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Forecasting and Analyzing Economic Activity with Coincident and Leading Indexes: The Case of Connecticut

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Abstract

We develop coincident and leading employment indexes for the Connecticut economy. Four employment-related variables enter the coincident index while five employment-related variables enter the leading index. The peaks and troughs in the leading index lead the peaks and troughs in the coincident index by an average of 3 and 9 months. Finally, we use the leading index in vector-autoregressive (VAR) and Bayesian vector-autoregressive (BVAR) models to forecast the coincident index, nonfarm employment, and the unemployment rate.

Keywords: coincident index; leading index; VAR and BVAR forecasts

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1. Introduction

Policymakers and economic analysts track the aggregate movement in the economy, that is, the business cycle. Most of this activity traces its roots to the work of Mitchell and Burns (1938) and their many followers. Forecasting the business cycle provides important information, if accurately done. Of course, to forecast the business cycle means that a clear definition of the business cycle exists. Gross domestic product (GDP) represents the most aggregate measure of economic activity. But GDP possesses a number of drawbacks. GDP numbers only appear quarterly and with some reporting lags. But even if available monthly, it would probably be inaccurate to chart the business cycle by this one variable alone, since some aspects of the aggregate economy may not be adequately represented in GDP. An alternative is to construct an index of variables, using more frequently available and timely data series, that move contemporaneously with the business cycle, typically referred to as a coincident index.

The United States Department of Commerce publishes a monthly index of coincident economic indicators that tracks the business cycle. This index includes measures of output, employment, income, and sales. The Department of Commerce also publishes a monthly index of leading economic indicators that attempts to forecast the business cycle. This index of leading economic indicators provides valuable information for forecasting the business cycle, either as measured by the index of coincident economic indicators or as articulated by the National Bureau of Economic Research.

Analysts frequently want to track not only national but also state and regional economic activity. As long as state and regional activity move closely with national activity, the national indicators can provide reasonable information about state and regional economic fortunes. The performance of state and regional economies, however, became much more diffuse in the United States during the 1980s, with different states and regions having dramatically different experiences with economic performance. As such, national coincident and leading economic indicators provided less-useful information for forecasting economic performance at the state and regional level. This problem stimulated interest in developing state and regional coincident and leading indexes of economic activity[i]

Knowledge about the local business cycle can provide critical information for policymakers and for many businesses. The construction industry, for example, responds quickly to changes in the local business cycle. In addition, sales of numerous items, such as cars and homes, depend on the local economic climate. Regional indexes can also inform foreign and domestic companies about potential regional markets. Further, the regional coincident index helps to date state business cycles. This is an important function, since official dates for state business cycles do not exist.

Charting the business cycle at the level of a state or region presents the analyst with a number of additional problems. The availability of data severely limits the set of useful variables when compared to the national level. Moreover, the timeliness of many data series become a serious issue. These problems frequently cause the researcher to limit the scope of analysis to coincident and leading employment indexes. We follow this path as well.

We present the first attempt to chart recent Connecticut employment cycles with newly constructed Connecticut coincident and leading employment indexes.[ii] The

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[i] Phillips (1994) examines and discusses the methods and issues involved in the construction of regional indexes of leading economic indicators. Moreover, he provides an extensive list of existing leading indicators at the state and regional level.

[ii] Our analysis explores "classical cycles," rather than "growth cycles." A classical cycle measures the ups and downs of the economy with absolute levels of those variables entering the indexes. A growth cycle, on the other hand, traces the ups and downs through deviations of the actual growth rate of the economy from its long-run trend rate of growth.

development of these indexes was assisted by Dr. Geoffrey H. Moore, Director of the Center for International Business Cycle Research (CIBCR) at Columbia University, and his staff.[iii] The CIBCR has participated in the development of many such indexes around the world. We use the leading employment index to forecast the coincident employment index, nonfarm employment, and the unemployment rate in Connecticut, using univariate and multivariate techniques. We find that significant differences exist in the ability to accurately forecast the coincident employment index and nonfarm employment during various phases of the most recent recession; fewer problems arise in the forecast of the unemployment rate. These findings we attribute to the unusual character of this most recent recession, especially with respect to the movement of employment. That is, the most recent recovery has sometimes been called the jobless recovery.

2. Method for Constructing Coincident and Leading Indexes

Coincident indexes include a number of economic series that collectively represent the current state of the economy. Each series in a coincident index contains some information about the turning points in the business cycle. Since series do not all show the same turning points, a coincident index provides a collective call on the business cycle. This averaging process produces better information about cyclical turning points than any one of the individual series in the index can generate on their own.

Leading indexes provide valuable information about the future path of the economy, combining information from several economic series and collectively forecasting future movements in the economy. As with coincident indexes, each series provides some information but it is unlikely that the individual series will show identical turning points.

