A New Monthly Index of the Texas Business Cycle

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Abstract:

The timing, length and severity of economic recessions and expansions in a state are important to businesses seeking to set up operations or expand in those areas. Given a limited amount of data at the state level and their sometimes inconsistent movements, it is not straight forward to define a state business cycle. In this article I attempt to measure the Texas business cycle using a technique developed by Stock and Watson (1989,1991) that statistically estimates the underlying comovement in broad indicators of the state's economy.

The new Texas Coincident Index (TCI) is constructed with the Texas unemployment rate, a quarterly Real Gross State Product measure due to Berger and Phillips (1995), and a nonfarm employment series that is benchmarked quarterly and is seasonally adjusted using the two-step approach described in Berger and Phillips (1993). Use of these components and the Kalman filter, which smoothes across variables as well as over time, results in an index which is much smoother and gives clearer signals of turning points than the old TCI produced by Phillips (1988). The new TCI exhibits cyclical patterns that are highly correlated with those of employment and RGSP, and matches well with recessions and expansions that were independently identified.

JEL classification: R11, E32

Key words: business cycles, indexes, Kalman Filter

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Introduction

During the 1970s and 1980s the business cycle in Texas was dominated by swings in oil prices. During this period, the performance of the Texas economy often deviated significantly from that of the national economy. During the 1990s, however, high tech industries grew strongly and by the end of that decade, Texas was known as one of the top high-tech states in the nation. When the high-tech sector began to weaken in late 2000 and a national recession began in March 2001, Texas followed the nation into recession, even though oil and gas prices were generally high.

The timing, length and severity of economic recessions and expansions can tell a lot about a region's economy. But accurately defining the business cycle at the state or regional level is a difficult task. While there is much confusion about what constitutes a recession even at the national level, business cycles at the regional level are even less well defined. For the national economy, economists often look at movements in broad measures of the macro-economy, such as Real Gross Domestic Product and employment. However, neither of these measures is broad enough to represent the underlying state of the economy. If a business cycle can be defined as a period where there is a broad expansion in many economic sectors followed by broad contraction, then combining the movements in coincident economic indicators would represent an effective way to measure the business cycle. The Conference Board (CB) calculates a coincident index of the U.S. economy by taking changes in four monthly macro economic indicators and weighting them by the inverse of their volatility.

Stock and Watson (1989,1991) estimate a single underlying unobserved variable that is consistent with the theoretical notion of the business cycle. While the resulting coincident index is very similar to the CB coincident index, the Kalman filter approach used by Stock and Watson allows the data to define the component weights that best define the underlying comovements in the component variables. The strong theoretical and empirical arguments supporting the SW (Stock and Watson) approach has led regional researchers to apply the methodology to regional economies. Clayton-Matthews and Stock (1988) apply the methodology to measures of employment, the income tax base, the sales tax base and the unemployment rate to create a coincident index for the state of Massachusetts. Crone (1988) uses three variables that are available for the 48 contiguous states – nonfarm employment, average weekly hours in manufacturing and the unemployment rate – to estimate coincident indexes for each of the 48 states.

This study adds to a growing body of regional business cycle literature by applying the SW methodology to calculate a coincident index for the Texas economy. The main contribution is to utilize two unique regional variables that promise to provide a more comprehensive and accurate description of the Texas business cycle. The first is a measure of nonfarm employment that is rebenchmarked to the unemployment insurance (UI) data (which represents about 98 percent of all nonfarm jobs) on a quarterly basis rather than the annual rebenchmarked series that is provided by the Bureau of Labor Statistics. The employment data is also seasonally adjusted by a two-step seasonal adjustment procedure that takes into account the different seasonal patterns in the two component series that makeup the Current Employment Statistics series. Berger and Phillips (1993, 1994) show that these adjustments improve the reliability and reduce the annual revisions to the nonfarm employment data. The second unique series is a quarterly estimate of Texas Real Gross State Product (RGSP) due to Berger and Phillips (1995). The RGSP estimates are benchmarked to estimates produced by the Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce. These quarterly estimates usually lag the reporting quarter by about 4 months versus the BEA data, which is annual and typically lags the end of the reporting year by more than 3 years.

Applying the SW methodology to the Texas unemployment rate, nonfarm employment and quarterly RGSP produces a coincident index that is smooth and seems to be a good reflection of the state's business cycle. Judging the usefulness and performance of a business cycle index, however, is not straight-forward. At the national level, a committee of economists define peaks and troughs of the U.S. business cycle that can be used to judge the timing and duration of business cycles as defined by the Conference Board (CB) and the Stock and Watson coincident indexes. To judge the performance of the new Texas Coincident Index (TCI), I compare it to an earlier (old) Texas Coincident Index (OTCI) produced by Phillips (1988) using the simple CB methodology. I find that the new TCI is much smother and is a better indicator of turning points in the Texas economy that were independently identified in Yucel and Thompson (2002).

If the coincident index is successful in filtering out a single autoregressive comovement common to all the component series, than shocks to each component series, after filtering out the movements in the coincident index and any idiosyncratic autoregressive patterns, should be independent of past shocks in the other series. I use an F-test to test this efficiency criterion and test this for both the old and the new coincident index and find that only the new index passes this test.

Business Cycle Indexes

The most common measures of the U.S. business cycle are the business cycle peak and trough dates established by the Business Cycle Dating Committee at the National Bureau of Economic Research (NBER). The NBER defines a recession as "a recurring period of decline in total output, income, employment, and trade, usually lasting from six months to a year, and marked by widespread contractions in many sectors of the economy." In contrast to common belief, "The NBER does not define a recession in terms of two consecutive quarters of decline in real GNP."[1] While the established peaks and troughs give the timing of U.S. recessions and expansions they give little information about neither the depth of recessions nor the strength of expansions. They also give little degrees of freedom for the time series modeler.

For a more complete description of the business cycle, the Conference Board produces a coincident index which combines the movements in employees on nonagricultural payrolls, personal income less transfer payments (in 1996 $), an index of industrial production, and manufacturing and trade sales (in 1996 $). Stock and Watson (1989) argue that while these variables are well-established, broad-based, timely measures of the economy, the simple average of the volatility-adjusted changes in the

[1] See http://www.nber.org/cycles.html

series do not ensure that the index best describes the underlying state of the economy. As an alternative, they propose a dynamic single-index factor model using the Kalman filter.

While SW propose a significant change to the construction of the coincident index, the components used in their model are essentially the same as those used by the Conference Board. The only difference is the employment variable. The CB uses total nonfarm employment while Stock and Watson use total hours worked. In this paper, I seek to improve upon the Texas Coincident index first proposed by Phillips (1988) by changing both the included variables and the estimation model.

