nearly 25 percent.

Projecting over the next two years, uncertainty about the direction of state fiscal policy has been reduced considerably. The legislature has solved the state's fiscal crisis—but at the expense of educational spending and by increasing taxes. Spending for other government services has also been cut.

Beyond 1989 the following can be anticipated. Severance tax revenue will decline further. Nevertheless, the tax rate increases adopted in late 1987 will put the state government in a position to grow faster than the Texas economy, and that could hinder future economic development in the state. On the positive side, renewed economic growth should bring reduced spending on transfers, freeing state government resources for expenditures on services that would further enhance economic growth.

Some changes in state fiscal policy could improve the long-term outlook for economic growth in Texas. Increased reliance on user fees and taxes like user fees and the substitution of a corporate income tax or a broader tax for the corporate franchise tax could make the state more attractive to business investment and labor. In the area of expenditures, increased state spending on education is a key to future economic development. Beyond fiscal years 1988 and 1989, resources freed by reduced transfer spending can be redirected to education. But the state government also needs to offer assurance that educational spending will not be cut should a future budgetary crisis arise.

Establishment of an economic stabilization fund could make credible the state's commitment to future educational spending. In addition, such a fund could avert a cycle in which taxes are further increased to stabilize state government spending during each succeeding economic downturn—a cycle that would induce growth in the state government at the expense of broader economic growth in the state.

1. Technically, the State of Texas is not permitted to run a deficit. Nevertheless, it can sell tax anticipation bonds to finance current spending from future tax revenue, provided the State Comptroller projects a bal-

anced budget over the next budget biennium—that is, the next two-year period for which the State of Texas budget is adopted.

2. See Stephen P. A. Brown, "New Directions for Economic Growth: Redesigning Fiscal Policies in Louisiana, New Mexico, and Texas," Federal Reserve Bank of Dallas *Economic Review*, July 1987, 13-20.

3. Brown, "New Directions for Economic Growth."

4. See Armen A. Alchian and William R. Allen, *University Economics: Elements of Inquiry*, 3d ed. (Belmont, Calif.: Wadsworth Publishing Company, 1972), 18-29.

5. See Thomas Romans and Ganti Subrahmanyam, "State and Local Taxes, Transfers and Regional Economic Growth," *Southern Economic Journal* 46 (October 1979): 435-44.

6. Brown, "New Directions for Economic Growth."

7. The annual growth rate of real state government expenditures during the 1984-87 period also was higher than that of real state personal income during the 1970s—a decade in which Texas personal income grew at remarkable rates.

8. For a recent survey of economic literature on the growth of government, see Dennis C. Mueller, "The Growth of Government: A Public Choice Perspective," *International Monetary Fund Staff Papers* 34 (March 1987): 115-49.

9. See Brown, "New Directions for Economic Growth," and Arnold C. Harberger, *Taxation and Welfare* (Boston: Little, Brown and Company, 1974).

10. Although broader than a corporate franchise tax, the corporate income tax is not as broad as a sales tax or personal income tax.

11. Local taxes have pushed sales tax rates higher than 6 percent in most areas of the state.

12. These figures are derived from 1982 data from the Office of Tax Analysis, Office of the Secretary, U.S. Department of the Treasury, "Tabulations from the 1982 Statistics of Income File for the Fiscal Relations Study," 14 December 1984, as cited by Daphne A. Kenyon, "Federal Income Tax Deductibility of State and Local Taxes," in *Federal-State-Local Fiscal Relations: Technical Papers*, vol. 1 (Washington, D.C.: U.S. Department of the Treasury, Office of State and Local Finance, September 1986), 449.

13. Legally, residents of Texas owe tax to the State of Texas for goods purchased out of state and imported to the state for personal use. These taxes are largely uncollected.

14. See Romans and Subrahmanyam, "State and Local Taxes, Transfers and Regional Economic Growth."

15. See Mueller, "The Growth of Government."

16. See Brown, "New Directions for Economic Growth."

17. Ibid.

18. Ibid.

19. Ibid.

Forecasting the Texas Economy: Applications and Evaluation of a Systematic Multivariate Time Series Model

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In an environment of economic uncertainty, careful analysis and accurate forecasting become more crucial than during stable periods when the likelihood of losses from unrealized expectations is relatively small. The recent volatility of the Texas economy provides an example of how improved accuracy in economic forecasts could help those who make private and public economic policy decisions.

Introduction

Texas is still adjusting to its changing economic environment that developed during 1986. At the same time that oil prices dropped roughly 50 percent, national economic growth slowed from its rate earlier in the expansion, reducing the pull on the Texas economy by the rest of the nation. Following these events, Texas nonagricultural employment in June 1987 dropped to 3.5 percent below its high in January 1986. Meanwhile, state personal income in 1986 fell by 4 percent in real terms and by the second quarter of 1987 still remained about 2 percent below its peak level in the first quarter of 1986.

The research reported in this article developed a multivariate time series model to forecast seven often-considered Texas economic variables. The seven Texas indicators selected were personal income, nonagricultural employment, the civilian labor force, the rotary rig count, housing starts, retail sales, and the Texas consumer price index (CPI).

For 1988, the model has forecasted a moderate expansion of the Texas economy, despite sluggish energy and housing activity. This forecasted growth is expected to occur at a pace more rapid than the state experienced earlier in the 1980s. Nevertheless, the growth rates in Texas projected for 1988 are lower than the state averaged from 1967 to 1979, and some Texas measures are forecasted to continue downward. Predicted to grow in 1988 are personal income, nonagricultural wage and salary employment, the civilian labor force, and retail sales. In addition, the Texas CPI should increase somewhat more rapidly than for 1980-86, but more slowly than for 1967-79. Housing starts should decline, though more slowly than for 1980-86. The rig count also should fall, but more slowly than for 1980-86.

The purpose of the present study has been to construct a model composed of linear forecasting equations that could predict the growth rates of each of seven Texas variables based on their own past growth rates, on growth rates in other Texas indicators, and on those of other national series. This research was based on using a systematic method of limiting the number of explanatory variables selected for use in constructing the forecasting equations.

Unlike many other types of forecasting models, the approach presented here uses well-defined, easily reproducible techniques for variable selection and for estimation.[1] To apply these techniques, the variables to be forecasted were chosen along with a set of decision rules specifying which variables would appear in the final forecasting equations.

After the equations were systematically specified, forecasts could be produced independently. Such an approach can be useful to analysts evaluating an industry's prospects, to policymakers projecting future events without a policy change, or to researchers testing alternative forecasting techniques.

The 1988 forecasts developed as part of this study resulted from a systematic methodology employing statistical relationships between selected variables. The modeling procedures thus proved systematic and replicable. Purely statistically based decision rules were used in selecting candidate variables for each of the seven forecasting equations. The object of the procedure reported here was to balance the informational advantages of including more variables with the statistical problems of including too many. Beyond the procedural elements, the only human judgment employed here was in the initial selection of the large array of candidate variables for inclusion in the final modeling equations and in the establishment of decision rules adopted for the construction of the model itself. The forecast accuracy produced by this method compared favorably with other nonjudgmental forecasting techniques. The model forecasts reported here can thus be used by themselves or as a base for making judgmental adjustments.

In building the present model, other useful information about the characteristics of the state's economy emerged. For example, some Texas economic variables were found to fluctuate somewhat cyclically, while others behaved idiosyncratically relative to normal business cycle fluctuations.

Building the present model provided extra information about the economy, suggesting that movements in some Texas indicators are influenced by national economic conditions, while others are linked to regionally specific events. The variables selected for the model were all assumed to exert no reverse influence on the national variables that drive the regional indicators.

For this research, a time series forecasting model was selected over a structural approach (see Appendix A). Although a time series model relies less on rigorous adherence to a theoretically based set of relationships than does a structural model, both commonly have imbedded in them assumptions about how an economy operates.

The remainder of this paper is organized as follows. The first section describes the forecasting strategies employed; the second focuses on the selection of the variables and development of a systematic model specification. The third section examines in detail the model-produced forecasts for the Texas economy, while the fourth section discusses additional information about the Texas economy that was developed during the selection of variables. A final section provides a brief summary of the methodology, followed by an evaluation of the model's strengths as a forecasting tool.