In other words, an expansion (contraction) means growth higher (lower) than the long-run trend rate of growth. As a result, all classical cycles associate with growth cycles, but not all growth cycles associate with classical cycles. Interest in growth cycles emerged during the 1960s when some economists pronounced the death of business cycles (Bronfenbrener 1969). The experience since the early 1970s has resurrected the classical business cycle.

[iii] Cullity (1993) and Klein (1993) provide recent commentary on the life's work of Geoffrey H. Moore and the CIBCR.

The combined information in leading indexes produces better predictions about future turning points.

The construction of the Connecticut coincident and leading employment indexes follows well-developed procedures used by the Department of Commerce and described in U.S. Department of Commerce (1977, 1984) and in Niemira and Klein (1994). These procedures adopt methods developed by National Bureau of Economic Research researchers Geoffrey H. Moore and Julius Shiskin in the 1950s.

The method proceeds as follows. We begin by constructing the coincident index. We then determine the turning points of the coincident index. Using these turning points, the coincident index sets the employment cycle dates in Connecticut. The dating of the employment cycle in Connecticut then facilitates the construction of the leading index. That is, given the employment cycle provided by the coincident index, we select series for inclusion in the leading index based on the leads in their turning points relative to the turning points in the coincident index. After identifying the components of the leading index, we construct the leading index.

Construction of Composite Indexes

The following discussion provides a step-by-step outline of the construction of the coincident and leading employment indexes for Connecticut. This discussion assumes that the components for the indexes have already been chosen. We merely outline the construction of the indexes in this sub-section.

Step 1 computes for each component series the monthly *symmetrical* percentage changes. Shiskin (1961) originally suggested symmetric treatment to ensure that positive and negative changes receive the same weight in the index. For level series, the difference in the monthly levels is divided by the average of the two monthly levels and multiplied by 100 to generate a percentage. More precisely, monthly symmetrical percentage changes (c_{it}) are calculated as follows:

(1) $$c_{it} = 200(X_{it} - X_{it-1}) / (X_{it} + X_{it-1}).$$

where X_{it} is the data for month t of component i. If a component is expressed in percentage, rather than level form, then monthly symmetrical percentage changes are calculated as follows:

(2) $c_{it} = X_{it} - X_{it-1}$.

Step 2 prevents more volatile components from dominating the index. The symmetrical percentage changes calculated in step 1 are divided by the long-run average of their absolute values so that the average of their absolute values equals one. The standardized monthly symmetric percentage changes (s_{it}) are calculated as follows:

(3) $s_{it} = c_{it} / A_i$,

where $A_i = \sum_{t=2}^{N} |c_{it}| / (N-1)$, and N is the number of months in the standardization period. The A's change only when the composite index is revised.

Step 3 averages the standardized monthly symmetrical percentage changes with equal weights across all components in the index. The process of scaling the percentage changes to prevent more volatile series from dominating the index implicitly provides a weighting scheme in the index. The average of the standardized components (r_t) is calculated as follows:

(4) $r_t = \sum_{i=1}^{M} s_{it} / M$,

where M is the number of components in the index.

Step 4 involves the calculation of the "raw" index with value 100 for the initial month. The series r_t measures the monthly symmetrical percentages change in the index. Thus, we can employ equation (1), where r_t replaces c_{it} and I_t, the index, replaces X_{it}. As a result, we have the following relationship:

(5) $r_t = 200(I_t - I_{t-1}) / (I_t + I_{t-1})$.

Solving for I_t as a function of I_{t-1} and r_t gives the up-dating formula for the index as follows:

(6) $I_t = I_{t-1}[(200 + r_t) / (200 - r_t)]$.

Shiskin (1967) proposed the reverse trend adjustment method to reduce false signals in coincident and leading indexes. Step 5 calculates the trend adjustment factor. To do so, a target variable is chosen, such as GDP for an overall index, or nonfarm employment for an employment index. The trend growth rate is calculated between the initial and terminal peaks of the target series. The trend in the "raw" series is subtracted from the trend in the target series to produce the trend adjustment factor.

Steps 6 to 8 complete the construction process. Step 6 adds the trend adjustment factor calculated in step 5 to the average of the standardized components (r_t) calculated in Step 3. Step 7 involves the calculation of the trend adjusted index by cumulating the average of the standardized components. Finally, step 8 computes the final index by dividing the index produced in step 7 by its average value in the base year.

Dating Employment Cycles

The Connecticut coincident employment index determines dates of employment cycle turning points. In this regard, we note the difference between specific and reference cycle analysis. Specific cycle analysis evaluates the chronology of movements in a variable or an index using the peaks and troughs identified for that variable or index. Reference cycle analysis examines the chronology of movements in a variable or an index using the chronology of movements in some other variable or index as a reference. As such, we develop the Connecticut coincident employment index in the context of specific cycle analysis. The turning points of the Connecticut coincident index then date the Connecticut cycles and serve as a reference cycle for the Connecticut leading employment index.