Employment Data

One of the most commonly used data series measuring the performance of the Texas economy is nonfarm payroll employment from the Current Establishment Survey (CES) program, produced by the Texas Employment Commission in cooperation with the Bureau of Labor Statistics. No other regional series is as timely or provides as much industry detail as the payroll data. One problem with the employment data, first discovered by Berger and Phillips (1993), is that the series is actually two different series spliced together and these two series have different seasonal patterns. The bulk of the data is based on reports filed by firms covered by unemployment insurance (UI), while the most recent ten to twenty-two months of data are based on a survey of business establishments. Running a standard census X-11 or X-12 seasonal adjustment procedure on the combined CES data series results in seasonal factors which are essentially based on the UI data. When these seasonals are applied to the establishment survey data at the end of the series, it often results in a January jump and other irregularities that are revised away when the data are rebenchmarked to the UI data every March.

Berger and Phillips (1993, 1994) describe a two-step seasonal adjustment process that estimates and applies two separate seasonal adjustment factors for the two separate parts of the data. In early 1994 the BLS, partly in response to the research by Berger and Phillips (BP), adapted a two-step adjustment procedure for the state employment data published at the one-digit SIC level. The procedure used by the BLS, however, differs slightly from the procedure used by BP. At the month that the survey data starts, often July, BP splice together the seasonal factors using the change in the survey data seasonals from June to July and then multiply this change by the June UI seasonal factor. More precisely, they define the two core series as X^B – the benchmark UI series, X^S – the establishment survey (ES) series, and then define the hybrid series which is the final published series as X^H . The hybrid series first reflects the changes in X^S in the transition month which is usually July[i]. For example, every year when the January data is released, the data from June of the previous year back 12 months is revised (benchmarked) to reflect the changes in the UI data (instead of changes in the ES). The data from July through the current month of January is estimated with the ES data and, as new data is released through the following December, it is based on changes in the ES data. Then when the January data is released the following year, another annual benchmark occurs and the process repeats itself. X^H in the transition month 7 is calculated by the BLS as:

(1) $$X_7^H = (X_7^S / X_6^S) * (X_6^B)$$

In order to seasonally adjust the series we divide by the appropriate seasonal factors (SF):

(2) $$SAX_7^H = (X_7^S / SF_7^S)/(X_6^S / SF_6^S) * (X_6^B / SF_6^B)$$

rearranging and substituting we get

(3) $SAX_7^H = X_7^H / ((SF_7^S / SF_6^S) * SF_6^B)$,

which is the equation that we use. BLS, however, uses the equation:

(4) $SAX_7^H = X_7^H / SF_7^S$ which is only correct if $SF_6^S = SF_6^B$

In month 8, the month after the transition month, we define

(5) $SAX_8^H = X_8^H / ((SF_8^S / SF_7^S) * SF_7^H)$,

where $\mathrm{SF}_7^{\mathrm{H}} = (SF_7^S / SF_6^S) * SF_6^B$

which is equal to the BLS value only if $SF_6^S = SF_6^B$. From period 8 to the end of the series the seasonal factors change in the same way as the BLS seasonal factors but the level differs based on the difference between $SF_6^S \textit{ and } SF_6^B$.

Using equations 3 and 5 ensures a smooth movement in the seasonally adjusted series at the transition point but the restriction that for any twelve-month period the seasonal factors average to one no longer holds for the establishment survey part of the data. Using equation 4 can cause an irregular movement at the transition point but retains the restriction that the seasonal factors average to one.

Another adjustment that BP make to the employment data is early benchmarking. Once a year, concurrent with the release of the January CES data, the BLS revises the previously estimated data based on a years worth of UI data, a process called benchmarking. The benchmark period covers from July two-years-prior to June of the previous year. Preliminary UI data for Texas at the three-digit North American Industrial

Classification System (NAICS) are available with about a three-quarter lag after the reporting quarter. Berger and Phillips (1993) show that this preliminary data is very close to the final data used for the annual benchmark and thus can accurately be used to estimate the benchmark revision.

Quarterly Real Gross State Product and the Unemployment Rate

The second series that we use in the coincident index is Quarterly Real Gross State Product (QRGSP). Berger and Phillips (B/P) (1995) estimate QRGSP at the Standard Industry Classification (SIC) division level using personal income, industry-level and aggregate price indexes, and for manufacturing, electric power usage. The data are benchmarked to annual RGSP produced by the Bureau of Economic Analysis of the U.S. Department of Commerce. For the period in which BEA's RGSP data are available, the quarterly estimates sum to the annual figures. For the period after the BEA data, the data represents preliminary data that will later be revised to sum to the BEA data. The BEA data is released with about a four-year lag while the B/P quarterly estimates are released with about a month lag. B/P employ the method of best linear unbiased interpolation and extrapolation due to Chow and Lin (1971).

The final data series used is the Texas unemployment rate produced by the Texas Workforce Commission. This monthly series is released about 20 days after the end of the reporting month and on the same day as the CES employment series. QRGSP and the unemployment rate are seasonally adjusted with the census X-11 procedure and the CES series is seasonally adjusted with the two-step procedure described earlier. The unemployment rate is inverted so that the directional movements are consistent with the other indicators. The three data series are plotted in Chart 1. As shown in the chart, the data move in similar cyclical patterns although the unemployment rate has many more cycles.

Applying the Stock/Watson Coincident Index Model to Texas

The structure of the S/W model is:

(6) $Y_t = \beta + \gamma(L)\Delta C_t + \mu_t$

(7) $D(L)\ \mu_t = \varepsilon_t$

(8) $\phi(L)\Delta C_t = \delta + \eta_t$

where $Y_t = \Delta X_t$ are the stationary first differences of natural logs of the n coincident component series (Texas employment, RGSP, and the inverted unemployment rate[ii]) and C_t is an unobserved scalar that presents the log of the unobserved state of the economy. L denotes the lag operator. The lag polynomials $\phi(L)$ and $D(L)$ are assumed to have finite orders *p* and *k*. The disturbances ε_t and η_t are assumed to be serially uncorrelated. The lag polynomial matrix D(L) is assumed diagonal so that the μ_t's in different equations are contemporaneously and serially uncorrelated with each other.