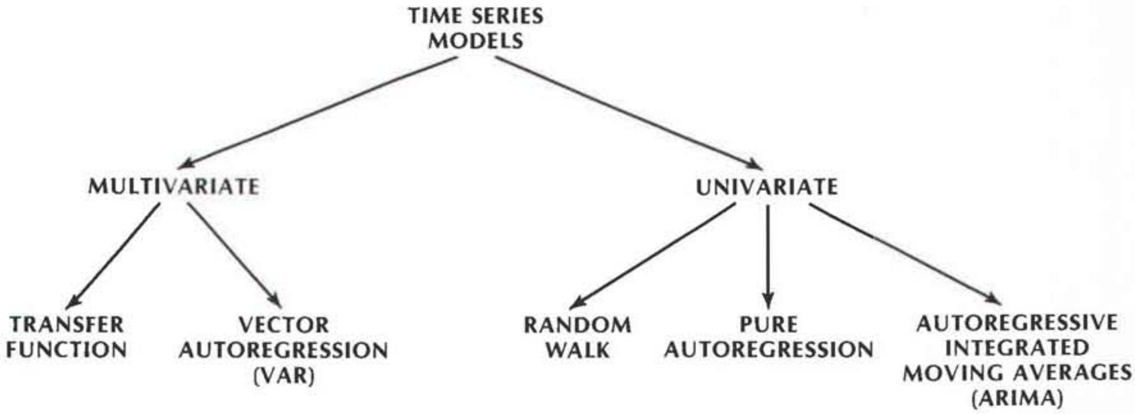
Devising a forecasting strategy

To develop a forecasting strategy, a suitable model was selected from among a variety of forecasting models available.[2] Because previous research with national forecasting models has suggested that time series models generally provide better forecast accuracy than structural models, the latter were excluded from consideration in order to concentrate on selecting an appropriate time series model.[3] In Figure 1, the choices of alternative time series models are shown diagrammatically.

Structural and time series models differ more in focus than in construction. Whereas a structural modeler would place a variable in an equation in accordance with an explicit theory, many time series modelers would include the variable only if it added significantly to forecast accuracy. Both procedures, however, begin with the assumption that of all conceivable economic relationships, only a relatively narrow set of these is likely to be usable. Few modelers, using either the structural or time series approach, would consider using data unrelated to the economy in an economic forecast. On the other hand, both approaches would probably include a large set of variables as candidates for a given economic relationship. It would thus be *possible* (though unlikely) to arrive at identical models using either approach.

With time series models, two approaches are again distinguishable—univariate methods and multivariate techniques. Univariate models attempt to describe a variable's behavior solely in terms of its past values. A multivariate approach, as used in the present model, assumes that a given economic variable is influenced not only by a vari-

Figure 1
Choice Sequence for a Time Series Forecasting Model[1]



1. See Appendix A for a description of the various times series models.

able's past values, but perhaps also by present and past values of other variables.

One problem common to most forecast modeling exercises is that one class of forecast accuracy is purchased only at the expense of another. Despite the ingenious approaches some analysts have used to address these common procedural problems, these models have not usually produced forecasts more accurate than univariate time series models. Although adding variables to a forecasting equation may improve the degree to which the equation describes the data (i.e., the "fit" of the model), including too many variables can reduce the analyst's confidence in the forecast by raising the standard error of the equation (i.e., lowering the statistical efficiency).[4]

To combat these problems, the research for this paper employed a systematic method of limiting the number of variables in the forecasting equations. An alternative method of dealing with this problem, using Bayesian vector autoregressive (VAR) models, is discussed in Appendix B.

Building a time series forecasting model: A systematic approach

Because the primary purpose of the present study was to construct and apply linear forecasting equations to predicting the 1988 Texas economy, a systematic approach was used that would predict the growth rates of seven seasonally adjusted Texas variables by their own-lagged growth rates and by lagged values of other regional and national series. Once the time series forecasting model was chosen, the systematic procedure for selecting variables with which to specify the forecasting equations could be applied. Not only was this approach in many ways easier to use than other models, but it was found to rely much less heavily than others on a model builder's sophistication and judgment.

In the construction of the present model, the selection of variables employed a multistep strategy to identify variables as effective candidates and to examine what some variables could offer in forecasting their own or other growth rates. The procedure began by considering what a variable might offer in forecasting through the inclusion of autoregressive terms (or own lags) in an equation describing the series.

The second step examined the information gain from including both other regional variables and national variables in the equations that included own lags. The need first was to explain as much of the movement of a particular variable as possible by its own past values and then to examine how much additional movement could be explained by another variable. After the information gained from each variable individually was examined, those explanatory variables which added significant information compared with a variable's past were examined in a multiple-regression context

Measuring Information Gain

The method used to develop the time series model for the present study focuses on a parsimonious specification of each equation. The systematic criteria needed for including a variable in the model are described here. If the addition of some variable would significantly reduce the standard error of an equation, then it was considered. The term "information gain" refers to the percentage reduction in standard error that resulted from the inclusion of a particular variable in an equation.[1] This term was a measure of the degree to which the addition of a given variable to an equation increased the information that the equation could provide about movements of its dependent variable.

The measure selected to assess information gain is a straightforward one. For example, consider two equations designed to forecast the same independent variable, equation A and equation B, where the variables in equation A are a subset of those in equation B. Also, suppose that equation B has one more variable than equation A but that the two equations are otherwise identical. Let SEE_A represent the standard error of estimate of equation A, and SEE_B be the standard error of estimate of equation B. The gain in information of equation B over equation A, then, must be the result of the inclusion of the variable in equation B but not in equation A. This information gain is the percentage difference in the standard error of estimate for equation B compared with that of equation A. That is,

(B.1) $$I_{BA} = [(SEE_A - SEE_B)/SEE_A] \times 100.$$

Hoehn and Balazsy show that the information-gain variable I and F values correspond to one another in the following form:[2]

(B.2) $$I = 1 - [n - k - 1 + g)/(n - k - 1 + qF]^{1/2},$$

where

q = the number of added variables in B compared with A,
n = the number of observations, and
k = the number of variables in B.

Thus, the minimum value of I suggesting that a new variable in B ought to be included in a forecasting equation is the value using the minimum value of F significant at some acceptable level, say .10.

The SEE's represent within-sample forecast errors. A positive value for I_A signifies a lower SEE value for B than for A, while a negative value for I_B means that equation B has poorer within-sample forecasting characteristics than A.

To determine the significance of the information gain that equation B offers over equation A, an F test may be used. A criterion for including a variable in a forecasting equation then would be some minimum percentage information gain that would be consistent with a level of significance characterized by some F value.

The statistical significance of information gains is measured by the F test built into the estimation procedure for the I, or information statistic. The joint significance test, or F test, for the c_i provides a "Granger causality" test (see Table 2 in text).[3] The information gain for each variable shown in Table 2 is expressed as a percentage reduction in the standard error of equation compared with the standard error of a corresponding two-own-lag model. If the F-test configuration of the I statistic is used, it can be shown that information gains of 2.043 percent or greater are significant at the .10 level for the number of observations tested. This means that a significant information gain occurs from the inclusion of variable A in an equation to forecast variable B whenever the percentage information gain is greater than 2.043. Variables that can make statistically significant contributions to the forecast accuracy of these equations become candidates for the final regression equations.

1. For a fuller discussion of the information-gain statistic, see James G. Hoehn and James J. Balazsy, Jr., "The Ohio Economy: Using Time Series Characteristics in Forecasting," Working Paper no. 8508, Federal Reserve Bank of Cleveland, December 1985.

2. See Hoehn and Balazsy, "The Ohio Economy."

3. "Granger causality" testing does not actually test the role of movements in one variable in causing movements in another variable, but it does assess the tendency of fluctuations in one variable to lead to fluctuations in some other variable. The test is nevertheless referred to as a test for "causal direction," a term intended to mean that either variable A generally leads variable B, or vice versa. The standard construction of such a test involves the regression of some dependent variable on several own lags and, in the same equation, on several lags of some other variable. The null hypothesis is that the coefficients on the lags of the other (not own) lags are zero. If the coefficients are not jointly statistically significantly different from zero, then the independent variable cannot be said to "Granger-cause" the dependent variable. With multiple lags, as in the present model, F tests are applied to evaluate whether or not significant information gains are derived from the inclusion of some collection of lags of a variable different from the dependent variable. See C. W. J. Granger and Paul Newbold, *Forecasting Economic Time Series*, 2nd ed. (Orlando, Fla.: Academic Press, 1986), 259-62.

to select the appropriate final model. Finally, after using this procedure to specify each equation, the resulting model was tested for its forecasting accuracy outside the sample period that had been used for actually estimating it.

Identifying cyclical tendencies. This first stage of model construction involved examining the cyclical tendencies of behavior in the data to be forecasted. The degree to which Texas indicators behave according to cyclical patterns can be useful not only in constructing a forecasting model of the state, but also in developing an understanding of how the Texas economy generally behaves.

Involved in this stage was a comparison of what a simple univariate model could provide with the characteristics of movement in the same variables as random walks (see Appendix A for an explanation of random walk models). A comparison of the random walk model's results with autoregressive models that accommodate correlations between rates of growth from one period to the next provided information about the cyclical behavior of a variable.[5]

Selecting other variables. Once autoregressive equations had been constructed, the forecasting information provided by other variables than own lags was evaluated to measure the information gain contributed (see Box). Based on the relative significance of the information provided by each variable, the following procedures were used to select candidate variables for the final forecasting equations.