Turning point choice includes mechanical procedures supplemented by rules of thumb and experienced judgment. The initial selection of turning points employs a computer program (the Bry and Boschan turning-point program) based on the procedures and rules developed at the National Bureau of Economic Research (see Bry and Boschan 1971). Three rules of thumb are applied to the computer generated turning points: (1) at least six months of opposite movement must occur to qualify as a turning point; (2) peaks (troughs) must be at least fifteen months apart; and (3) when cycles are indicated, the highest and lowest points in the index are selected as peaks and troughs. (If the data are flat at the turning point, then the most recent month in the flat region is selected as the turning point.) These rules of thumb trace their roots to Burns and Mitchell (1946) and continue to be applied by the CIBCR. Finally, turning points must pass muster through the experienced judgment of the researcher. Turning points can be rejected because of special one-time events that produce spikes in the data, indicating turning points. Experienced judgment excludes exogenous shocks that are not cyclical in nature. See Bry and Boschan (1971) and Boehm and Moore (1984) for more details concerning the process of selecting turning points

3. Connecticut Coincident and Leading Employment Indexes

The possible data series in Connecticut available to construct coincident and leading indexes proved to be limited. In fact, our indexes must because of these data limitations reflect employment conditions only. Moreover, historical data exist only since 1969, which restricts our indexes to begin at that date. While employment conditions are closely related to aggregate economic activity, they are, however, not identical. For example, in the last recession, the NBER business cycle dates for the nation are a peak in July 1990 and a trough in March 1991 for a duration of 10 months while the national employment cycle dates based on the coincident employment index constructed by the CIBCR are a peak in June 1990 and a trough in December 1991 for a longer duration of 18 months.

Connecticut Coincident Employment Index

A useful coincident index must contain information that is promptly accessible and needs little later revision. This requirement focuses our attention on monthly data that are available with a short time lag.

A coincident index at the national level can include measures of income, sales, production, and employment. At the state level, however, such a broad array of monthly information is not available in a timely fashion. After considering the available data and performing preliminary turning-point analyses, we decided to limit our Connecticut coincident index to focus on employment variables only.[iv] The Connecticut coincident employment index is a composite indicator of four individual employment-related series -- the total unemployment rate (inverted), nonfarm employment, total employment, and the insured unemployment rate (inverted). Total employment and the unemployment rate are based on a survey of about 600 Connecticut households. The insured unemployment rate, on the other hand, comes from the data on unemployment insurance claims filed with the state. Finally, nonfarm employment is based on the survey of employers by the state. We return to the different sources of data when we discuss our results in the conclusion. All data are seasonally adjusted and come from the Federal Reserve Bank of Boston's electronic data base and from the Connecticut Labor Department.

Coincident and leading employment indexes were first constructed at the national level (see Moore 1981, 1985) and have also been considered at the state level (see Conger 1981, and Loeb 1983). The CIBCR produces coincident and leading employment indexes for the national economy. The coincident employment index contains five components -- nonfarm employees on payroll (nonfarm employment), total employment, the total unemployment rate (inverted), the insured unemployment rate (inverted), and nonfarm

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[iv] When examining possible variables for inclusion in the coincident index, we considered real personal income, electricity sales, retail sales, a manufacturing output index, and gross state product. Real personal income, which equals Connecticut nominal income divided by the U.S. consumer price index, has a 6-month publication lag and is only available on a quarterly basis. Timeliness of data availability eliminated this variable. Electricity sales, which included commercial, industrial, and residential components, proved to be highly erratic, even after computing moving average representations. Moreover, it did not pick up cycles. Retail sales data have only been available since 1987. In addition, the reliability of this series is questionable, since the sample size used by the Bureau of the Census of the Department of Commerce leads to a small sample in Connecticut, a small state. The Connecticut Labor Department computes a manufacturing output index. Sources at the Labor Department cautioned us about the reliability of this data series. Finally, gross state product appears only as annual data with at least a two year lag.

hours. As seen above, we replicate this set of variables except for nonfarm hours in the Connecticut coincident employment index.[v]

Figures 1 and 2 plot the Connecticut coincident employment index from 1969 to December 1994. Turning points are determined using the method described in Section 2 and are denoted by asterisks. As frames of reference, the charts contain the national business cycle recessions as shaded areas in Figure 1 and the national employment cycle in Figure 2. With the exception of the latest employment recession, the coincident index closely tracks the national business-cycle and employment recessions. The early 1970s employment recession in Connecticut began with a peak in December 1969 and ran until the trough in October 1971. The mid-1970s recession had a peak in May 1974 and a trough in November 1975. In these two recessions, the recovery in Connecticut lagged behind the national recovery by several months. The early 1980s recession in Connecticut overlaps the two national recessions with a peak in February 1980 and a trough in January 1983.