The state equation is obtained by combining equations 7 and 8. As shown in Stock and Watson (1991) the transition equation for the state is given by

$$(9)\quad \begin{bmatrix} C^*_{t-1} \\ \mu^* \\ C_t \end{bmatrix} = \begin{bmatrix} \delta \\ 0_{(p+nk)x1} \end{bmatrix} + \begin{bmatrix} \phi^* & 0 & 0 \\ 0 & D^* & 0 \\ Z_c & 0 & 1 \end{bmatrix} \begin{bmatrix} C^*_{t-1} \\ \mu^*_{t-1} \\ C_{t-2} \end{bmatrix}$$

$$+\begin{bmatrix} Z'_c & 0 \\ 0 & Z'_\mu \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \eta_t \\ \varepsilon_t \end{bmatrix}$$

where:

$$C_t^* = [\Delta C_t \Delta C_{t-1} \ldots \Delta C_{t-p+1}]'$$

$$\mu_t^* = [\mu'_t \mu_{t-1'} \ldots \mu_{t-k+1'}]'$$

$$\phi^* = \begin{bmatrix} \phi_1 \ldots \phi_{p-1} & \phi_p \\ I_{p-1} & 0_{(p-1)x1} \end{bmatrix}$$

$$D^* = \begin{bmatrix} D_1 \ldots D_{k-1} & D_k \\ I_{n(k-1)} & 0_{n(k-1)xn} \end{bmatrix}$$

$Z_c = [\ 1 \quad 0_{1x(p-1)}]$

$Z_\mu = [\ I_n \quad 0_{nxn(k-1)}]$

The measurement equation is obtained by writing equation 8 as a linear combination of the state vector.

$$(10) \quad Y_t = \beta + [\gamma Z_c \quad Z_u \quad 0_{n+1}] \begin{bmatrix} C_t^* \\ \mu_t^* \\ C_{t-1} \end{bmatrix}$$

Equations (11) and (12) can be written:

(11) $\alpha_t = \mu_\alpha + T_t\alpha_{t-1} + R\zeta_t$

(12) $Y_t = \beta + Z\alpha_t + \xi_t$

The Kalman filter is then applied to this state space representation of the model. Let $\alpha_{t\backslash\tau}$ denote the estimate of α_t based on $(y_1,\ldots,y_\tau)$, let $E[\xi_t\xi'_t] = H$, $E[\zeta_t\zeta'_t] = \Sigma$ and $P_{t\backslash\tau} = E[(\alpha_{t/\tau} - \alpha_t)(\alpha_{t/\tau} - \alpha_t)']$. Given this notation the prediction equations for the Kalman filter are

(13) $\alpha_{t/t-1} = \mu_\alpha + T_t\, \alpha_{t-1/t-1}$

(14) $P_{t/t-1} = T_t\, P_{t-1/t-1}\, T'_t + R\Sigma R'$

The forecast of Y_t at time t-1 is $Y_{t\backslash t-1} = \beta + Z\alpha_{t/t-1}$ and the updating equations for the filter are

(15) $\alpha_{t/t} = \alpha_{t/t-1} + P_{t/t-1}Z'F_t^{-1}\nu_t$

(16) $P_{t/t} = P_{t/t-1} - P_{t/t-1}Z'\, F_t^{-1}Z\, P_{t/t-1}$

where $F_t = E[\nu_t\nu_t] = Z\, P_{t/t-1}Z' + H$ and $\nu_t = Y_t - Y_{t\backslash t-1}$.

The state vector $\alpha_{t/t-1}$ and its covariance matrix $P_{t/t-1}$ are estimated with the assumed parameters in T_t, R, Σ, H and Z and the initial values for $\alpha_{t/t}$ and $P_{t/t}$. The Gaussian maximum likelihood estimates of the parameters are found by maximizing Γ over the parameter space where Γ is defined[iii]:

(17) $$\Gamma = -\frac{1}{2}\sum_{t=1}^{T}\nu'_t F_t^{-1}\nu_t - \frac{1}{2}\sum_{t=1}^{T}\ln(\det(F_t))$$

Texas nonfarm employment, unemployment rate and a QRGSP are first converted to first difference of logs (except the unemployment rate which is just differenced) and normalized by subtracting its mean difference and dividing by the standard deviation of its differences. This results in β=0 and δ=0 in equations (6) and (8).

The scale of the $\gamma(L)$ coefficients is fixed by setting the variance of η to unity, and the timing of the coincident index is fixed by setting $\gamma(L)= 0$ for all L for employment in equation (8). In the model for Texas, the values p=2 and k=2 are used so that a second order autoregressive process is assumed for the idiosyncratic movements in the components shown in equation (7) and for the coincident index movements shown in equation (8). For the equations for RGSP and the unemployment rate it is assumed that $\gamma(L)= 0$ for all L^s where s>2, so that these variables are allowed to influence the coincident index from zero to two lags. Statistically insignificant lags are dropped so long as diagnostic tests described below do not deteriorate.

As shown in Equation 8, the Kalman filter models each of the component series as left-hand-side variables with the (unobserved) coincident index on the right hand side. Given this structure, quarterly variables are modeled as a function of current and past values of the monthly latent series. In this way, quarterly data enter into the equations with monthly data. More precisely:

(18) $\Delta X_t = \gamma(L)\Omega(L)\Delta C_t + \mu_t$

where $\Omega(L) = 1 + 2L + 3L^2 + 2L^3 + 3L^4$ and $\Delta X_t = X_t - X_{t-3}$, with t representing months.

Also, the timing of the index is determined by the most recent data available since the program reduces the dimension of the vector equation for the missing data.[iv]

Table 1 shows the models parameters and standard errors. As shown in the table, the T-statistics for employment, RGSP and the two lags of the unemployment rate are highly significant. The autoregressive coefficients for employment and the unemployment rate imply that after taking into account the movement in the coincident index the remaining series has a negative autocorrelation. Autoregressive parameters for RGSP were insignificantly different from zero suggesting that once the smoothed movements in the coincident index were regressed on RGSP, the idiosyncratic movements were white noise. This suggests that the autoregressive pattern in the estimated coincident index is the same as that of RGSP. The autoregressive pattern in the coincident index suggests that shocks to the economy are highly persistent.

Diagnostic tests were performed on the comovement in indicators and their idiosyncratic components were modeled correctly. The tests, described in Clayton-Matthews and Stock (1999), verified that one-step ahead forecast errors $\varepsilon_{t/t-1}$ are uncorrelated with past values of itself, the forecast errors of the other indicators and past changes in the indicators. In each regression, the dependent variable is one of the one-step ahead forecast errors of the component series, and the independent variables consist of a constant and six lags of the forecast errors or indicators. An F-test is then performed on the joint significance of each regression. The results shown on the top of Table 2, generally, confirm the whiteness of the errors and thus the validity of the model[v].

The bottom half of Table 2 shows the cumulative dynamic multipliers and the component shares. As shown here, employment gets the greatest weight in the model followed by the unemployment rate and QRGSP. The largest weight on employment is a good result given the improved reliability of the series with the adjustments described earlier, the smoothness of the series as shown in Chart 1, and the series timeliness. While RGSP gets only a ten percent weight in the index, movements in the index are still a good reflection of changes in this broad economic indicator. As discussed earlier, the cyclical movements in the coincident index mimic the cyclical pattern of RGSP. As shown in Chart 2, changes in the coincident index mimic closely the changes in Texas RGSP.

The initial transformations to the data create a coincident index that is a normalized driftless composite index with a unit-variance shock. This index is then given an average rate of change that is equal to the weighted average changes of the component series. I follow this procedure so that the index is easily comparable to a CB-type coincident index created for Texas by Phillips (1988). The components of the old TCI are CES employment and the Texas Industrial Production Index.

