A New Quarterly Output Measure For Texas

Franklin D. Berger
Manager of Research Support
Federal Reserve Bank of Dallas

Keith R. Phillips
Economist
Federal Reserve Bank of Dallas

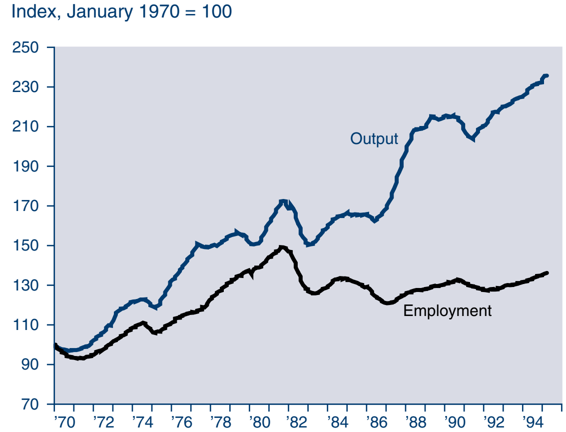
Analysis of output and employment data can sometimes lead to different conclusions about economic performance. For example, after peaking in 1981, Texas manufacturing employment generally declined during the rest of the decade. Manufacturing output, however, increased throughout the period.

Texas' transition from boom to bust during the 1970s and 1980s illustrates how the Texas economy often performs differently from the nation's. The uniqueness of the state's economy makes it important to gather timely state-specific data to measure regional economic performance. Two frequently used measures of regional economic activity are state nonfarm payroll employment and the unemployment rate. While these measures are timely and useful, labor is only one input into the production process. Productivity, through its effect on wages and earnings, directly impacts workers' standard of living. Output embodies the utilization and productivity of labor and capital. Therefore, it is a more comprehensive measure of economic well-being than employment measures.

Analysis of output and employment data can sometimes lead to different conclusions about economic performance. For example, after peaking in 1981, Texas manufacturing employment generally declined during the rest of the decade. Manufacturing output, however, increased throughout the period. As Figure 1 shows, employment data alone could lead one to conclude that manufacturing activity was on a long-term decline, yet the output data show that this was not the case.

The measurement of regional output generally has been restricted to the industrial sector, which has attracted special attention because of its strong cyclical nature and its availability of information relative to the nonindustrial sector. While timely monthly manufacturing indexes are available for several states, manufacturing represents only about 19 percent of total output,

Figure 1
Texas Manufacturing Output and Employment



SOURCES OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce; Bureau of Labor Statistics, U.S. Department of Labor; Federal Reserve Bank of Dallas.

on average. Fortunately, a more comprehensive measure of regional output has become available in recent years. The Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce estimates nominal gross state product (NGSP) and real gross state product (RGSP). Although these data are available for sixty-one industry classifications for all fifty states and the District of Columbia, they are rarely used for current analysis or mentioned in the media because they lack timeliness and are annual. As of April 1995, the latest RGSP data available were for 1991.

In this article, we estimate quarterly measures of Texas RGSP that lag the reporting quarter by about four months. For the period in which BEA's RGSP data are available, our quarterly estimates sum to BEA's annual figures. For the period after the BEA data, our results represent preliminary RGSP estimates that will be revised later to sum to the BEA data. Statistical measures of fit show that simple models based on changes in personal income and price indexes do well in estimating changes in RGSP at the Standard Industrial Classification (SIC) division level.[1] Based on our results, Texas' real output has grown strongly during the 1990s, although in 1993 and 1994 it grew somewhat more slowly than the nation's. Also, Texas RGSP growth has been stronger than employment growth in the 1990s, indicating overall productivity growth of about 2 percent.

What is RGSP?

RGSP is the regional equivalent of real gross domestic product (RGDP) as reported in the national income and product accounts. To avoid double-counting, industry-specific RGSP is measured so that the sum of RGSP across all industries equals total real output. That is, each industry's RGSP is a measure of value-added and is different from the total number of units produced or the total sales of an industry.