The extended recession of the late 1980s and early 1990s provides an unusual episode. The coincident index indicates that the employment cycle entered recession in March 1988 and bottomed out in June 1992. This recession far exceeds the length of the national business cycle recession, a finding that will not surprise serious observers of the Connecticut economy. The index also seems by visual inspection to be bouncing along the bottom and not recovering. Moreover, it is somewhat surprising that the downturn started earlier and the bottom occurred earlier than the conventional wisdom now holds. While one is tempted not to call the turning point, we do so for two reasons. One, several individual components of the coincident index indicate a turn. And two, the leading index began moving up in May 1991. We discuss the individual components of the coincident index next and discuss the leading index below.

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[v] Total nonfarm hours is the product of average weekly nonfarm hours and total nonfarm employment. We could only get data on average weekly hours in manufacturing, and construction.

Focusing on individual components, the insured unemployment rate turned in January 1992 while the unemployment rate series turned in February 1992, both preceding the June 1992 turn in the coincident index. The nonfarm employment turned in December 1992, but this series continued to bump along at the bottom of the trough through December 1994. Finally, total employment had not turned till the end of 1993. A turn since then may be difficult to identify due to data revisions from January 1994 forward. In sum, the coincident index signals a trough in June 1992, but the call is not yet a strong one. We report the turn largely because of the information contained in our leading index (see below).

Connecticut Leading Employment Index

Since our coincident index is based on employment information, so is our leading index. The leading employment index constructed by the CIBCR at the national level includes six components -- the average work week of manufacturing production workers, the short-duration (less than 15 weeks) unemployment rate (inverted), the initial claims for unemployment insurance (inverted), overtime hours in manufacturing, the layoff rate (inverted), and the ratio of voluntary to involuntary part-time employment. These variables are chosen because their movements lead the movements in the employment cycle as measured by the coincident employment index.

We could only get the first three of these six variables for Connecticut; overtime hours in manufacturing, the layoff rate, and the ratio of voluntary to involuntary part-time employment are not available. We add two additional variables to the three we have to construct the Connecticut leading employment index, a composite index of five individual employment-related series -- the average workweek of manufacturing production workers, short-duration (less than 15 weeks) unemployment rate (inverted), initial claims for unemployment insurance (inverted), Hartford help-wanted advertising, and total housing permits. While not an employment-sector variable, housing permits are closely related to construction employment.[vi]

Each of these variables has some intuitive appeal. The average workweek is one of the first employment variables that manufacturing firms adjust, by changing overtime hours or part-time work, in response to an up-turn or a slowing in the economy. Changes in the numbers employed generally occur a few months later, since such changes are more costly and less easily reversed. The initial claims for unemployment insurance is one of the first steps taken by someone who loses his/her job. So, this variable quickly reflects job market changes. The short-duration unemployment rate measures changes in those unemployed for 15 weeks or less. This variable also quickly reflects changes in the job market. The help-wanted index provides some prediction about future jobs.[vii] Finally, housing permits captures the intention to build in the near future, which is closely related to construction employment.

Figure 3 plots the leading index from 1969 to December 1994. The chart contains the Connecticut employment cycle recessions, as determined by the coincident index, as shaded areas. Our data series does not go back far enough to identify a peak in the leading index in the late 1960s. The leading index does show cyclical peaks in September 1973, leading by 8 months the peak in the coincident index; in December 1979, leading by 2 months; and in March 1988, leading by 0 months.[viii] The leading index shows cyclical

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[vi] When examining possible variables for inclusion in the leading index, we considered new business incorporations. Data on new business incorporations, however, have a 6-month publication lag, making it unsuitable for our purposes.

[vii] We also used the New England help-wanted advertising index. It performed about as well as, if not slightly better than, the Hartford variable. We do not have the luxury of a Connecticut help-wanted advertising index. We decided to adopt the Hartford index as it is not subject to spurious movements outside Connecticut. At the same time, it may not always capture the full flavor of the Connecticut help-wanted advertising information.

[viii] The leading index also reaches a peak in October 1987 followed by monthly declines in November and December 1987 and January 1988. It turns up in February and March 1988 before turning down once again. The program identifies the turning point (peak) in March

troughs in November 1970, leading by 11 months the trough in the coincident index; in April 1975, leading by 7 months; in September 1982, leading by 4 months; and in May 1991, leading by 13 months. Thus, leads at peaks and troughs average 3 and 9 months, respectively. Table 1 reports the leads of the index and its components

As noted above, one reason for calling a cyclical trough in June 1992 in the coincident index was the information contained in the leading index, which itself shows a trough in May 1991 thus predicting an upturn. What contributions do the individual components to the leading index provide for this result? All five components of the leading index possess turning points that lead the June 1992 trough in the coincident index. More specifically, the average workweek of manufacturing production workers troughed in May 1991, leading by 13 months the trough in the coincident index; Hartford help-wanted advertising troughed in December 1991, leading by 6 months; the short-duration unemployment rate troughed in April 1991, leading by 14 months; initial claims for unemployment insurance troughed in August 1991, leading by 10 months; and total housing permits troughed in January 1991, leading by 17 months. In sum, the leading index possesses a strong signal that the Connecticut economy is in recovery. This conclusion, however, needs qualification, since the coincident index, although having turned in June 1992, still suggests that this recovery is not yet robust as of December 1994.