The coincident index represented by the smoothed state of the Kalman filter is shown along with the old Texas coincident (Chart 3). As shown in the chart, the new coincident index is much smoother than the old index and has fewer periods that change directions for short periods of 3-to-6 six months and then reverse directions. One measure of smoothness is the sum of the autoregressive coefficients of the series – the closer the autoregressive parameter is to one (while remaining less than one), the greater the persistence of shocks and the smoother the cycle. The autoregressive coefficients of the new TCI, as highlighted in Table 1, sum to .98 while the autoregressive coefficients for the old TCI sum to .75[vi]. The new TCI is thus smoother and once it changes directions is more likely to continue in the new direction than the old TCI.

Yucel and Thompson (2002) look at a host of data and other available information on the Texas economy since 1972 and use this information along with their own knowledge of the state's economy to define recessions in Texas. The shaded areas of Chart 4 highlight their results along with changes in the TCI. As shown in the chart, the new TCI matches well the turning points defined by these economists. The TCI declined during recessions and remained positive throughout the expansion periods except for a -.1 percent annual rate of decline in December 1974 and -.06 percent annual rate of decline for the first three months of 1990. As shown in Chart 5 the old Texas Coincident index declined during the recessions but also had frequent declines during expansion periods.

While a graphical comparison of the indexes is useful, a more formal definition of what constitutes a recession or expansion signal allows a more precise performance comparison. Neftci (1982) estimates a sequential probability formula, which uses changes in the index to compute the probability of recession. While this technique has typically been used with leading indexes, its use with coincident indexes is also straightforward.

The Neftci probability of recession estimation highlights the clearer recession and expansion signals given by the new TCI. For the three recessions over the time period, the probability of recession given by the new TCI twice rose above 90 percent at the exact month of the turning point, as defined by Yucel and Thompson, and once lagged by one month (Chart 6). In comparison, using the old TCI the 90 percent recession probabilities came with a one-month lag for one recession and with a four-month lag for the other two recessions. Throughout most of the long expansion periods the probability of recession based on the new TCI remained very close to zero except when it rose to 10 percent in January 1975 and 18.5 percent in May 1991. During these same two periods the old TCI rose above 90 percent – giving two false signals of recession. Both of these periods marked very weak activity in the states’ economy, although not weak enough to be classified as a recession by Yucel and Thompson. There were also several periods were the probability of recession based on the old TCI rose past 50 percent (but not reaching 90 percent) such as late 1988 and early 1999.

For the two troughs (no trough has yet been identified for the recession beginning in April 2001) the timing of the expansion signal given by the new TCI was a two-month lag (Chart 7). For the old TCI, the expansion signal came with a one-month lag and a four-month lead. Thus the timing of troughs seems a bit more consistent with the new TCI but with so few observations it is hard to make judgments concerning the overall performance at troughs. In terms of defining recessions, however, the application of the Neftci probability of recession estimation shows that the new TCI has had fewer false signals and closer timing to actual turning points than the old TCI.

To further compare the new TCI with the old TCI, I perform the whiteness test shown in Table 2 on movements in the old TCI. Since the change in the old TCI is measured as the average of the volatility adjusted changes in the two component series, the errors of each series regressed on the old TCI are perfectly correlated. Thus the results of the whiteness test on each variable are the same. As shown in Table 3, the errors of the components are not predictable from their past errors but are predictable from past changes in the series themselves so that the simple equal weighting system used is inefficient at filtering out the autoregressive comovement in the components.

Summary

In this paper a dynamic single factor model due to Stock and Watson (1991) was used to create a new Texas coincident index that can be used to monitor the business cycle in the state. The new index is constructed with the Texas unemployment rate, a quarterly RGSP measure due to Berger and Phillips (1995), and a nonfarm employment series that is benchmarked quarterly and is seasonally adjusted using the two-step approach described in Berger and Phillips (1993). Use of these components and the Kalman filter, which smoothes across variables as well as over time, results in an index which is much smoother and gives clearer signals of turning points than the old TCI produced by Phillips (1988). The new TCI exhibits cyclical patterns that are highly correlated with those of employment and RGSP, and matches well with recessions and expansions that were independently identified in Yucel and Thompson (2002). The new TCI is available on the Dallas Fed web site at www.dallasfed.org.

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[i] Although officially the benchmark runs though March, most often the BLS has available and uses the UI data through June. Each year the Dallas Fed calls to verify when the benchmark data ends.
[ii] The unemployment rate is measured in differences of levels instead of differences of natural logs since it is already measured as a percentage.
[iii] The software code to run the S/W model was provided by Alan Clayton-Matthews of the University of Massachusetts, Boston.
[iv] While this adjustment provides a more timely index it is realized that since some data is missing that will later be incorporated, the most recent values of the series may be subject to a significant degree of revision.
[v] The model was estimated monthly in real-time from April 2001 to January 2003. The coefficients of the model were found to be stable and the significance tests in Table 1 and the white noise tests in Table 2 validated that the structure of the model did not change over this real-time estimation period.
[vi] Higher orders of the autoregressive process were estimated until the residuals were white noise – resulting in a fifth order autoregressive process for the old TCI. The regression F-statistic was significant at the .01 level and the P-value for the chi-square that the first six autoregressive coefficients on the residuals of the regression were jointly equal to zero was .38.