If a variable, X, provided a degree of information gain that was above some threshold level of significance in a forecasting equation for a variable, Y, variable X would then become a candidate for inclusion in the final forecasting equation for variable Y. Candidacy would not, however, imply automatic inclusion in the final equation.

For the present model, the power that a given regional data series could offer in forecasting changes in some other regional series could be assessed by performing regressions to estimate the standard error of the equation as specified by the following:

$$(1) \qquad y_t = a_1 + b_1 y_{t-1} + b_2 y_{t-2} + c_1 x_{k,t-1} + c_2 x_{k,t-2} + u_t ,$$

where y and x are two regional series. If the series x_k significantly increased the predictive power of an equation designed to forecast y, then the standard error of this bivariate equation would be significantly lower than for the autoregression (in which the constraint $c_1 = c_2 = 0$ was imposed).

Stepwise model specification. In the present study, once the regional and national variables were identified as candidates for each final forecasting equation, these equations were constructed through the application of stepwise linear regression.[6] Thus, each identified candidate variable was either included or not included in the forecasting equation according to whether its coefficient obtained a predetermined significance level. Candidate variables were accepted in an equation if they obtained t statistics of 1.64 or more in absolute value when entered.[7]

Not every candidate variable that was included in an equation under the t-statistic rule remained in the equation, however. There was also a rule for the removal of some variables that previously had been entered. If the inclusion resulted in the reduction of any previous entrant's t statistic below an absolute value of 1.64, then the prior entrant was removed from the equation. This rule thus reduced the importance of the order in which variables were added.[8]

A stepwise equation was constructed for each variable, using data for the period from the fourth quarter of 1967 to the fourth quarter of 1982. The resulting model was used to forecast from one to six quarters ahead for the period from the first quarter of 1983 through the last quarter of 1986. New parameter estimates were obtained for each succeeding quarter to approximate the forecasting model in practice and to use additional information offered by the most recent data elements. Although new parameter estimates were made for each succeeding quarter, the models were not identified again for each of these iterations. Thus, the same variables and lag configurations were included each time.[9]

The stepwise procedure was used, for example, to construct an equation for Texas personal income that included a constant plus one lag of Texas payroll employment, two lags of the Texas CPI, and one lag of Texas retail sales. The estimating equations are presented in Appendix C, covering data for the first quarter of 1967 through the third quarter of 1986.

The model's forecast for the 1988 Texas economy

Applying the time series forecasting model produced a nonjudgmental forecast of Texas economic performance in 1988, as measured by seven regional variables examined by the model's equations (see Table 1). The forecasting results, though not including any judgmental amendments, were found to be very accurate for a systematically produced forecasting procedure. Since the application of judgment in developing a forecast is commonly found to improve forecast accuracy still further, the forecasting model presented here thus provides a useful starting point for developing a judgmentally adjusted forecast.

Table 1
TEXAS ECONOMIC GROWTH FORECASTS FOR 1988, WITH HISTORICAL COMPARISONS
(Annualized percentage change)

Period	TXINCOME	TXNONAG	TXCIVLF	TXRIG	TXRETAIL	TXCPI	TXHOUSING
1988:I-1988:IV	3.28	2.71	3.55	-5.13	2.76	5.17	-6.91
1980:I-1986:IV	3.18	1.87	3.34	-15.75	1.46	5.07	-11.37
1967:I-1979:IV	5.17	4.65	3.68	7.46	4.67	7.27	2.91

The present model's 1988 forecasts for the Texas economy generally showed recovery in the wake of the 1986 downturn and in the wake of weakness in 1987. The model forecasted an increase in personal income of about 3.3 percent over 1987 and projected a rise in payroll employment of about 2.7 percent. A rising civilian labor force, growing retail sales, and some acceleration in the Texas CPI were also components of the model's forecasts. Nevertheless, the model also forecasted slight declines in drilling activity in 1988, when compared with 1987, and also projected reductions in housing starts.

Also shown in Table 1, in addition to the forecasted 1988 growth rate for each variable, was the average annual growth rate for two selected historical periods, 1967-86 and 1980-86. For each Texas indicator, the results in Table 1 show that the model predicted either a faster rate of growth or a slower rate of decline than the actual performance of each variable for the period 1980-86. Conversely, the model projected slower growth (including episodes of negative growth) than occurred during the 1967-79 period, when all the Texas variables grew on average.

For example, the model projected a decline of 5.1 percent for the Texas rig count in 1988, as compared to average annual declines of 15.8 percent for the period 1980-86, and average annual increases of 7.5 percent for the earlier 1967-79 period. Likewise, the 6.9-percent decline forecasted for Texas housing starts in 1988 was less severe than the reductions of 1980-86 but was clearly less positive than the 2.9-percent average rate of growth of 1967-79. Payroll employment should grow in 1988, according to the forecast, at a rate more rapid than the annual average for 1980-86 and more slowly than the average for 1967-79.

The forecasts of each variable in the model tended to be highly interrelated with the forecasts of other variables in the model. For example, both payroll employment and retail sales appeared in the personal income equation, while retail sales appeared in the payroll employment equation, along with one lag of payroll employment. The coefficients on these independent variables were positive. Accordingly, forecasted increases in these variables reinforced the forecasted increases in the variables they could be considered to "explain." Thus, forecasts of more rapid retail sales

Table 2
UNIVARIATE PROPERTIES OF TEXAS VARIABLES

Series	Mean	Standard deviation	Autocorrelation at lag 1	2	3	4	Information gain (Percent)
TXINCOME	0.0109	0.0107	0.28	0.26	0.19	0.20	5.72
TXNONAG	0.0089	0.0080	0.77	0.55	0.31	0.11	36.72
TXCIVLF	0.0090	0.0071	-0.10	-0.14	0.08	0.03	0.63
TXRIG	0.0039	0.0991	0.46	0.30	0.13	0.03	10.63
TXRETAIL	0.0089	0.0221	0.13	0.03	-0.25	-0.06	-0.54
TXCPI	0.0159	0.0110	0.62	0.56	0.52	0.52	24.99
TXHOUSING	-0.0078	0.1445	0.16	0.06	-0.14	0.06	0.04

growth reinforced projected nonfarm employment growth, while upward movements in both retail sales and employment led to projected expansions in personal income.

In addition, the presence of own lags in a number of the equations provided information about the fluctuations in growth rates of a variable over time. Of the three right-hand-side variables in the Texas rig count equation, for example, two variables were own lags. The forecast for the Texas rig count in 1988 reflected the effect on the model of recent rig count data. The effect of past values was also partly responsible for the forecasted 1988 decline of 6.9 percent in Texas housing starts. These constructions reflected the information content of the data, as identified in the two stages of the model's construction. This pattern of autoregressive relationships captured the notion of momentum in a series.

While these relationships were determined solely through the use of statistical selection and estimating techniques, they would also provide a foundation for the development of judgmentally adjusted models. For example, under circumstances that normally determine a positive predictive relationship of a certain value between one variable and another, the explicit recognition of the usual nature and degree of this predictive relationship could aid the forecaster in choosing to consider why some special event might alter both the relationship and a forecast based upon it. In this context, such as the one developed in this study, the claim can be made that multivariate time series forecasting models can serve as bases of, rather than substitutes for, judgmentally grounded forecasts.

Other information developed about the Texas economy

In addition to providing forecasting information, the model and the steps in the course of its construction yielded other significant information about the Texas economy. This information fell into two basic categories: (1) the cyclical behavior of the Texas series and (2) the relationship between each variable and other regional and national variables.

Cyclical behavior. The degree of cyclical tendency imbedded in movements in each of the seven Texas variables is shown in Table 2. The degree of correlation between growth rates at points in time with growth rates one, two, three, and four quarters back also are depicted. The data in this table revealed significant positive persistence in growth rates for Texas personal income (*TXINCOME*), Texas nonagricultural payroll employment (*TXNONAG*), the Texas rig count (*TXRIG*), and the Texas consumer price index (*TXCPI*). Thus, these indicators could, to a greater or lesser degree, be characterized as displaying cyclical behavior. However, the civilian labor force (*TXCIVLF*), retail sales (*TXRETAIL*), and housing starts (*TXHOUSING*) revealed no significant autocorrelation.

The behavior of some of these variables ran counter to what seemed to be the conventional wisdom about their normal performance. It is interesting to note that despite claims one sometimes sees in the newspapers about "housing cycles," no such cycle appears to have existed in Texas during the sample period. This finding did not suggest that other variables than own lags could also be useless in forecasting housing construction in Texas, but it did suggest that homebuilding does not traditionally display persistent patterns of high or low growth. The data also demonstrate that a high rate of retail sales growth in one quarter told little about the fortunes of retailing in previous or future quarters.