Table 1 also reports extra cycles identified by the turning point program. For example, the turning points identified in the average workweek in manufacturing, the short duration unemployment rate, and initial claims for unemployment insurance in 1984 and 1985 link closely with the structural shift out of manufacturing that began to occur in 1984. The turning points suggested in 1980 and 1981 associate with the national business cycle of the time that possessed two mini-recessions and a short recovery. We do not see this pattern in our coincident index and thus have identified these signals as extra turning

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1988. The peak may, in fact, have occurred earlier in October 1987, 5 months ahead of the peak in the coincident index.

points. Finally, the blizzard of 1978 that effectively closed the state for several days probably explains the troughs in the initial claims for unemployment insurance and housing permits authorized in February 1978.

4. Using the Leading Index to Forecast Economic Activity

The leading employment index typically moves in advance of the coincident index and its components. Thus, it can predict turning points in economic activity. Simple rules include looking for a 2- or 3-month reversal in the direction of movement of the index. More sophisticated analysis combines such simple reversals with a threshold criterion that specifies upper and lower bounds on the monthly growth rate in the index. Monthly movements within such a band do not signal reversals from the previous turning point. That is, the movements in the index must break out of the band to signal a reversal. Even more sophisticated analysis specifies rules for observing sequential signals in the leading and coincident indexes as described in Zarnowitz and Moore (1982) and Moore (1990).

We pursue a different path in this paper. Rather than calling turning points, we employ our leading index to forecast the level of and some of the components in the coincident index. We develop two multivariate forecasting models that include the leading and coincident employment indexes, nonfarm employment, and the unemployment rate. These models are estimated for three initial sample periods using monthly data from 1970 to 1984, 1970 to 1987, and 1970 to 1990. Out-of-sample recursive forecasts are generated by continuous updating and reestimation and are evaluated for three corresponding subperiods -- 1985 to 1987, 1988 to 1990, and 1991 to 1993.

More specifically, we estimate three models -- univariate models for each variable, a 4-variable unrestricted vector autoregressive model (VAR), and a 4-variable Bayesian VAR (BVAR). The univariate models provide a benchmark against which we can judge the performance of the VAR and BVAR models. BVAR models generally dominate unrestricted VAR models (i.e., Sims 1980) because such models generally suffer from overparameterization, producing fewer degrees of freedom and multicollinearity.

Consequently, inefficient estimates and large out-of-sample forecasting errors emerge. This problem frequently causes researchers to eliminate lags or insignificant variables based on statistical tests.

Rather than eliminating longer lags or insignificant variables and forcing their coefficients to zero, the BVAR approach imposes restrictions that these coefficients approach zero, but do not vanish.[ix] If these coefficients possess strong effects, the data can override this specification. We assume normal prior distributions with zero means, except for the mean of the first own lag, which is set to unity, and small standard deviations that decrease with lag length for the model coefficients.

The standard deviation of the prior distribution for lag m of variable j in equation i for all i, j, and m -- S(i, j, m) -- is specified as follows:

$$S(i, j, m) = \{w g(m) f(i, j)\} s_i / s_j;$$

$$f(i, j) = 1, \quad \text{if } i = j;$$
$$= k \quad \text{otherwise } (0 < k < 1);$$
$$g(m) = m^{-d}, \ d > 0.$$

The term s_i is the standard error of a univariate autoregression for variable i. The ratio s_i / s_j scales the variables to account for differences in units of measurement and allows the specification of the prior without consideration of the magnitudes of the variables. The parameter w is the standard deviation on the first own lag and describes the overall tightness of the prior. The tightness on lag m relative to lag 1 is given by the function g(m), assumed to have a harmonic shape with decay factor d. The tightness of variable j relative to variable i in equation i is represented by the function f(i, j). In the BVAR model reported here, the overall tightness (w) and the harmonic lag decay (d) are set at 0.2 and 2,

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[ix] For example, see Litterman (1981), Todd (1984), Doan, Litterman and Sims (1984), Litterman (1986), and Spencer (1993).

respectively. A symmetric interaction function -- f(i, j) -- is assumed with k = 0.5.[x] The lag-length in each model is 12 and the variables are specified in levels. This allows comparisons between the three models. In the Bayesian approach, variables can be specified in levels rather than in differences, since it depends entirely on the likelihood function, which has the same shape regardless of the presence of nonstationarity (Sims et al. 1990). Furthermore, Sims et al. (1990) note that, "Bayesian inference need take no special account of nonstationarity." (p. 136)[xi]