Chart 1
Components of the New Texas Coincident Index

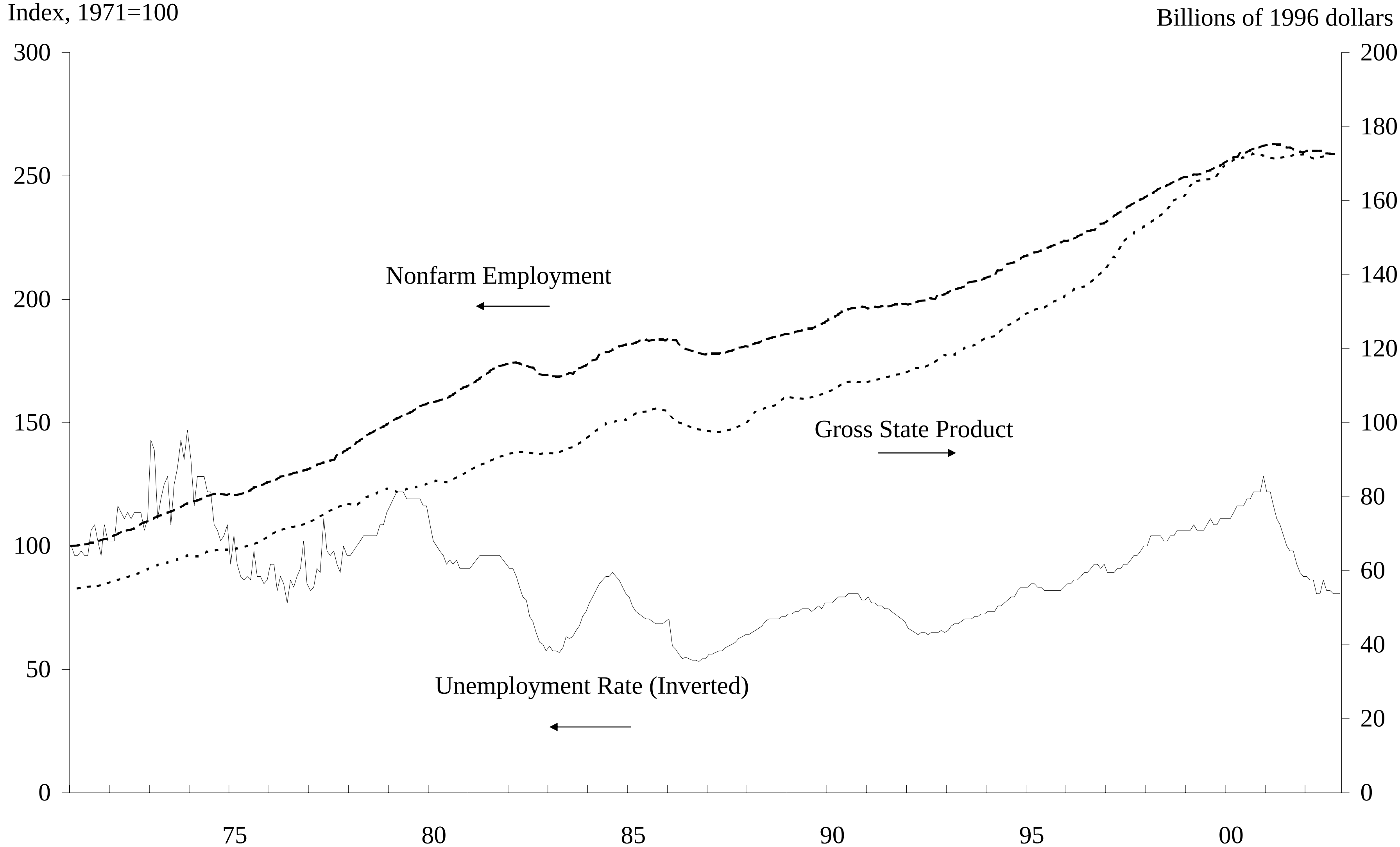


Chart 2
Cyclical Changes in New Texas Coincident Index and Real GSP

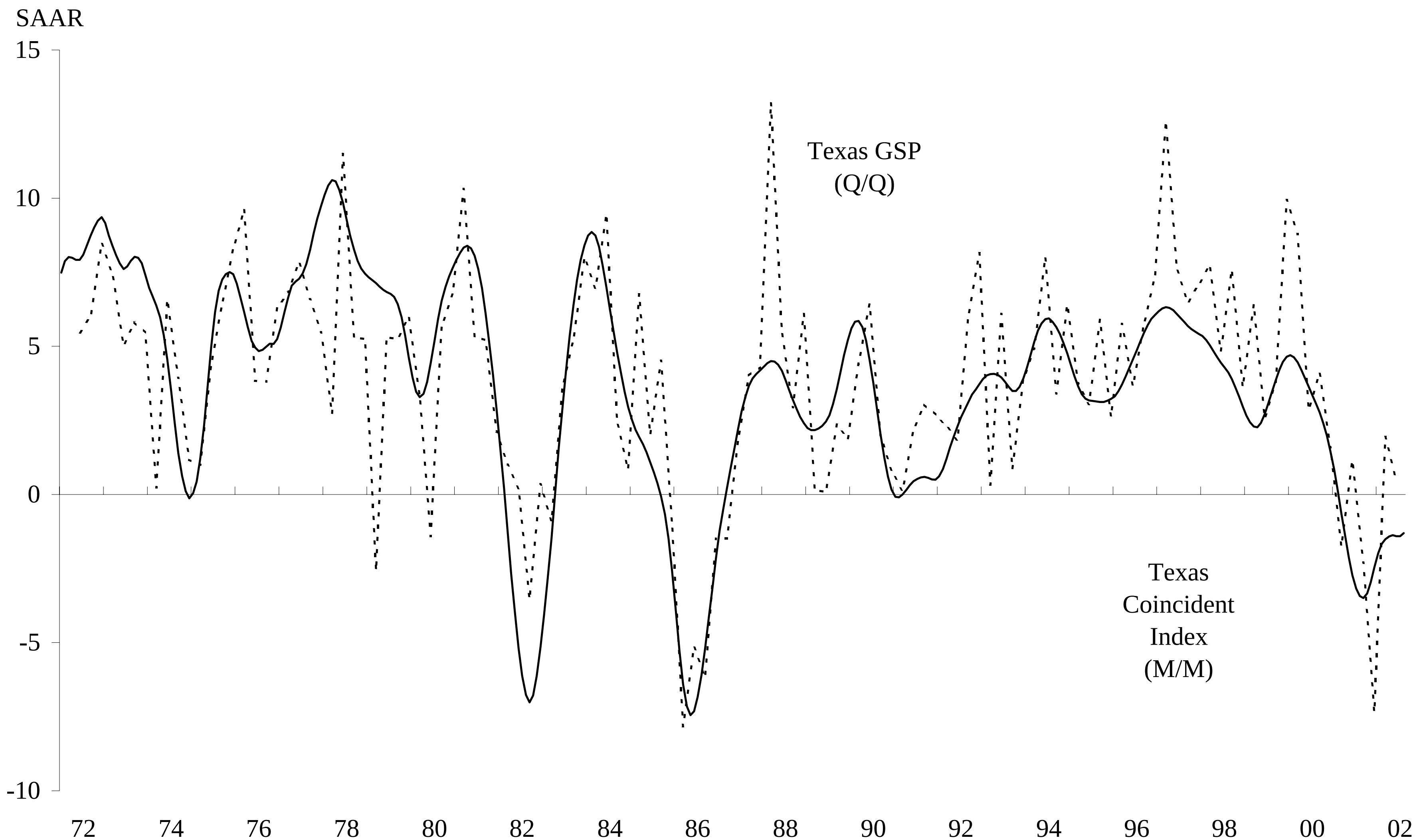