Effect of adding own lags. The significant autocorrelation in the first four series noted suggested persistence in growth rates that could be used in assessing regional patterns of economic activity. It was useful to estimate the information gain possible from including two own lags of a variable in comparison to the forecast information provided by the random walk model (see Appendix A).

The information-gain statistics for all seven variables are shown in Table 2. Two own lags of each of the first four series noted—Texas personal income, Texas nonagricultural employment, the Texas CPI, and the Texas rig count—all provided information gains at the .05 level of significance over the forecasting information provided by a random walk model. The information-gain data revealed, for example, that including two own lags in a forecasting equation for one-quarter-ahead projections of Texas payroll employment would result in a standard error that was 36.7 percent less than that of a purely random walk model. Conversely, the information-gain statistics suggested that civilian labor force data moved as a random walk with drift.

Effect of other regional variables. The procedure also identified which Texas variables were related most closely to other information specific to Texas. Significant information gains were found for 12 different leading relations involving regional variables. Besides providing useful benchmarks for the the selection of candidate regional variables for the final forecasting equations in the present model, the data in Table 3 also might shed some light on leading and lagging relations among Texas economic variables. In each case, at least one of the regional variables increased the forecast information compared with two own lags in every case (except for Texas housing starts, *TXHOUSING*).

The regional variables that provided such information were not the same for every equation. As a result, a variable that was a candidate for inclusion in one forecasting

Table 3
INFORMATION-GAIN STATISTICS

Variables	*TXINCOME*	*TXNONAG*	*TXCIVLF*	*TXRIG*	*TXRETAIL*	*TXCPI*	*TXHSTOT*
Regional variables							
TXINCOME	—	0.2124	0.3294	0.2094	0.0594	4.2635	0.8565
TXNONAG	13.2220	—	-0.0463	-0.0013	3.0289	5.8055	0.7628
TXCIVLF	-0.8279	0.0901	—	0.2700	-0.8379	6.8826	-0.6274
TXRIG	8.7488	1.8193	-0.3901	—	-1.1695	0.5150	-0.9201
TXRETAIL	4.3382	4.0779	2.2625	2.2543	—	3.9481	-0.6925
TXCPI	4.6575	-0.0615	1.8509	1.2755	-1.0932	—	-1.1812
TXHSTOT	0.7100	-0.3419	-0.0295	-1.3596	-1.2851	-0.7332	—
National variables							
EEPRPD	8.0364	2.3005	1.6075	13.4430	-1.3311	0.9451	0.7126
GNP82	-0.5014	1.3682	-1.3022	-1.1414	-1.3906	0.6764	4.8865
USPY	-1.3456	2.2115	-1.1489	-0.3177	-1.2299	0.9278	-4.1017
USIP	-0.5253	-0.6095	-0.9344	-0.8850	-0.7424	3.0281	6.6889
JCOIN	-0.2927	-0.7246	-0.8515	-0.9209	-1.0150	4.9866	7.0931
JLAG	1.6808	4.6839	-0.3944	0.5926	2.5559	-1.1034	4.3330
JLEAD	-0.5555	1.7593	-0.7724	-0.4426	1.1648	-0.0807	-0.4935
RATIO	2.1640	3.7264	-0.8042	1.0328	0.8689	-0.1530	-0.8128
USNAG	-0.5309	-0.8454	-0.8295	-0.8364	-0.6537	5.3980	6.3440
UST	-0.7095	-1.3406	-0.9506	-0.7408	-1.3022	1.4729	6.2414
INSURUS	-1.2553	-0.6819	-1.2491	-0.0262	-1.2640	0.8887	2.0370
STR	0.2664	0.9015	-0.8891	-0.1953	-1.1934	0.5974	4.6131
CPIMSA	1.3029	-1.1358	1.4861	3.3540	-1.0195	12.7910	-1.2617
PPIFG	0.5052	-0.6344	-1.0711	2.7691	-1.3795	3.4218	-0.2566
RMFEDFUN	-0.3181	-1.3794	-0.9747	-1.0390	1.9972	5.6187	6.9403
FYAAAI	0.0037	-0.8284	-0.8637	-0.1345	0.9390	13.5590	1.3650
M1	0.1623	0.8236	0.7861	-0.6926	-0.3726	-0.2896	2.8737
M2	-1.1843	2.2179	-0.8560	-1.0649	1.8316	-0.0481	-0.2822
M3	-1.0284	1.7814	-0.4311	-1.1710	-0.4518	2.2444	0.6001

NOTES: 1.

Level/value	*F*	*t*
0.90	2.5176	2.043
0.95	3.2703	3.012
0.99	4.9424	5.063

2. See Box for a discussion of the measurement of information gain.

equation would not necessarily be included in other forecasting equations.

An examination of the rows in Table 3 showed, however, that some variables did provide significant forecasting information in equations for several other variables. Lags of retail sales (*TXRETAIL*) appear to have provided significant forecasting information in more cases than did any other regional variable. This variable provided a significant *t* statistic in contributing forecast information for five of the six other regional variables.

Although the significance of these relationships was expressed in terms of their contribution to the reduction in the forecasting error for the model, attempts to derive some economic content from the statistical information in Table 3 ought not to be considered perverse. For example, retail sales may serve as a proxy for overall regional demand.

This role would explain why fluctuations in retail sales foreshadowed changes in personal income and nonagricultural employment, the two variables to which it made its most significant forecasting contribution. Rising regional demand also might be linked to immigration and to the entry or reentry of local workers to the labor force, a relation that could explain the tie between retail sales growth and subsequent labor force expansion. As a proxy for overall regional demand, retail sales possibly could also offer information about the extent of demand-pull that drives inflation, since fluctuations in retail sales also foreshadowed fluctuations in the Texas CPI.

Some pure forecasting relationships, however, despite an apparent contribution, have questionable economic content. On the basis of the information-gain statistics, retail sales also seemed to provide forecasting information about the rig count, although the contribution to rig count forecasting improvement was smaller than for the other four variables for which a significant information gain was registered. It should be noted that in using a purely objective criterion for selecting the final forecasting equation, retail sales was not chosen as an adequate forecasting variable. Indeed, the only final forecasting equations in which retail sales appeared were those for retail sales and for the Texas CPI. As a potential inclusion in regional forecasting equations, the retail sales variable was often called but rarely chosen.

An examination of the columns in Table 3 shows that a number of regional variables made significant contributions to forecast accuracy in the cases of Texas income and the Texas CPI, but no regional variables contributed significantly to forecast accuracy for Texas housing starts. In the case of personal income, fluctuations in nonagricultural employment, in the Texas rig count, in retail sales, and in the consumer price index all foreshadowed fluctuations in Texas personal income. The significance of oil and gas extraction to Texas economic activity could be seen in the rig count's leading relation to personal income, although the forecasting relationship was not strong enough to place the rig count among the right-hand-side variables in the final personal income forecasting equation.

The effect of national variables. The roles of national series in forecasting Texas variables similarly could be measured to those of the Texas series. Regressions were performed to estimate the standard error for a form of equation 1, where x_k was the quarterly logarithmic growth rate of each (in separate equations) of the 19 national variables.

The *I* statistics calculated from these standard errors also appear in Table 3. Again, for an information gain to be significant at the .10 level, a gain of at least 2.043 percent was needed. Of 133 information-gain statistics for national variables, 29 were significant at the .10 level. National variables made significant contributions to forecasting information in the cases of six of the seven Texas variables. Only the Texas civilian labor force failed to derive significant forecasting information gains from national variables.

An examination of the array of national variables that contributed significantly to the forecasting information for Texas variables suggested the importance of the energy industry to Texas. No national variable contributed more often to significant information gains in Texas forecasting equations than the refiners' cost of crude petroleum (*OILPRICE*). Increases in this variable led the increases in Texas personal income, Texas nonagricultural employment, and the Texas rotary rig count. The U.S. index of lagging indicators, however, contributed to significant information gains as often as did the refiners' acquisition cost of crude oil.

An examination of each column in Table 3 demonstrated the relative significance of forecasting information gains derived from national variables in each forecasting equation. Fluctuations in the national interest rate variables clearly played important roles in foreshadowing changes in Texas housing starts, a fact that could be rationalized by the significance of interest rates in determining monthly payments for home buyers. The role of inflationary expectations in determining interest rates could explain why the only other variable for which these rates provide forecasting information was the Texas CPI.