One way to measure value-added is to calculate the gross market value of the goods and services produced by an industry and subtract the value of intermediate products and services purchased. BEA uses this method to calculate NGSP for the goods-producing sectors. To estimate NGSP in the goods-producing industries, BEA subtracts an estimate of purchased services from the estimates of value-added reported by the Census Bureau. To construct RGSP, BEA deflates these series by national industry-specific implicit price deflators. For noncensus years, BEA uses the Annual Survey of Manufactures (ASM) and other data to interpolate and extrapolate the census value-added data.[2] Because census value-added data are not available for the service-producing sectors, BEA uses another method of estimation for these sectors.

An alternative way to measure value-added is to calculate the sum of payments made to the factors of production. In other words, the value added by a firm or industry can be measured by the value of labor and capital combined with intermediate inputs to produce output.[3] In estimating RGDP and RGSP for the service-producing industries, BEA measures payments to labor and capital. Specifically, gross state product (GSP) in service-producing industries is calculated by adding: (1) employee compensation and proprietors' income and (2) indirect business tax and nontax liability and capital charges.[4] The industry totals are then deflated by the national industry implicit price deflators.

A practical approach to expanding the RGSP data

The long reporting lag and the data's annual frequency severely limit the usefulness of RGSP as a timely measure of regional trends or business cycles. To increase the periodicity and timeliness of the RGSP data, we first look for timely monthly or quarterly series that might move in a fashion similar to RGSP. Using standard statistical techniques, we examine the relationship between the annualized candidate series and RGSP and use these results to interpolate RGSP at a higher frequency and to extrapolate RGSP forward in time.

Knowledge of RGSP's construction provides insight into possible data series and techniques to construct timely monthly or quarterly RGSP measures.[5] As previously described, industry-level RGSP is constructed differently for service-producing industries than for goods-producing (manufacturing, mining, and construction) in-

BEA Releases 1992 GSP Data

BEA released 1992 GSP data shortly before press time for this article. While unable to incorporate the new data fully into our analysis, we are able to check the accuracy of our 1992 forecasts. On the whole, the magnitude of the errors is consistent with the errors estimated for 1990 and 1991. The out-of-sample forecasting results for RGSP for 1992:

Industry	Percent error
Goods-producing sectors	
Agriculture	3.8
Mining	−5.5
Construction	9.2
Durable manufacturing	−2.3
Nondurable manufacturing	−4.0
Service-producing sectors	
Transportation, communication, and public utilities	1.7
Wholesale trade	−.7
Retail trade	−.9
Finance, insurance, and real estate	1.5
Services	−.6
Government	.9
Total RGSP	.2
Weighted sum of absolute errors	2.1

Table 1
Composition of Texas Gross State Product, 1991

Industry	Labor costs/GSP	Industry RGSP/ Total RGSP
Goods-producing sectors		
Agriculture	.90	.018
Mining	.46	.073
Construction	.94	.037
Durable manufacturing	.76	.082
Nondurable manufacturing	.48	.078
Service-producing sectors		
Transportation, communication, and public utilities	.53	.120
Wholesale trade	.64	.070
Retail trade	.66	.098
Finance, insurance, and real estate	.36	.153
Services	.90	.162
Government	.96	.107

SOURCE OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce.

dustries. The difference in construction and the general availability of more monthly and quarterly series relating to the goods-producing sectors warranted a separate investigation into the estimation of RGSP in these two sectors. We start with a discussion of the service-producing industries.

RGSP in the service-producing industries is calculated by summing the factor payments to labor and capital and dividing this total by the national implicit price deflator for the industry. BEA's estimates of payments to labor (primarily employees' compensation and proprietors' income) come mostly from state personal income data also produced by BEA. For example, in 1987 personal income data represented 93 percent of the employees' compensation and proprietors' income components of GSP.[6] Because state personal income data are available quarterly at the SIC division level and represent most of the labor component of GSP, these data are a likely candidate for estimating nonindustrial output on a more timely basis.