Chart 3
New Texas Coincident Index and Old Texas Coincident Index

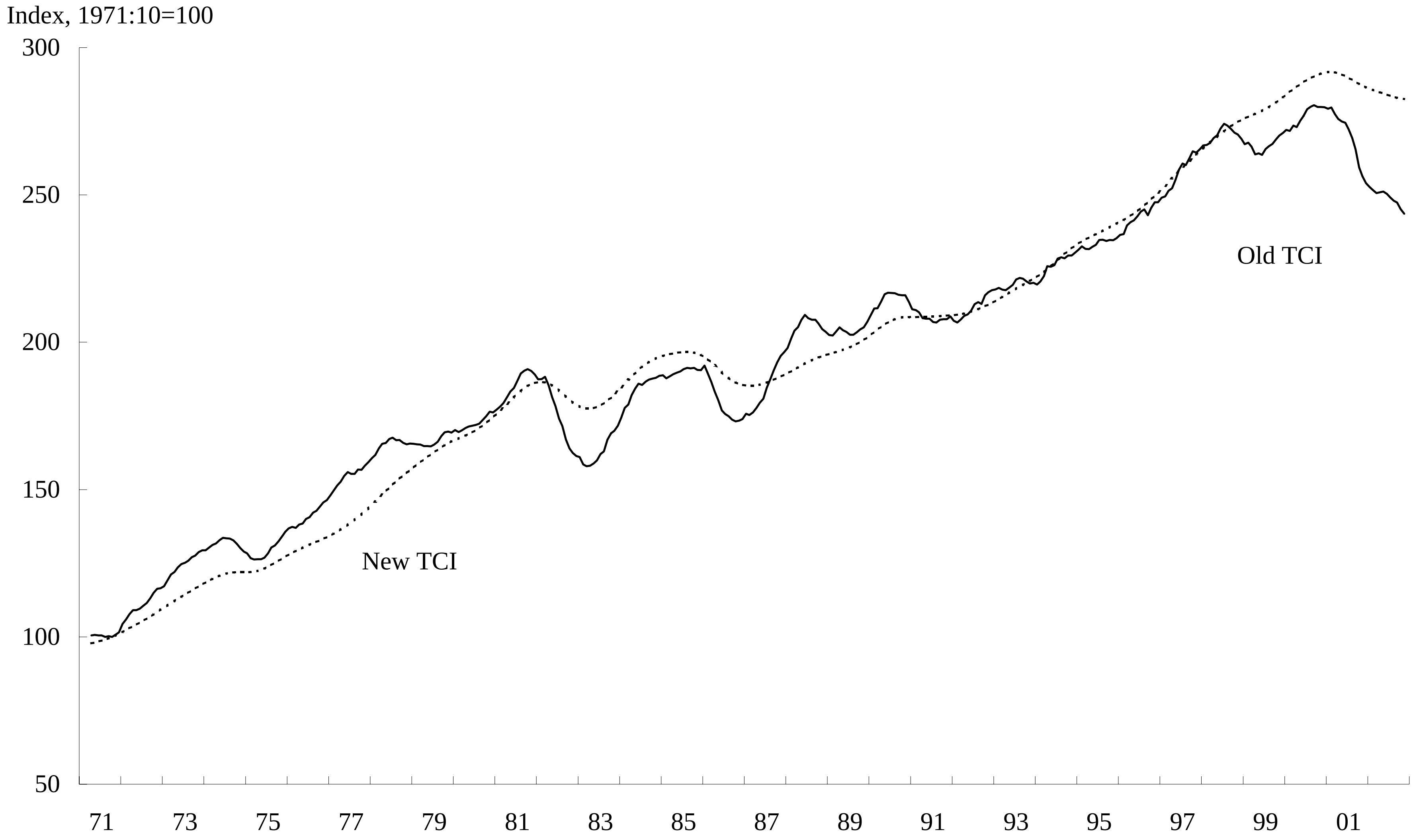
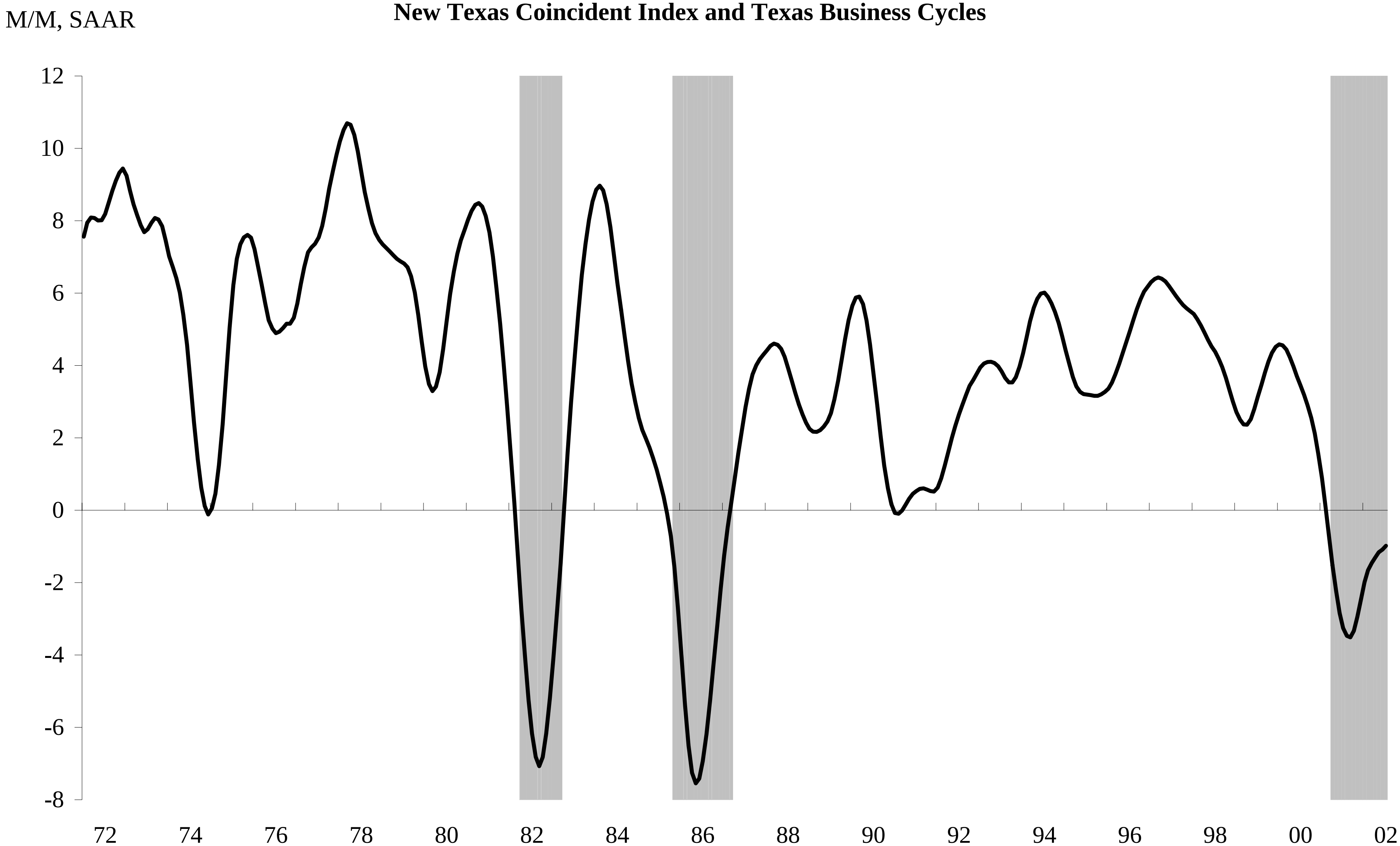
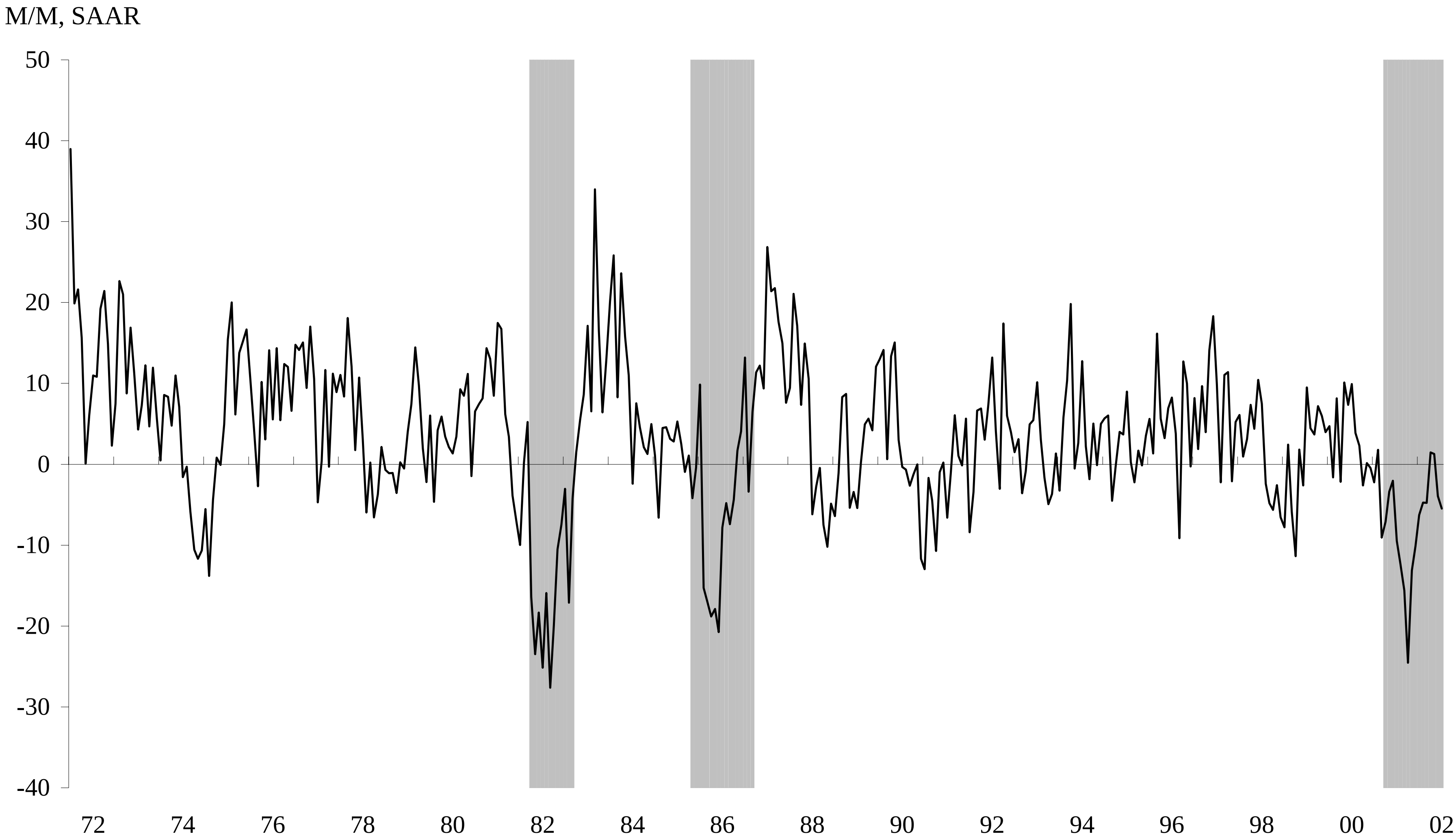