Of the 29 Texas variables for which national variables provided significant forecast information gains, 18 appeared in equations where either housing starts or the Texas CPI were the dependent variables. It was interesting to note that although the U.S. index of leading economic indicators did not play a significant forecasting role in any Texas equations, the ratio of leading to lagging indicators did play significant roles in two equations—personal income and nonagricultural employment.[10]

Testing the model's forecasting accuracy

Although all forecasts are subject to error, testing the forecasting accuracy of different models can suggest how well the model incorporated information from the data. While a particular model might not be the most accurate for all periods or for all forecasting horizons, testing past accuracy could suggest which models would likely provide the greatest accuracy in the future.

Perhaps the fairest means of testing a model would be to estimate it using only the data up to some particular time in the past, and then to forecast up to the present and com-

Table 4
ORDER OF ACCURACY FOR METHODS BY TYPE OF MODEL[1]

	TXINCOME	*TXNONAG*	*TXCIVLF*	*TXRIG*	*TXRETAIL*	*TXCPI*	*TXHOUSING*
1	SW	BJ	SW	BJ	SW	SW	BJ
	AR2	SW	BJ	SW	BJ	AR2	SW
	BJ	AR2	AR2	AR2	AR2	BJ	AR2
2	SW	BJ	SW	BJ	SW	AR2	SW
	AR2	SW	AR2	AR2	BJ	BJ	BJ
	BJ	AR2	BJ	SW	AR2	SW	AR2
3	SW	BJ	SW	AR2	AR2	AR2	SW
	AR2	AR2	AR2	SW	BJ	BJ	BJ
	BJ	SW	BJ	BJ	SW	SW	AR2
4	SW	BJ	SW	SW	SW	AR2	SW
	AR2	SW	BJ	AR2	AR2	BJ	BJ
	BJ	AR2	AR2	BJ	BJ	SW	AR2
5	SW	BJ	SW	AR2	SW	AR2	SW
	AR2	AR2	BJ	BJ	AR2	SW	BJ
	BJ	SW	AR2	SW	BJ	BJ	AR2
6	SW	BJ	SW	AR2	SW	AR2	SW
	AR2	AR2	AR2	BJ	AR2	SW	BJ
	BJ	SW	BJ	SW	BJ	BJ	AR2

1. See Appendix C for identification of variables and methods

pare the results with the actual values for the variables of interest. This type of experiment would be logically equivalent to using all available data to forecast up to the present, and then waiting to see how well the forecast would approximate future realizations.

For the present model, in evaluating the relative accuracy of the final forecasting equations, a measure of out-of-sample forecast accuracy was used to compare the stepwise equations with other forecasting procedures. This measure was the root-mean-square error (*RMSE*) of the forecasts.[11] A useful benchmark for forecast comparison proved to be the Box-Jenkins ARIMA model.

To utilize this approach, Box-Jenkins ARIMA models were constructed for each forecasted variable used in the present model. As an additional benchmark for assessing the forecast accuracy of the stepwise equations, the accuracy of forecasting equations that contained only two own lags of regional variables was also compared with that of the stepwise equations.

The out-of-sample forecast accuracy of both types of forecasting equation—stepwise, Box-Jenkins ARIMA, and the two-own-lag model—was assessed by comparing *RMSE*'s for each quarter-ahead forecast for the period from the fourth quarter of 1983 through the fourth quarter of 1986. The model with the lowest *RMSE* in each case was considered to be the most accurate of the three models. In Table 4, the most-accurate, second-most-accurate, and least-accurate equations were noted for each quarter-ahead forecast. In the table, the stepwise model was denoted as *SW*, the Box-Jenkins ARIMA model as *BJ*, and the two-own-lag model as *AR2*.

As an example of the information provided by the table, the one-quarter-ahead forecast for Texas personal income was considered. Here, the order of accuracy was SW, AR2, and BJ. This order signified that the stepwise model had the lowest root-mean-square error for a one-quarter-ahead forecast, while the AR2 model had the second-lowest root-mean-square error. The highest root-mean-square error in a one-quarter-ahead forecast for Texas personal income was that of the BJ model.

It should be noted that of the 42 comparisons (one-through six-quarter-ahead forecasts for each of seven Texas variables), the model based on this study's stepwise forecast modeling strategy had the lowest root-mean-square error in 24 cases. The Box Jenkins ARIMA procedure and the AR2 procedure each had the lowest root-mean-square error in nine cases, for a total of 18 cases for these two univariate forecasting methods together.

The greater accuracy of the present SW forecasting procedure was also more consistent across various quarters ahead than that of the Box-Jenkins procedure. The data in Table 4 demonstrated that the Box-Jenkins models were more accurate in the nearer end of the forecast range, while the episodes of minimum error for the AR2 and SW models were about evenly distributed between the near and far ends of the forecast spectrum.

For example, of the nine cases in which the Box-Jenkins models had the lowest root-mean-square errors, six (66.7 percent) were in the one- through the three-quarter-ahead forecasts. Of the AR2 models, nine cases of minimum root-mean-square error, five (55.6 percent) were in the four- through the six-quarter-ahead forecasts. Of the 24 cases where the stepwise model had the lowest root-mean-square errors, 11 (45.8 percent) came in forecasts for one of the first three quarters ahead, and 13 (54.2 percent) came in forecasts for one of the last three quarters ahead.

Some types of equations have been found more accurate in forecasting for one type of variable than for other variables, regardless of length of the forecast horizon. The present stepwise model was more accurate at every forecast horizon in predicting personal income and the civilian labor force, and it was also almost always more accurate in forecasting retail sales and housing starts, although none of the procedures forecasted retail sales or the civilian labor force very accurately. The stepwise procedure generated a purely random walk configuration in forecasting the civilian labor force. But in all quarters ahead except the first, that configuration was more accurate in the out-of-sample forecasting for the civilian labor force.

The Box-Jenkins model was consistently more attractive in forecasting Texas payroll employment, although the differences in root-mean-square errors between any of these three types of equations in the payroll forecasts were particularly small. The Box-Jenkins model was not clearly dominant, however, in forecasting any variable besides payroll employment, but during the out-of-sample periods, the AR2 model most often showed greater accuracy in forecasting the Texas CPI and the rig count.

Conclusion

The purpose of this paper has been to demonstrate the construction of a time series forecasting model and to apply the resulting equations in the model to forecasting the Texas economy for 1988. The procedure produced a forecasting model that required a minimum of analytical judgment while projecting relatively accurate forecasts. Statistical criteria were used to measure and select suitable variables for each forecasting equation. Testing the method showed it to be a useful procedure for a variety of forecasting situations.

The methodology for the multivariate time series model demonstrated here appears to offer several advantages for forecasting a regional economy, both as a forecasting exercise itself and as a basis for developing a judgmental forecasting model. The most obvious advantage is that following this procedure can produce a model that, on average, provides greater out-of-sample forecast accuracy than do some other traditionally accurate forms of time series models. The model developed in this study demonstrated greater accuracy than both the Box-Jenkins ARIMA equations and the second-order autoregressive equations.

A second advantage offered by the technique presented is that it can serve as a basis for judgmentally adjusted forecasts in ways that univariate time series models cannot. Specifically, the model presented offers information about forecasting relationships between different variables as well as about some useful autoregressive forecasting relationships.

A third contribution is that the model can provide additional nonforecast information about the past relationships between the variables under consideration. It can also determine the time series properties of the individual variables, as well as demonstrating which variables are statistically most closely related to other indicators. The method further has the strength of reproducibility, because it can be applied equally well to different sets of data, a variety of variables, and alternative time periods.

The characteristics of the model presented here and its strengths in application to forecasting thus demonstrate that the model developed in this study can provide a useful, flexible tool in a variety of forecast settings.

1. In an attempt to identify a forecasting model whose results could outperform Box-Jenkins ARIMA equations, Hoehn developed a series of strategies for the specification of multivariate time series transfer function models for Texas. See James G. Hoehn, "A Regional Forecasting Procedure Applied to Texas," Working Paper no. 8402, Federal Reserve Bank of Cleveland, September 1984. Other variants on this general strategy also appear in James G. Hoehn and James J. Balazsy, Jr., "The Ohio Economy: A Time Series Analysis," *Economic Review*, Federal Reserve Bank of Cleveland, Third Quarter 1985, 25-35; and in "The Ohio Economy: Using Times Series Characteristics in Forecasting," Working Paper no. 8508, Federal Reserve Bank of Cleveland, December 1985. These models proved to have consistently greater (root-mean-square error) forecast accuracy than the Box-Jenkins ARIMA models. The model presented here is based on the approaches reported by Hoehn in 1984 and by Hoehn and Balazsy in 1985 (see above).

2. For example, the forecasting model of Texas used by M. Ray Perryman of Baylor University Forecasting Service, Waco, Texas, contains both structural and ARIMA equations.