We measure the out-of-sample forecast accuracy with four different measures -- root mean squared errors (RMSE), Theil U-statistics, mean errors (ME), and mean absolute errors (MAE) for 1- through 6-month-ahead forecasts. If A_{t+n} denotes the actual value of a variable in period (t+n), and ${}_tF_{t+n}$ the forecast made in period t for (t+n), then for T observations the RMSE, Theil U-statistic, ME, and MAE are defined as follows:

$$RMSE = [\Sigma(A_{t+n} - {}_tF_{t+n})^2 / T]^{0.5};$$

$$U = [\Sigma(A_{t+n} - {}_tF_{t+n})^2 / \Sigma(A_{t+n} - A_t)^2]^{0.5};$$

$$ME = \Sigma(A_{t+n} - {}_tF_{t+n}) / T;$$

and

$$MAE = \Sigma|(A_{t+n} - {}_tF_{t+n})| / T.$$

The RMSE depends on the units of measurement (e.g., the RMSE for nonfarm employment in measured in thousands while the RMSE of the unemployment rate is in percent). As a result, comparisons of forecast accuracy cannot be made across variables. The U-statistic is unit free and easier to use. The U-statistic measures the ratio of the root mean square error

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[x] Doan (1990) recommends 0.1 or 0.2 for the overall tightness prior and 1 or 2 for the harmonic lag decay parameter; we choose 0.2 and 2, since these generally yield the most accurate out-of-sample forecasts. Similarly, k = 0.5 generally yields the most accurate forecasts.

[xi] See also Sims (1988) for a discussion on Bayesian skepticism on unit-root econometrics.

(RMSE) of the model forecasts to the RMSE of naive, no-change forecasts. The U-statistic, therefore, implicitly compares forecasts to the naive model. When the U-statistic equals 1, then the model's forecasts match, on average, the naive, no-change forecasts. A U-statistic greater than 1 indicates that the naive forecasts out perform the model forecasts. A U-statistic less than 1 demonstrates that the model's forecasts out perform the naive forecasts. A value much less than one, however, does not necessarily mean that the forecasts are accurate, since this result may only reflect extremely inaccurate no-change forecasts. This issue becomes especially applicable for series with trend.

The ME and MAE, like the RMSE, depend on the units of measurement but are reported because together they help to determine whether the model consistently forecasts too high or too low. If the mean error matches the magnitude of the mean absolute error and is positive (negative), then the model consistently underestimates (overestimates) the variables.

We generate the four accuracy statistics using the Kalman filter algorithm in RATS.[xii] We estimate the models for the initial period 1970:1 to 1984:12 and forecast up to 6-months-ahead. We then add one more observation to the sample, reestimate the models, and again forecast up to 6-months-ahead. This process continues forward until the 6-month-ahead forecast hits the end of our first out-of-sample forecast period in 1987:12. Based on the out-of-sample forecasts, we compute the RMSEs, Theil U-statistics, MEs, and MAEs for the 1- through 6-month-ahead forecasts. Next, we reestimate the models for the expanded period 1970:1 to 1987:12 and forecast, using the same procedure, through the second out-of-sample forecast period from 1988:1 to 1990:12. We compute RMSEs, Theil U-statistics, MEs, and MAEs for the 1- and 6-month-ahead forecasts. Finally, we again reestimate the models for the period 1970:1 to 1990:12 and forecast, using the same procedure, through the third out-of-sample forecast period from 1991:1 to 1993:12.

[xii] All statistical analysis was performed using RATS, version 3.1.

This out-of-sample forecasting strategy allows careful consideration of forecast performance over the last business cycle in Connecticut. That is, we first examine the final three years of the expansion in the late 1980s just prior to the last recession. The second three year period largely captures the slide into recession where the peak was dated in March 1988. The final three year period captures the latter stages of the recession, including the initial phase of recovery with the trough dated in June 1992.

Tables 2, 3, and 4 report the out-of-sample accuracy statistics for the coincident index, nonfarm employment, and the unemployment rate, respectively. Several general observations emerge. The RMSEs and MAEs generally increase with an increase in the forecast horizon, showing the deterioration in accuracy. In some cases, the Theil U-statistics improve with an increase in forecast horizon, which may occur because of inaccurate naive forecasts at longer horizons.

The multivariate models produce more accurate forecasts than the univariate models for the first two subperiods, implying that useful information exists in other variables. Moreover, the BVAR forecasts also generally outperform the VAR forecasts in the first two subperiods. These finding confirm those of Dua and Miller (1995), Dua and Ray (1995) and Dua and Smyth (1995).