Chart 4
New Texas Coincident Index and Texas Business Cycles



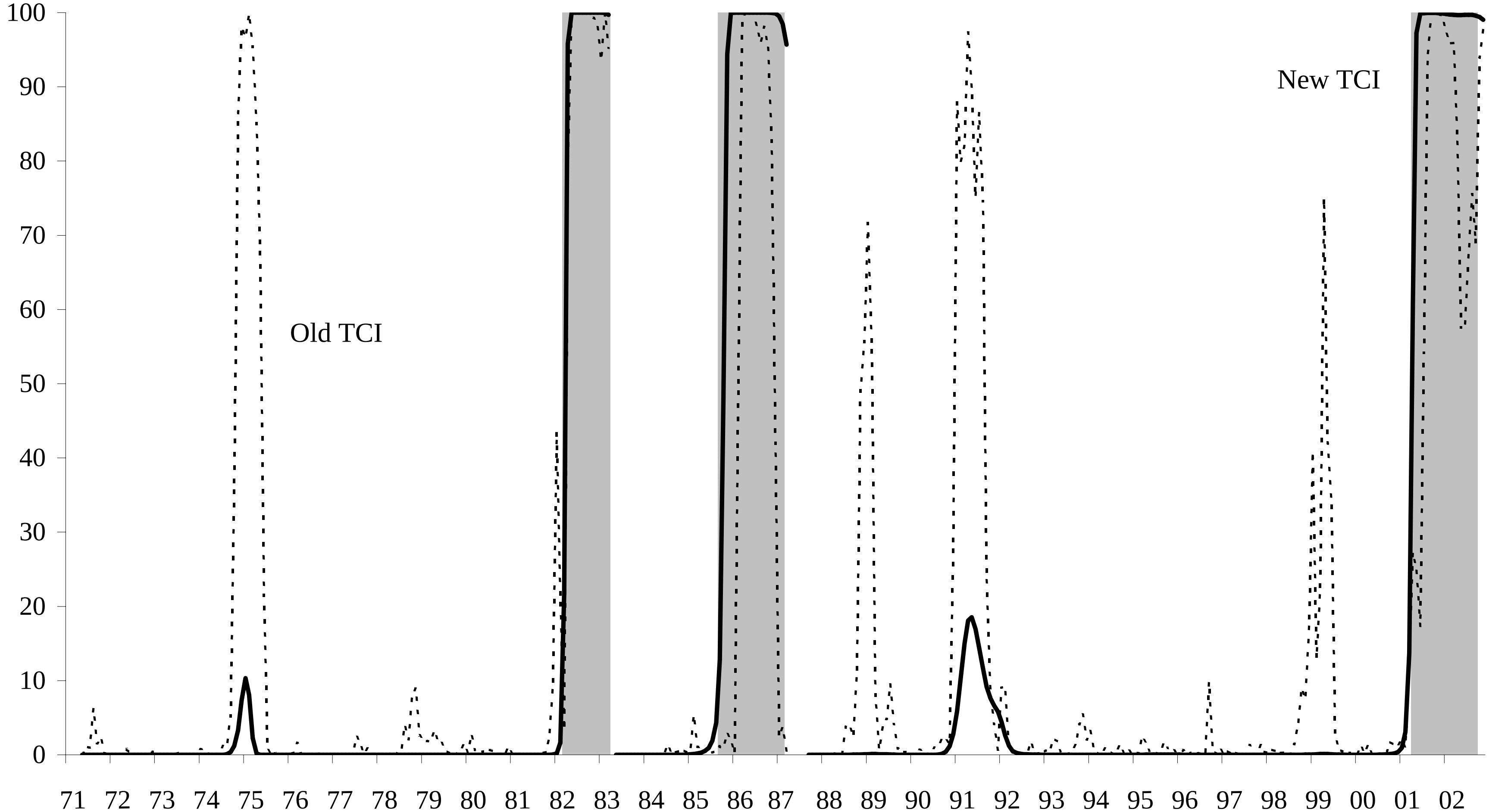
NOTE: Shaded areas represent Texas recession as defined by Yucel and Thompson.