RGSP's nonlabor component comprises primarily sales and property taxes levied by state and local governments, corporate profits with inventory valuation adjustment, corporate capital consumption allowances, business transfer payments, net interest, rental income of individuals, and subsidies less the current surplus of government enterprises. For the census years 1977, 1982, and 1987, much of the information for estimating nonlabor charges for the service-producing industries comes from various censuses and company-specific data reported by various regulatory agencies. For noncensus years, much of the data are interpolated and extrapolated using wages and salaries from the personal income data.[7]

Although information on capital utilization generally is not available or is costly to obtain on a timely basis, the lack of it may not be a significant impediment to estimating RGSP in the service-producing sectors. One reason is that personal income is the basis for much of the year-to-year movement in capital charges. Another reason is that the service-producing sectors are generally labor intensive. As Table 1 shows, the share of value-added represented by the labor component is above 60 percent in the service-producing sectors, with the exceptions of the finance, insurance, and real estate (FIRE), and transportation, communication, and public utility (TCPU) industries. In services and government—which together represent slightly more than 25 percent of RGSP—labor's share is 90 percent or more.

For changes in the labor component of RGSP to be a good representation of changes in total RGSP, the variance of the labor component should be high relative to the variance of the capital component, or the movements in the labor and capital components should be highly correlated, or both.[8] The variance decomposition of RGSP in Table 2 shows that, for most industries, the variance of RGSP is due mainly to the variance of the labor component and the covariance between labor and capital. This is particularly true for the government and for service sectors in which the capital component has varied little over time. The main exception is the FIRE sector. Overall, the variance decomposition of RGSP suggests that, for most service-producing industries in Texas, extrapolating RGSP solely on the basis of changes in the labor component is worthwhile.

As mentioned earlier, BEA estimates RGSP in the goods-producing industries using a different approach. For farming, mining, construction, and manufacturing, BEA estimates RGSP directly, using census data on value-added in production. For farming, mining, and construction in the noncensus years, BEA estimates RGSP mainly using changes in earnings from the personal income data. This method suggests that, for most years, changes in labor income should be a good representation of changes in RGSP in these industries. The results in Tables 1 and 2 also suggest that changes in the labor component could be useful in approximating changes in total RGSP for the agriculture and construction industries. The variance of capital is relatively high for mining, and the absolute value of the covariance

Table 2
Variance Decomposition of Texas Real Gross Product

Variance of RGSP = variance of labor component + variance of capital component + 2 × covariance

Industry	Total variance	Labor variance	Capital variance	2 × covariance
Goods-producing sectors				
Agriculture	789.5	1,370.2	271.8	–852.5
Mining	5,548.3	2,945.5	4,550.1	–1,947.3
Construction	7,474.5	4,936.5	618.1	1,919.9
Durable manufacturing	8,320.4	5,796.3	921.1	1,603.0
Nondurable manufacturing	16,332.5	871.4	13,040.5	2,420.6
Service-producing sectors				
Transportation, communication, and public utilities	23,715.1	6,596.3	6,508.5	10,610.3
Wholesale trade	15,334.5	5,796.5	2,345.5	7,192.5
Retail trade	21,268.0	6,320.4	4,857.7	10089.9
Finance, insurance, and real estate	39,903.2	3,389.1	22,529.7	13,984.5
Services	60,862.7	48,562.8	716.9	11,583.1
Government	9,667.5	8,296.9	106.4	1,264.2

SOURCE OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce.

suggests that only a small portion of the changes in the capital component can be accurately predicted by changes in the labor component.

BEA uses state-level value-added data from the ASM to estimate manufacturing RGSP in the nonbenchmark years. Thus, from a pragmatic approach, it is unclear if the personal income data would be a good representation of RGSP in the manufacturing sector. Labor's low factor share and its relatively low contribution to the variance of nondurable manufacturing RGSP, as Tables 1 and 2 show, also indicate that the labor component may be a poor predictor of nondurable manufacturing RGSP. Fortunately, for durable and nondurable manufacturing, electric power usage data are available to proxy capital usage.[9]

Finally, determining how to account for price changes is an important issue in using personal income data to estimate RGSP. As explained earlier, BEA deflates nominal GSP by national industry-specific implicit price deflators to calculate RGSP. Implicit price deflators are simply the ratio of nominal to real gross product originating. Real gross product originating is derived by separately deflating the value of production and the cost of materials. It is not apparent whether changes in the implicit price deflators would be more closely tied to changes in industry-specific price deflators or to changes in more general price deflators such as the consumer price index (CPI). Therefore, we examine several industry-specific and general price deflators to determine which—when combined with the personal income data—have the greatest ability to explain changes in RGSP.