Additional observations are variable specific. For the coincident index, the RMSEs and MAEs are the lowest in the first subperiod and the highest in the last subperiod for the VAR and BVAR models, which is expected since the last two subperiods include turning points. In addition, the BVAR forecasts are marginally more accurate than the VAR forecasts in the first two subperiods. The multivariate models both produce forecasts that are less accurate than the univariate models in the last subperiod. This finding may reflect the fact that the coincident index remains flat after the last trough. Moreover, the MEs and MAEs for this third subperiod indicate that all three models -- multivariate and univariate -- consistently overpredict the index especially at longer horizons.

The RMSEs, MAEs, and Theil U-statistics for the VAR and BVAR models of nonfarm employment, on average, indicate that the first two subperiods have the most accurate forecasts while the third subperiod has the least accurate forecasts. In addition, the BVAR forecasts outperform the VAR forecasts in the first subperiod. Univariate forecasts of nonfarm employment outperform the multivariate forecasts in the third subperiod, probably, once again, because nonfarm employment remains flat after the most recent turning point. Finally, the MEs and MAEs indicate that all three models consistently overpredict nonfarm employment at the longer horizons in the middle subperiod. Moreover, the multivariate models overpredict nonfarm employment in the third subperiod while the univariate model does not.

The VAR and BVAR models more accurately forecast unemployment than the univariate models in the first two subperiods. In addition, the BVAR model marginally outperforms the univariate model in the third subperiod. These findings may reflect the fact that the unemployment rate variation has been larger than nonfarm employment and the coincident index since the most recent turning point. The MEs and MAEs do not signal consistent underestimation in any of the three subperiods. Nonetheless, forecasts are, on average, worst in the last subperiod and best in the second subperiod.

Overall, the multivariate models perform reasonably well for the three variables during the first two subperiods; the last subperiod results are less encouraging.

5. Conclusion

We report on the construction of coincident and leading employment indexes for the Connecticut economy. These new pieces of information provide valuable information to followers of the Connecticut economy, including policymakers. The coincident index measures the ups and downs of the employment cycle in the Connecticut economy and provides a reference cycle to monitor recession and recovery. The leading index provides a forecast of future movements in the coincident index and its component parts (e.g., the unemployment rate and nonfarm employment).

We provide a series of three out-of-sample forecasting tests of three different time series models -- one univariate and two multivariate models. The three subperiods capture the final stages of the boom in Connecticut from 1985 to 1987, the downturn into the recession from 1988 to 1990, and the bottoming of the recession and the slow recovery from 1991 to 1993. The multivariate models work reasonably well in the first two subperiods, but not in the third. The univariate models generally work better in the third subperiod.

What does this mean? Much discussion has occurred, especially concerning the Connecticut (and New England) economy, about the jobless recovery in the early 1990s. The consistent overprediction of the coincident index and nonfarm employment provides support for this view. That is, previous recoveries experienced much sharper rebounds in employment than we have seen in the early 1990s.

Structural changes may be influencing the accuracy of our measures of employment. Nonfarm employment is based on a survey of state employers that includes major employers and some small firms. It does not capture start-up firms, except with a lag, and the self-employed. Corporate downsizing, the termination of service units and the rehiring of similar services on a consulting basis, and the growth of home-office workers and independent contractors suggest that official statistics may underreport actual nonfarm employment. The unemployment rate (and total employment), on the other hand, is based on a survey of about 600 Connecticut households. This survey captures start-up firms and the self-employed. The sample size, however, makes the series subject to higher variation. Whether such differences in measurement can in fact explain our findings go well beyond the goal of this paper. Rather we note strong evidence of a major structural shift that makes our multivariate forecasting models for the coincident index and nonfarm employment less accurate than univariate models.

These speculations are supported to some extent by our findings for forecasting the unemployment rate. That is, the BVAR model provides marginally better unemployment rate forecasts than the univariate model in the third subperiod where the forecasting of the coincident index and nonfarm employment is best accomplished with univariate models.

Another explanation of our findings begins with the assumption that the measurement of employment is accurate. If so, then the deterioration of the forecasting ability of the multivariate models suggests that structural change within the Connecticut economy has been dramatic enough to render forecasting models based on historic data obsolete. In other words, the new structure of the economy cannot be adequately captured by the old structure.