3. For surveys of regional structural models, see Roger Bolton, "Regional Econometric Models," *Journal of Regional Science* 25 (November 1985): 495-520. See also Lawrence R. Klein, "The Specification of Regional Econometric Models," The Regional Science Association, *Papers* 23 (1969): 105-15; and Lawrence R. Klein and Norman J. Glickman, "Econometric Model-Building at Regional Level," *Regional Science and Urban Economics* 7 (March 1977): 3-23.

4. One price of increasing forecast accuracy by adding variables to a forecasting equation is the inefficiency of the estimates resulting from fewer degrees of freedom and possible problems with multicollinearity. For a discussion of the issue of econometric estimate efficiency, see, for example, Jan Kmenta, *Elements of Econometrics* (New York: The Macmillan Company, 1971); or Robert S. Pindyck and Daniel L. Rubinfeld, *Econometric Models and Economic Forecasts*, 2nd ed. (New York: McGraw-Hill Book Co., Inc., 1981).

5. Cyclical behavior is the persistence of relatively high or low growth rates over some period. It is in the nature of a business cycle, for example, for relatively high growth rates to persist. This is the upswing period of the cycle. As the economy heads for the downswing portion, growth rates decline and become negative. If an indicator is characterized by random, rather than persistent, increases or declines, its behavior cannot be said to be cyclical, even though the value of the indicator rises and falls. That is, if movement in an indicator is simply a random, nonpersistent variation around some line of drift, that movement is not cyclical. The examination of cyclical behavior through attempts to characterize aggregate variables as random walks is a hallmark of the real business cycle (RBC) literature. See, for example, Charles R. Nelson and Charles I. Plosser, "Trends and Random Walks in Macroeconomic Times Series: Some Evidence and Implications," *Journal of Monetary Economics* 10 (September 1982): 139-62. These authors argue that they can accurately characterize fluctuations in real GNP as a purely random walk with drift and thus argue further that there really is no such thing as a business cycle in the normally accepted sense of that term.

6. For a discussion of stepwise regression routines, see N. R. Draper and H. Smith, *Applied Regression Analysis* (New York: John Wiley and Sons, Inc., 1966), 163-73; and C. W. J. Granger and Paul Newbold, *Forecasting Economic Time Series*, 2nd ed. (Orlando, Fla.: Academic Press, Inc., 1986), 178-81. The algorithm used in the present study is employed by the Statistical Analysis System (SAS), but similar routines are available in a number of other statistical programming packages.

7. The statistical problems associated with a pretest estimation procedure such as a stepwise regression are well documented. The effect of such a procedure is to produce possibly biased values of the F and t test statistics, so that the true significance level will be greater than that implied by the observed value of the test statistic. For a discussion of this problem, see Pindyck and Rubinfeld, *Econometric Models and Economic Forecasts*, 93-94 and George G. Judge, R. Carter Hill, William Griffiths, Helmut Lütkepohl, and Tsoung-Chao Lee, *Introduction to the Theory and Practice of Econometrics* (New York: John Wiley and Sons, Inc., 1982), 579-85. Because the aim of the present research was to adopt a systematic method of selecting variables, no attempt was made to correct for this problem. The forecast performance of the resulting models was the result of interest, and the models selected by the stepwise procedure performed well on this dimension.

8. The stepwise procedure used here can reduce the likelihood that the order in which the variables are entered will make a difference in the equation specification. The procedure has the disadvantage, however, that more nearly optimal decision rules for variable insertion could have been used. Specifically, the procedure used maximizes unadjusted $\bar{R}^2$, rather than maximizing adjusted $\bar{R}^2$ or minimizing standard error of estimate. The standard unadjusted $\bar{R}^2$ maximization rule was used for convenience in the present study, since it was the one built into SAS. The optimization of the decision rules will be examined in subsequent modeling research.

9. Finally, in a consideration of stepwise construction and out-of-sample results, it should be noted that it was necessary to forecast national variables to serve as inputs in the out-of-sample forecasts for the seven Texas variables. In the construction of the national variable forecasting equations, the same procedure was used, except that the Texas variables were excluded *a priori* even from consideration as candidates in national forecasting equations (results available on request).

10. This ratio is sometimes considered a leading indicator of the index of leading economic indicators.

11. The root-mean-square error is calculated as:

$$RMSE_k = \left[1/N \sum_k (\dot{y}_{t+k} - y_{t+k})^2 \right]^{1/2}$$

where

$RMSE$ = the root-mean-square error of the forecast,
k = the forecast horizon (i.e., 1, 2, . . . 6 quarters ahead),
N = the number of quarters for which the forecast was computed,
$\dot{y}_{t+k}$ = the forecasted value of the series, and
y_{t+k} = the actual value of the series.

Appendix A

Reconciling Different Econometric Models

The discussion in this Appendix shows how econometric models with different theoretical grounding are derivable from a model with only a single set of explanatory variables. In other words, the right-hand-side variables that specify these various models can originate from a common specification or set of equations. The model selected for the present study was the transfer function specification because it provides a less commonly examined formulation than the others.

Although different types of econometric forecasting models may rely on an economic theory for their specification and may use different statistical techniques for estimation, they do have features in common. For example, they all use essentially the same data. Presented below is a simple reconciliation of some of these types of models.

Comparison of the theoretical base for structural and time series models

Structural models. Structural models use detailed relationships based on economic theory to describe the economy being modeled. As such, they are often used to test the conformity of empirical relationships with economic theory. They are thus particularly well suited to evaluating the interactions within the economy that future events or policy changes are likely to produce. In addition, structural models are often used for forecasting. Their major drawback in forecasting is their dependence on forecasts of variables that are outside the explanatory realm of the model itself.

Time series models. Time series models, on the other hand, are designed specifically for forecasting. In constructing time series models, the focus is normally on the specifications of equations that forecast economic fluctuations with a minimum of error, rather than on the consistent expression of a particular economic paradigm. Thus, they do not usually try to establish economic theory-based relationships.

It would be rare, even in the context of a time series model, however, to specify equations totally on the basis of statistically identified relationships. In the construction of both structural models and time series models, prior information is used to select a subset of variables to be considered in the model equations (i.e., in their specification). This is true even when purely statistical criteria are used to choose appropriate candidates from an array of possible variables.

To illustrate the similarities and differences between structural and time series models, suppose that a modeler is trying to forecast the future values of three variables, say x, y, and z. Also, suppose it is believed that movements in some of these variables are related to movements in the others. However, for forecasting purposes, it is not necessary in choosing variables to believe that such movements in one variable "cause" changes in the others (although structural models seem to assume this). It is only necessary that these comovements can be used predict what is most likely to happen in the future, thus helping to guide the selection of useful variables for the modeling equations.

Equations A.1-3 describe a general (linear) relationship between the variables x, y, and z. For each equation, both the current and the lagged values of any pair of variables can affect the other, but the lagged values only have an effect one period in the past. Likewise, the lagged values of a variable can affect its current value at most for one period, as shown below:

$$\text{(A.1)} \quad x_t = a_0 + a_1 x_{t-1} + a_2 y_t + a_3 y_{t-1} + a_4 z_t + a_5 z_{t-1} + u_t,$$

$$\text{(A.2)} \quad y_t = b_0 + b_1 y_{t-1} + b_2 x_t + b_3 x_{t-1} + b_4 z_t + b_5 z_{t-1} + e_t, \text{ and}$$

$$\text{(A.3)} \quad z_t = c_0 + c_1 z_{t-1} + c_2 x_t + c_3 x_{t-1} + c_4 y_t + c_5 y_{t-1} + v_t.$$

Under appropriate assumptions about which coefficients should be zero (i.e., which variables should *not* appear in which equations), this model can conform either to a structural specification, to (one or more) time series specifications, or to some combination.

Structural specification

To obtain a simple structural model from these equations, one need only remove the lagged values of the dependent variables, which is equivalent to assuming the following about the coefficients:[1]

$$\text{(A.4)} \quad a_1 = a_3 = a_5 = 0,$$

$$\text{(A.5)} \quad b_1 = b_3 = b_5 = 0, \text{ and}$$

$$\text{(A.6)} \quad c_1 = c_3 = c_5 = 0.$$

If it is further assumed, say, that neither x nor y will affect z, then

$$\text{(A.7)} \quad c_2 = c_4 = 0.$$

and the model has two endogenous variables, x and y, and an exogenous variable, z.

Time series specifications

The five time series specifications described below include the random walk, the pure autoregression, autoregressive integrated moving averages (ARIMA), vector autoregression (VAR), and transfer function (see Figure 1 in the text for a diagrammatic representation of these models).