The model

The procedure we use to distribute RGSP across quarters within-sample and to extrapolate RGSP out-of-sample is the method of best linear unbiased interpolation and extrapolation, introduced by Chow and Lin (1971).[10] A key feature of the Chow–Lin procedure is the restriction that the quarterly in-sample values sum to the annual data. Prior to running the procedure, we run OLS regressions to test the appropriate dynamics of the equations. OLS regressions of the following form have been run for each SIC division:

$$\ln(RGSP_{it}) = \beta_0 + \beta_1 \ln(E_{it}) - \beta_2 \ln(P_{it}) + e_t,$$

where E is earnings (wages and salaries, other labor income such as employer contributions to privately administered pension and welfare funds, employer contributions for social insurance, and proprietors' income with inventory valuation) from the personal income data; P is the price deflator used for the industry; i and t are industry and time subscripts; the betas are estimated coefficients; and ln refers to the natural log of the series. We run the equation on annual data from 1969 to 1989 and test the errors, e_t,

Table 3
Summary Measures of Volatility and Model Fit

Industry	Adjusted R^2: Personal income model	Adjusted R^2: Employment model	Variance of growth rates
Goods-producing sectors			
Agriculture	.716	N.A.	.025
Mining	.192	–.054*	.008
Construction	.750	.645	.007
Durable manufacturing	.805	.751	.007
Nondurable manufacturing	.378	.023*	.005
Service-producing sectors			
Transportation, communication, and public utilities	.473	.479	.001
Wholesale trade	.394	.295	.003
Retail trade	.749	.384	.002
Finance, insurance, and real estate	.377	.194	.004
Services	.829	.248	.0004
Government	.299	–.023*	.0002

N.A. = not applicable.

* The equation is not statistically significant at the 5-percent level.

SOURCES OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce; Bureau of Labor Statistics, U.S. Department of Labor.

for stationarity with the Augmented Dickey–Fuller (ADF) test.[11] In the levels form of the equation, we find the errors to be nonstationary across all industries, suggesting that the models be run in first differences. Because the small number of observations reduces the reliability of the ADF tests, we make out-of-sample comparisons using the Chow–Lin procedure on both the levels and differenced forms of the equation. The mean weighted out-of-sample errors for 1990 and 1991 are smaller for the differenced equations than for the levels equations—further evidence that the differenced form of the model is appropriate.

Series differences have been calculated as the natural log of the series minus the natural log of the series four quarters earlier. The Chow–Lin procedure performed on the differenced data creates a quarterly estimate of the percentage change in RGSP by industry. To transform these changes into levels, the Chow–Lin procedure initially is performed on the levels of the data, and the quarterly level estimates for 1969 are used with the series of estimated changes to estimate industry output during the entire period. These RGSP estimates do not exactly sum to the actual annual RGSP estimates. To ensure that the quarterly estimates sum to the annual RGSP data, we treat these estimates as independent variables and use them in the Chow–Lin procedure with the annual RGSP data. This treatment ensures that the final quarterly in-sample RGSP estimates are restricted to sum to the annual RGSP data. This procedure allows the model's dynamics to be correctly specified while restricting the quarterly in-sample series levels to sum to the annual data.

We perform this procedure on each of the eleven SIC divisions. For the durable and nondurable manufacturing equations, electric power usage data are included as a measure of capital usage. The Durbin–Watson statistics from the differenced regressions show little evidence of autocorrelation so no adjustment to the errors was performed. The *F*-statistics from the regressions are all significant, and the adjusted R^2s show strong predictive power. Although the information in Tables 1 and 2 suggests that the personal income data would be a good predictor of changes in RGSP, we examine another model that avoids the necessity of using price deflators in estimating RGSP.