Chart 5
Old Texas Coincident Index



NOTE: Shaded areas represent Texas recession as defined by Yucel and Thompson.

Chart 6
Probability of Recession, New TCI and Old TCI



NOTE: Shaded areas represent Texas recession as defined by Yucel and Thompson.

Chart 7
Limited Data Show Both Indexes Signal Expansions

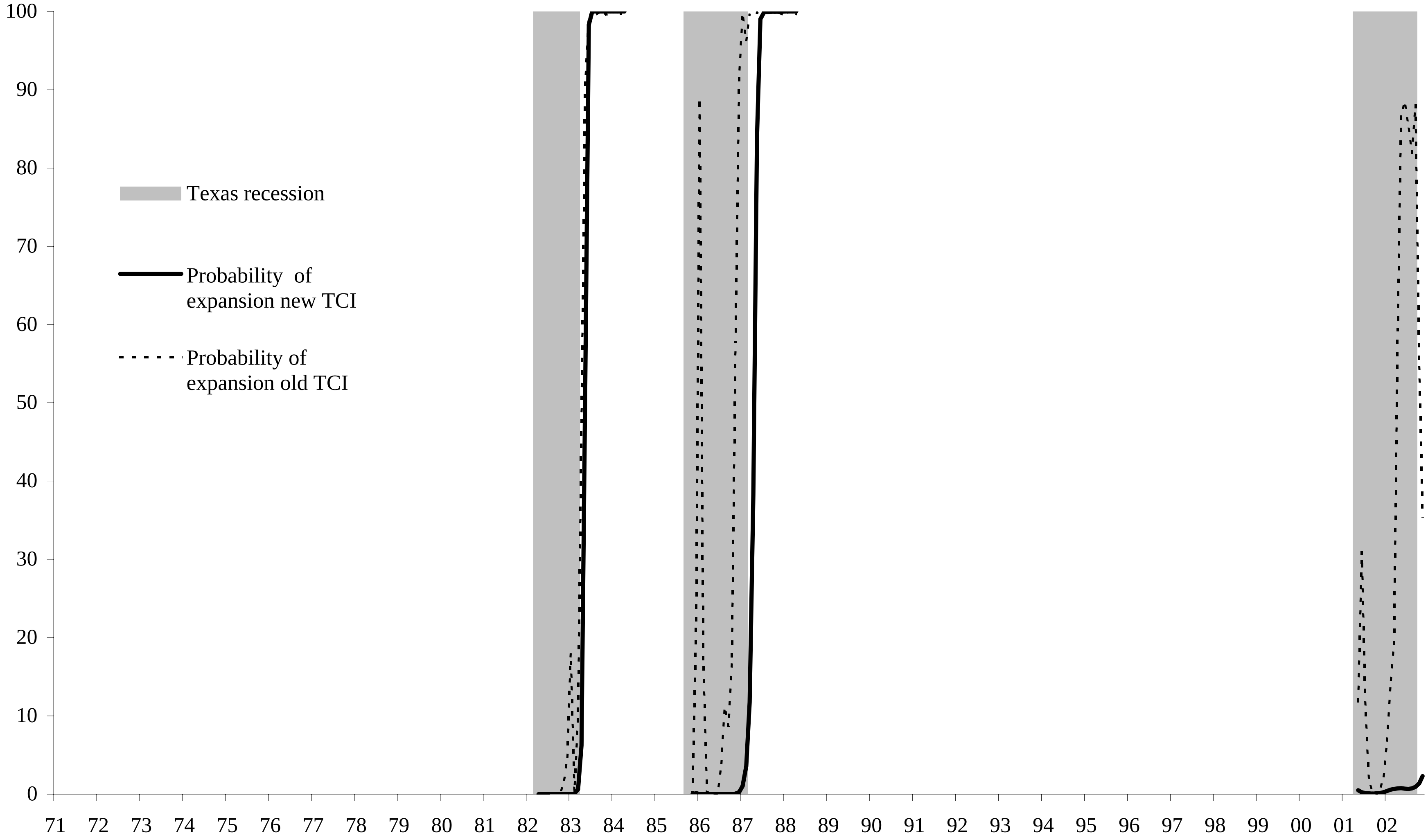


Table 1

Parameter Estimates and T-Statistics

April,1971-November, 2002

Model run Jan., 2003

	Coefficient	**T-stat**
bEMP	0.065	4.310
bGSP	0.006	3.920
bUN1	-0.145	-4.180
bUN2	0.125	3.905
arEMP1	-0.210	-3.091
arEMP2	-0.119	-1.838
arUN1	-0.242	-4.489
arUN2	-0.087	-1.621
sEMP	0.652	22.257
sGSP	0.790	15.273
sUN	0.913	26.328
coinindxar1	1.811	29.281
coinindxar2	-0.834	-14.015

Table 2

Whiteness Tests and the Cumulative Dynamic Multipliers

F-Statistics for 6-lag specification test

April,1971-November, 2002

Model Run January, 2003

	Dependent Variable		
Indep.Var. (lags 1-6)	*eEMP*	*eGSP*	*eUN*
eEMP	1.42	1.48	0.43
eGSP	0.85	0.48	1.48
eUN	1.23	2.23**	2.06*
EMP	1.20	0.97	0.20
GSP	0.68	0.21	1.31
UN	1.19	2.13*	1.97*

Multipliers

	Multiplier	*Share*
EMP	10.6	65.4
GSP	1.6	10.1
UN	-4.0	24.5

*,**,*** denotes jointly significant at the 10%, 5%, and 1% levels, respectively. Ho: Coefficients are jointly zero

Table 3
Whiteness Test for the Old Texas Coincident Index

F-Statistics for 6-lag specification test
January, 1967-November, 2002
Model Run January, 2003

	Dependent Variable	
Indep. Var. (lags 1-6)	*eEMP*	*eTIPI*
eEMP	0.49	0.50
eTIPI	0.50	0.49
EMP	5.16***	5.15***
TIPI	3.80***	3.81***

*,**,*** denotes jointly significant at the 10%, 5%, and 1% levels, respectively. Ho: Coefficients are jointly zero