Random walk. A random walk model assumes that the value of a variable at a given time, t, is a random deviation from some mean value. Frequently, that mean value, when the data are expressed as growth rates, represents the average rate of growth (or drift) of the series being examined. The random walk specification for the variables above could be obtained by setting all coefficients except a_0, b_0, and c_0 equal to zero. Thus, each variable's growth rate would be equal to its mean value plus (or minus) a random error term that is serially uncorrelated and has a constant variance, σ_ε^2. This growth rate would then be a random variable, with no tendency to show prolonged increases or decreases. That is, the variable would be acyclic.

Since a random walk formulation ignores cyclical patterns, the increases in a model's explanatory power through the inclusion of autoregressive (or own-lag) terms show that the variable in question may be subject to cyclical behavior. If there are significant correlations between past and present growth rates of a variable, then some cyclical patterns in the data apparently exist. If significant correlations do not appear, then movements in that variable are not cyclical, even if such movements can be explained through the inclusion of different indicators (that are not own lags) in other types of equations.

Pure autoregression. Under a pure autoregression, the current value of a variable is assumed to depend on its own lagged values, so that the value of y_t today would be determined only by its past values. A univariate autoregression captures the tendency of some economic variables to show cyclical behavior or "momentum"—that is, for higher or lower growth rates in the past to persist into the future.

An autoregressive specification with one lag on each variable would be obtained by setting the following:

(A.8) $$a_2 = a_3 = a_4 = a_5 = 0,$$

(A.9) $$b_2 = b_3 = b_4 = b_5 = 0, \text{ and}$$

(A.10) $$c_2 = c_3 = c_4 = c_5 = 0.$$

Autoregressive integrated moving averages. ARIMA models assume not only that past changes in a variable persist in the future but also that past values of the random error (e_t, u_t or v_t) affect the current error term. Thus, the error term for x_t might be written as

(A.11) $$e_t = z_t - \gamma z_{t-1}.$$

When represented in this way, the error term is noted as a moving average.

The assumptions about the coefficients of the independent variables given for the pure autoregression still hold. Because the assumption of a moving-average error term makes the equation nonlinear in the parameters, special methods of estimating these parameters are necessary.[2]

Vector autoregression. If the forecaster is unwilling to assume that some variables are endogenous and others are exogenous, then he can make use of the time series information contained in the data when estimating the model. One approach would be to assume that everything was dependent on everything else by including lags of all variables in each equation (including the dependent variable). To capture the time series properties, the forecaster can omit the current values of the right-hand-side variables. That is, he can assume that

(A.12) $$a_2 = a_4 = 0,$$

(A.13) $$b_2 = b_4 = 0, \text{ and}$$

(A.14) $$c_2 = c_4 = 0.$$

When all the variables of interest are included in the equations in this fashion, the model is an unconstrained VAR. When the number of variables in the system becomes large—or when the analyst wishes to incorporate information more than one period in the past by adding more lags—the need for the imposition of prior information arises. In such a case, the number of parameters could rapidly approach the number of observations in that data.[3]

Transfer function. As an alternative to the pure vector autoregressive specification, an analyst may wish to assume that past values of some variables only affect a subset of other variables in the system. Such a system is classed as a transfer function because the influence of some variables only works in one direction, without any feedback from some other variables in the system.

The original model described above would reflect this if, for example, past values of z influenced x and y but were not influenced by their past values. Then, in addition to eliminating the contemporaneous coefficients in equations A.8-A.10 above, the following would be assumed about the model:

(A.15) $$c_3 = c_5 = 0.$$

This transfer specification most closely approximates the model discussed in the main body of this paper because national variables were assumed to influence regional variables, but not the converse.

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1. Although it may still be necessary to take into account some time series aspects of the data when estimating the model, this is a separate issue from the specification of the model itself.

2. For a fuller discussion of moving average models, see Robert S. Pindyck and Daniel L. Rubinfeld, *Econometric Models and Economic Forecasts*, 2nd ed. (New York: McGraw-Hill Book Company, 1981); or George E. P. Box and Gwilym M. Jenkins, *Time Series Analysis: Forecasting and Control* (San Francisco: Holden-Day, 1970).

3. Efforts to incorporate prior information in VAR models are described in Appendix B.

Appendix B

Vector Autoregressive Models

Although both Bayesian and unconstrained vector autoregressive models have been used to forecast regional economies, Bayesian VAR models have become more common.[1]

In the Bayesian VAR approach, numerous variables and lags are included in each forecasting equation. In fact, variables of interest to the forecaster would be included in each equation. All relevant variables are included because economic agents have information about these variables, and this information influences the agents' expectation and therefore their economic behavior.

In order to reduce the statistical problems stemming from overparameterization, both the estimate and the variance of parameter values are limited by the imposition of prior information that the analyst assumes to be true about the data's time series behavior. One common set of such prior information is that the data conform to a so-called random walk (see the description in Appendix A). By limiting the distribution of the parameters, this approach reduces the problems normally attendant on the inclusion of a large number of parameters in forecasting equations. But this reduction occurs only at the cost of introducing a new form of bias into parameter estimates through the imposition of the prior distribution. The results have not been entirely successful, because forecasting models of the Texas economy did not perform as well as the simpler-to-produce Box-Jenkins ARIMA models.[2]

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1. For an example of an unconstrained VAR model, see Anatoli Kuprianov and William Lupoletti, "The Economic Outlook for Fifth District States in 1984: Forecasts from Vector Autoregression Models," *Economic Review*, Federal Reserve Bank of Richmond, January/February 1984, 12-23. Also see Paul A. Anderson, "Help for the Regional Forecaster: Vector Autoregression," *Quarterly Review*, Federal Reserve Bank of Minneapolis, Summer 1979, 2-7. Also see Hossain Amirizadeh and Richard M. Todd, "More Growth Ahead for Ninth District States," *Quarterly Review*, Federal Reserve Bank of Minneapolis, Fall 1984, 8-17.
2. See James G. Hoehn, William C. Gruben, and Thomas R. Fomby, "Time Series Models of the Texas Economy: A Comparison," *Economic Review*, Federal Reserve Bank of Dallas, May 1984, 11-23; and "Some Times Series Methods of Forecasting the Texas Economy," Research Paper no. 8402, Federal Reserve Bank of Dallas, April 1984.

Appendix C

Forecasting Modeling Equations

(1) $$TXINCOME_t = \underset{(-0.059)}{-0.0001} \underset{(-2.08)}{- 0.23} \times TXINCOME_{t-1} + \underset{(5.44)}{0.76} \times TXNONAG_{t-1} + \underset{(4.12)}{0.36} \times TXCPI_{t-2} + \underset{(2.55)}{0.11} \times TXRETAIL_{t-1}$$

$$df = 72 \quad \bar{R}^2 = .47 \quad Q(24) = 37.84$$

(2) $$TXNONAG_t = \underset{(0.86)}{0.00082} + \underset{(10.12)}{0.76} \times TXNONAG_{t-1} + \underset{(2.60)}{0.068} \times TXRETAIL_{t-1} + \underset{(1.97)}{-0.01} \times M2_{t-1}$$

$$df = 73 \quad \bar{R}^2 = .65 \quad Q(24) = 31.49$$

(3) $$TXCIVLF_t = \underset{(10.59)}{0.0088}$$

$$df = 76 \quad \bar{R}^2 = \text{n/a} \quad Q(24) = 18.37$$

(4) $$TXRIG_t = \underset{(-0.36)}{-0.0033} + \underset{(0.89)}{0.11} \times TXRIG_{t-1} + \underset{(0.61)}{0.066} \times TXRIG_{t-2} + \underset{(4.41)}{0.59} \times OILPRICE_{t-1}$$

$$df = 73 \quad \bar{R}^2 = .36 \quad Q(24) = 17.66$$

(5) $$TXRETAIL_t = \underset{(3.39)}{0.0091} + \underset{(0.62)}{0.071} \times TXRETAIL_{t-1} \underset{(-2.43)}{- 0.30} \times JLAG_{t-2}$$

$$df = 74 \quad \bar{R}^2 = .06 \quad Q(24) = 40.92$$

(6) $$TXCPI_t = \underset{(-1.06)}{-0.0019} \underset{(-0.83)}{- 0.12} \times TXCPI_{t-1} + \underset{(0.64)}{0.062} \times TXCPI_{t-2} + \underset{(2.77)}{0.30} \times TXNONAG_{t-2} + \underset{(1.78)}{0.58} \times TXRETAIL_{t-1} +$$
$$\underset{(4.31)}{0.99} \times CPIMSA_{t-1} + \underset{(3.22)}{0.54} \times FYAAAI_{t-1} \underset{(-3.07)}{- 0.056} \times FYAAAI_{t-2}$$