Payroll employment is available for the nonagricultural industries we have studied; therefore, an alternative method of estimating RGSP is to estimate labor productivity by industry and multiply these estimates by the employment data.[12] The model we estimate is

$$\Delta \ln\left(\frac{RGSP_{it}}{EMP_{it}}\right) = \beta_0 + \beta_1 \Delta \ln EMP_{it} + e_{it},$$

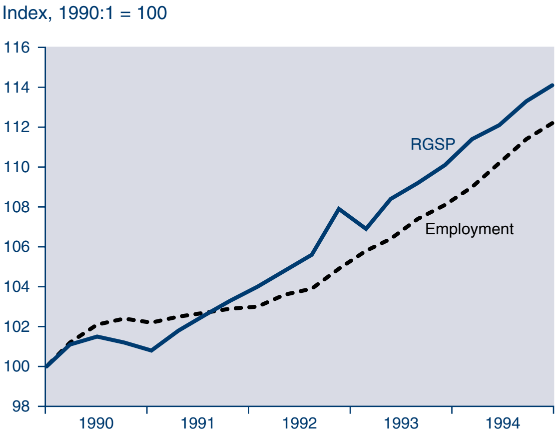
where Δ indicates first differences and *EMP* is nonagricultural employment. β_0 represents the long-run productivity growth rate, and β_1 represents the relationship between employment and productivity. This equation is run for each SIC division, except agriculture, using the Chow–Lin procedure. By first adding the natural log of employment to both sides of the equation, this model's fit can be compared with the fit of the personal income model. As previously stated, for the durable and nondurable manufacturing equations, electric power usage is included as a measure of capital usage.

As Table 3 shows, the adjusted R^2s from the employment model are generally much lower than the adjusted R^2s from the personal-income model. The main exception is the TCPU industry, which has a slightly better fit using the employment model.

Results

To evaluate the out-of-sample performance of our estimates, only data through 1989

Figure 2
Texas Employment and Real Gross Product



SOURCES OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce; Bureau of Labor Statistics, U.S. Department of Labor.

are included in the regressions. The out-of-sample errors give additional information on the model's performance by simulating how the model would have performed had we used it prior to the availability of the 1990 and 1991 RGSP data. As Table 3 shows, the out-of-sample errors vary across industries, with goods-producing industries generally experiencing the largest errors. These out-of-sample errors are consistent with the in-sample measures of fit (*Table 4*). Although the adjusted R^2s for the agriculture and construction industries show that the model explains a fairly large percentage of the fluctuations in growth in these industries, variance measures show that these industries are particularly volatile.

Because of the large out-of-sample errors in the agriculture, mining, and construction industries, we experiment with adding real production measures to the regressions for these industries. For example, when we add the number of residential permits and the square feet of nonresidential permits to the construction equation, we find the coefficients of these measures to be jointly statistically insignificant. Similarly, the addition of a measure of agricultural production to the equation for this industry, and oil and gas production was added to the mining equation yields no significant increases in fit for either industry.

The main source for the large error for nondurable manufacturing in 1991 is a very large drop in reported RGSP for the chemicals industry. This large drop is inconsistent with personal income and employment data for that industry.

Although several industries experience large out-of-sample errors, the average absolute errors and the errors for total RGSP are generally low for the two years. The mean weighted absolute error is 2.2 percent for 1990 and 3.9 percent for 1991. The error for total RGSP is 0.6 percent for 1990 and –1.6 percent for 1991. When one considers that the nation was in recession in parts of 1990 and 1991, the model seems to perform well, at least in the aggregate.

To calculate our final RGSP estimates, we rerun the Chow–Lin procedure and include the data through 1991 and calculate out-of-sample estimates for the period from first-quarter 1992 through fourth-quarter 1994. Figure 2 shows that while Texas employment declined only slightly during the national recession from July 1990 to March 1991, Texas RGSP declined for two consecutive quarters. Thus, the RGSP data suggest that the Texas economy was weaker during this period than the employment data indicate. Figure 2 also shows that during the 1990s real output growth has outpaced employment growth, indicating an overall increase in labor productivity of about 2 percent.[13]

During the 1990s, real output growth has been stronger in Texas than in the nation, al-

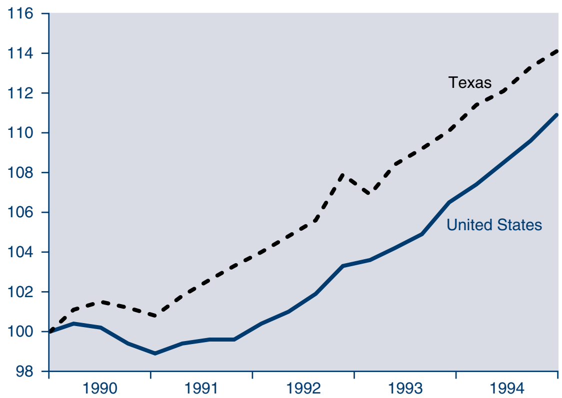
Table 4
Out-of-Sample Forecasting Results for RGSP, 1990 and 1991*

Industry	Percent error 1990	Percent error 1991	Deflator used
Goods-producing sectors			
Agriculture	11.7	14.0	Agriculture PPI
Mining	12.0	1.9	Mining PPIs
Construction	4.1	10.2	Total CPI
Durable manufacturing	.7	1.8	Total CPI
Nondurable manufacturing	1.6	–20.8	Total CPI
Service-producing sectors			
Transportation, communication, and public utilities	–1.2	3.0	TCPU CPI
Wholesale trade	–4.5	–4.0	Total CPI
Retail trade	–1.0	–2.4	Total CPI
Finance, insurance, and real estate	–1.5	–3.1	Total CPI
Services	–.03	–.1	Services CPI
Government	–.3	–.1	Total CPI
Total RGSP	.6	–1.6	
Weighted sum of absolute errors	2.2	3.9	

* The model used is equation 2 in the text, in which the variables are in first differences of natural logs. We use the models' estimates of quarterly changes to estimate quarterly log levels by the method described in the text. The quarterly log levels are exponentiated and summed to produce an estimate of annual RGSP. The percentage difference between the annualized estimate and actual RGSP is shown in the table. A negative number indicates an overestimate of RGSP, while a positive number indicates an underestimate.

Figure 3
Texas and U.S. Real Gross Product

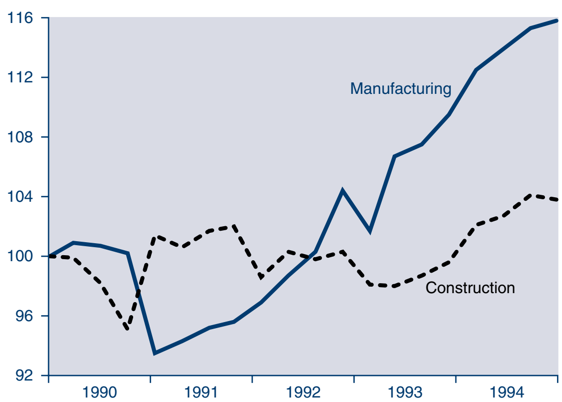
Index, 1990:1 = 100



SOURCE OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce.

Figure 4
Texas Construction and Manufacturing Output

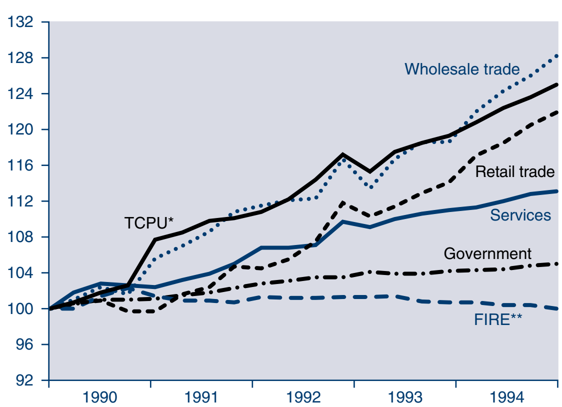
Index, 1990:1 = 100



SOURCE OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce.

Figure 5
Texas Service-Producing Industries' Output

Index, 1990:1 = 100



* Transportation, communication, and public utilities.
** Finance, insurance, and real estate.