$$df = 69 \quad \bar{R}^2 = .70 \quad Q(24) = 36.80$$

(7) $$TXHOUSING_t = \underset{(1.30)}{0.021} + \underset{(0.30)}{0.033} \times TXHOUSING_{t-1} \underset{(-2.90)}{- 2.44} \times USIP_{t-1} \underset{(-2.84)}{- 2.37} \times JLAG_{t-2} \underset{(-2.15)}{- 0.23} \times RMFEDFUN_{t-1}$$

$$df = 72 \quad \bar{R}^2 = .24 \quad Q(24) = 24.83$$

(8) $$OILPRICE_t = \underset{(-2.27)}{-0.055} + \underset{(2.40)}{0.31} \times OILPRICE_{t-1} + \underset{(3.47)}{6.65} \times CPIMSA_{t-1} \underset{(-1.86)}{- 3.13} \times CPIMSA_{t-2} \underset{(-1.00)}{- 1.21} \times PPIFG_{t-1}$$

$$df = 72 \quad \bar{R}^2 = .31 \quad Q(24) = 23.02$$

(9) $$USIP_t = -0.0048 - 0.12 \times USIP_{t-1} + 0.16 \times USIP_{t-2} + 0.70 \times JLEAD_{t-1} + 0.26 \times CPIMSA_{t-2} + 0.0060 \times$$
(−0.86)(−0.80) (1.54) (6.23) (0.99) (0.48)

$$RMFEDFUN_{t-1} + 0.23 \times M3_{t-2}$$
(1.07)

$$df = 70 \quad \bar{R}^2 = .54 \quad Q(24) = 40.88$$

(10) $$JLAG_t = -0.00084 + 0.35 \times JLAG_{t-1} + 0.13 \times JLAG_{t-2} - 0.42 \times GNP82_{t-1} + 0.99 \times JCOIN_{t-1} - 0.23 \times$$
(−0.55) (3.17) (1.59) (−2.05) (6.47) (−2.02)

$$JLEAD_{t-1} + 0.38 \times PPIFG_{t-1} + 0.068 \times FYAAAI_{t-1} + 0.68 \times M1_{t-1} - 0.39 \times M1_{t-2}$$
(2.62) (2.44) (5.20) (−2.82)

$$df = 67 \quad \bar{R}^2 = .76 \quad Q(24) = 22.92$$

(11) $$CPIMSA_t = 0.0020 + 0.64 \times CPIMSA_{t-1} + 0.23 \times CPIMSA_{t-2} + 0.11 \times JCOIN_{t-1} - 0.075 \times RATIO_{t-2} - 0.025 \times$$
(1.22) (5.69) (2.29) (3.16) (3.58) (−0.25)

$$UST_{t-2} + 0.14 \times PPIFG_{t-1} + 0.013 \times RMFEDFUN_{t-1} - 0.035 \times FYAAAI_{t-2}$$
(2.21) (3.85) (−2.93)

$$df = 68 \quad \bar{R}^2 = .80 \quad Q(24) = 25.80$$

(12) $$RMFEDFUN_t = -0.19 + 0.29 \times RMFEDFUN_{t-1} - 0.27 \times RMFEDFUN_{t-2} - 3.32 \times JLAG_{t-1} + 2.32 \times JLAG_{t-2} + 16.03 \times$$
(−4.06) (2.50) (−2.35) (−3.14) (2.35) (5.44)

$$USNAG_{t-1} - 3.49 \times CPIMSA_{t-1} + 10.09 \times CPIMSA_{t-2} + 2.89 \times M1_{t-1}$$
(−1.05) (3.08) (1.83)

$$df = 68 \quad \bar{R}^2 = .44 \quad Q(24) = 18.57$$

(13) $$FYAAAI_t = 0.0044 + 0.25 \times FYAAAI_{t-1} - 0.15 \times FYAAAI_{t-2} + 0.12 \times OILPRICE_{t-1} + 0.13 \times OILPRICE_{t-2} +$$
(0.30) (2.11) (−1.15) (1.52) (1.82)

$$0.036 \times CPIMSA_{t-1}$$
(0.039)

$$df = 71 \quad \bar{R}^2 = .18 \quad Q(24) = 16.03$$

(14) $$M2_t = 0.0024 + 0.32 \times M2_{t-1} + 0.090 \times M2_{t-2} + 0.070 \times JCOIN_{t-1} + 0.14 \times CPIMSA_{t-1} - 0.36 \times PPIFG_{t-1} - 0.14 \times$$
(0.77) (3.17) (0.98) (−1.42) (0.86) (−3.46) (−1.39)

$$PPIFG_{t-2} - 0.11 \times FYAAAI_{t-1}$$
(−6.24)

$$df = 69 \quad \bar{R}^2 = .69 \quad Q(24) = 25.80$$

(15) $$GNP82_t = 0.0044 - 0.20 \times GNP82_{t-1} + 0.26 \times JLEAD_{t-1} + 0.16 \times M2_{t-2}$$
(3.55)(−1.66) (4.55) (1.43)

$$df = 73 \quad \bar{R}^2 = .35 \quad Q(24) = 16.64$$

(16) $$JCOIN_t = \underset{(1.54)}{0.0064} + \underset{(6.63)}{0.47} \times JLEAD_{t-1} - \underset{(-1.66)}{0.56} \times CPIMSA_{t-1} + \underset{(1.09)}{0.35} \times CPIMSA_{t-2} + \underset{(2.72)}{0.032} \times RMFEDFUN_{t-1} - \underset{(-1.53)}{0.060} \times FYAAAI_{t-1}$$

$df = 71 \quad \bar{R}^2 = .55 \quad Q(24) = 33.43$

(17) $$JLEAD_t = \underset{(1.15)}{0.0079} + \underset{(4.29)}{0.64} \times JLEAD_{t-1} + \underset{(1.73)}{0.21} \times JLEAD_{t-2} + \underset{(0.99)}{0.40} \times USPY_{t-1} + \underset{(0.93)}{0.29} \times USPY_{t-2} - \underset{(-3.32)}{0.87} \times JCOIN_{t-1} - \underset{(-0.99)}{0.32} \times CPIMSA_{t-1} - \underset{(-4.25)}{0.19} \times FYAAAI_{t-1} + \underset{(0.060)}{0.018} \times M2_{t-1}$$

$df = 68 \quad \bar{R}^2 = .60 \quad Q(24) = 16.95$

(18) $$RATIO_t = \underset{(0.36)}{0.00085} - \underset{(-4.50)}{0.94} \times JCOIN_{t-1} + \underset{(6.39)}{0.81} \times JLEAD_{t-1} + \underset{(2.11)}{0.28} \times JLEAD_{t-2} - \underset{(-1.18)}{0.32} \times PPIFG_{t-1} - \underset{(-1.91)}{0.097} \times FYAAAI_{t-1}$$

$df = 71 \quad \bar{R}^2 = .49 \quad Q(24) = 32.78$

(19) $$UST_t = \underset{(2.19)}{0.0020} + \underset{(4.04)}{0.16} \times JCOIN_{t-1} - \underset{(-2.24)}{0.20} \times JCOIN_{t-2} + \underset{(1.94)}{0.073} \times JLEAD_{t-2} + \underset{(2.61)}{0.57} \times USNAG_{t-2} - \underset{(-1.75)}{0.017} \times FYAAAI_{t-1} - \underset{(-2.17)}{0.023} \times FYAAAI_{t-2}$$

$df = 70 \quad \bar{R}^2 = .53 \quad Q(24) = 24.07$

(20) $$PPIFG_t = \underset{(-0.75)}{-0.00074} + \underset{(2.37)}{0.29} \times PPIFG_{t-1} + \underset{(1.80)}{0.21} \times PPIFG_{t-2} + \underset{(0.45)}{0.039} \times M1_{t-2}$$

$df = 73 \quad \bar{R}^2 = .12 \quad Q(24) = 26.83$

(21) $$M1_t = \underset{(2.52)}{-0.0025} + \underset{(1.45)}{0.14} \times M1_{t-1} + \underset{(2.76)}{0.24} \times M1_{t-2} - \underset{(-2.63)}{0.33} \times PPIFG_{t-2} - \underset{(-7.14)}{0.15} \times FYAAAI_{t-1}$$

$df = 72 \quad \bar{R}^2 = .61 \quad Q(24) = 19.76$

(22) $$M3_t = \underset{(8.89)}{0.0090} - \underset{(-1.16)}{0.015} \times OILPRICE_{t-2} - \underset{(-2.43)}{0.30} \times PPIFG_{t-1} - \underset{(-1.57)}{0.010} \times RMFEDFUN_{t-1} - \underset{(-1.83)}{0.039} \times FYAAAI_{t-2}$$

$df = 72 \quad \bar{R}^2 = .23 \quad Q(24) = 121.74$

NOTE: Figures in parentheses in the specification equations are t statistics.