SOURCE OF PRIMARY DATA: Bureau of Economic Analysis, U.S. Department of Commerce.

though over the past two years this has not been the case, as shown in Figure 3. The relative strength of national output growth in recent years has come from large gains in labor productivity; employment growth was faster in Texas during both years.

Manufacturing and construction output in Texas accelerated in 1994 after weakness in the early 1990s (*Figure 4*). Output growth in most of the service-producing industries has been strong throughout much of the 1990s (*Figure 5*). The trade and TCPU industries have performed the strongest, while the government and FIRE industries have been weak.

Summary and conclusion

Giese (1989) states that "the important contribution of BEA's GSP data is that they provide a more accurate and comprehensive measure of regional output than other regional data." Although RGSP can be very useful to the regional analyst, its main drawbacks are its annual periodicity and lack of timeliness. In this article, we set out to improve the RGSP data for Texas by increasing its periodicity and timeliness. The method we use is best linear unbiased distribution and extrapolation, developed by Chow and Lin (1971). We find that the Chow–Lin procedure in first-difference form using personal income and various price measures does quite well in out-of-sample forecasts for 1990 and 1991.

We use the procedure to produce RGSP data for each SIC division through the fourth quarter of 1994 and show that real output in the state has not grown as fast as in the United States over the past two years. The data developed in this article are available by accessing Dallas Fed's free electronic bulletin board—Fed Flash—at (214) 922-5199 or (800) 333-1953. The new quarterly output measures should enhance analysts' ability to understand current economic conditions in Texas.

Notes

The authors thank Steve Brown, Bill Gilmer, Lori Taylor, and D'Ann Petersen for helpful comments.

[1] The SIC-division-level industries are agriculture; construction; mining; durable goods manufacturing; nondurable goods manufacturing; finance, insurance, and real estate; services; retail trade; wholesale trade; transportation, communication, and public utilities; and government.

[2] For more information about the calculation of GSP, see Beemiller and Dunbar (1993); Trott, Dunbar, and Friedenberg (1991); and Giese (1989).

[3] Strictly speaking, the exhaustion of nominal value-added by payments to the factors of production

requires the assumption of linear homogeneous production functions and perfectly competitive labor markets. While recognizing that the usage may not be precise, for the purposes of this article all nonlabor payments will be referred to as capital payments.

4 Although BEA also calculates these categories for the goods-producing sectors, total gross product for the goods-producing sectors is not calculated as the sum of these four categories but is based on census value-added data. In the goods-producing industries, the capital component is estimated as the residual of total gross product minus the other components, which are measured directly.

5 Before BEA began producing the GSP data in 1988, many regional analysts used the Kendrick–Jaycox (K–J) methodology to estimate GSP. Essentially, K–J methodology allocates GDP (by industry) to the states by using each state's earnings' share of total U.S. earnings. The availability of the BEA data essentially makes the K–J method obsolete. For a comparison of the BEA data to estimates calculated with the K–J methodology, see Giese (1989).

6 Most of the difference is employers' contributions to social insurance, which come from another source.

7 For more information on the sources of the capital estimates, see the table on page 36 of Beemiller and Dunbar (1993).

8 The higher the absolute value of the covariance between the labor and capital components (for given variances in the labor and capital components), the less information is lost by estimating RGSP with just the labor component. For example, if labor and capital were perfectly correlated, then one could calculate RGSP using some constant multiple of the labor component.

9 Previous research validates the use of electric power consumption as a proxy for capital usage (Moody 1974).

10 The authors wish to thank Jeffery W. Gunther for transforming Chow and Lin's exposition into working computer code.

11 For more information on testing for stationarity in the residuals using the Augmented Dickey–Fuller (ADF) test, see Engle and Yoo (1987).

12 A variant of this method would be to use estimates of U.S. productivity by industry to proxy Texas productivity. Although it would be interesting to test the ability of this method, U.S. productivity estimates are not available with the necessary industry detail, timeliness, and periodicity.

13 In calculating productivity growth, it was assumed average weekly hours worked remained constant over this period. Also, the employment data do not include the agricultural sector. A comparison of growth in nonfarm RGSP with growth in the nonfarm employment data gives approximately the same productivity growth as indicated in Figure 1.

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