Table 2
Out-of-Sample Forecasts of the Coincident Index

Month-Ahead	N	Univariate Model	VAR Model	BVAR Model
		RMSE U ME MAE	**RMSE U ME MAE**	**RMSE U ME MAE**
		1985.01-1987.12	***1985.01-1987.12***	***1985.01-1987.12***
1	36	0.669 0.998	0.634 0.945 -	0.590 0.880 -
2	35	0.182 0.518	0.122 0.521	0.041 0.473
3	34	1.039 0.994	0.918 0.878 -	0.822 0.786 -
4	33	0.415 0.823	0.206 0.735	0.045 0.643
5	32	1.407 1.004	1.116 0.797 -	1.023 0.730
6	31	0.748 1.177	0.199 0.809	0.023 0.821
		1.735 0.996	1.303 0.749 -	1.192 0.685
Averag		1.056 1.437	0.230 0.921	0.060 0.929
e		2.130 1.011	1.478 0.701 -	1.357 0.644
		1.449 1.744	0.141 1.040	0.195 1.129
		2.611 1.045	1.710 0.684	1.533 0.614
		1.923 2.145	0.030 1.321	0.410 1.268
		1.599 1.008	**1.193 0.792 -**	**1.086 0.723**
		0.962 1.307	**0.145 0.891**	**0.100 0.877**
		1988.01-1990.12	***1988.01-1990.12***	***1988.01-1990.12***
1	36	0.614 0.830 -	0.624 0.844 -	0.553 0.747 -
		0.203 0.503	0.986 0.481	0.150 0.432
2		0.940 0.753 -	0.919 0.737 -	0.797 0.639 -
3	35	0.432 0.729	0.234 0.741	0.336 0.600
		1.182 0.690 -	1.159 0.677 -	0.997 0.583 -
	34	0.738 0.915	0.496 0.918	0.604 0.738
4	33	1.529 0.703 -	1.411 0.649 -	1.260 0.579 -
		1.045 1.120	0.753 1.138	0.877 1.046
5	32	1.883 0.714 -	1.677 0.636 -	1.528 0.579 -
		1.361 1.508	1.027 1.359	1.173 1.285
6	31	2.222 0.720 -	1.954 0.633 -	1.772 0.574 -
		1.699 1.857	1.360 1.638	1.506 1.544

Average		**1.395**	**0.735**	**-0.913**	**1.105**	**1.291**	**0.696**	**-0.809**	**1.046**	**1.151**	**0.617**	**-0.774**	**0.941**
		1991.01-1993.12				***1991.01-1993.12***				***1991.01-1993.12***			
1	36	0.612	0.829	-0.248	0.442	0.806	1.091	-0.486	0.657	0.769	1.041	-0.566	0.622
2	35	1.082	0.821	-0.537	0.803	1.474	1.119	-0.997	1.224	1.499	1.138	-1.214	1.275
3	34	1.494	0.836	-0.870	1.129	2.146	1.201	-1.569	1.842	2.276	1.274	-1.948	1.951
4	33	1.939	0.866	-1.319	1.409	2.913	1.300	-2.285	2.527	3.159	1.410	-2.821	2.821
5	32	2.483	0.917	-1.843	1.879	3.715	1.373	-3.045	3.204	4.161	1.537	-3.813	3.813
6	31	3.092	0.978	-2.395	2.412	4.544	1.438	-3.828	3.919	5.240	1.658	-4.875	4.875
Average		**1.784**	**0.875**	**-1.202**	**1.346**	**2.600**	**1.254**	**-2.035**	**2.229**	**2.851**	**1.343**	**-2.540**	**2.560**

Note: N is the number of observations. RMSE is the root-mean-square-error. U is the Theil U-statistic. ME is the mean error. MAE is the mean absolute error.

Table 3
Out-of-Sample Forecasts of Nonfarm Employment

Month-Ahead	N	Univariate Model RMSE	U	ME	MAE	VAR Model RMSE	U	ME	MAE	BVAR Model RMSE	U	ME	MAE
		1985.01-1987.12				***1985.01-1987.12***				***1985.01-1987.12***			
1	36	5.563	0.951	0.263	4.177	5.331	0.911	-1.655	4.248	4.844	0.828	-0.868	3.666
2	35	7.980	0.892	0.541	6.191	7.278	0.814	-2.888	5.975	6.260	0.700	-1.536	4.919
3	34	9.715	0.808	1.085	7.561	8.717	0.725	-4.042	6.779	7.230	0.601	-1.987	5.742
4	33	10.010	0.696	1.029	7.213	9.183	0.639	-5.111	7.234	7.119	0.495	-2.653	5.631
5	32	10.634	0.615	1.282	8.790	9.481	0.548	-5.802	7.641	7.329	0.424	-2.836	5.625
6	31	11.302	0.552	1.923	9.699	9.577	0.468	-5.745	8.156	7.240	0.354	-2.571	6.142
Average		**9.201**	**0.752**	**1.021**	**7.272**	**8.261**	**0.684**	**-4.207**	**6.672**	**6.670**	**0.567**	**-2.075**	**5.288**
		1988.01-1990.12				***1988.01-1990.12***				***1988.01-1990.12***			
1	36	5.118	0.969	-1.786	3.730	5.102	0.966	-2.036	3.667	4.670	0.884	-2.282	3.348
2	35	7.775	0.898	-3.772	5.903	7.701	0.889	-4.071	5.622	7.177	0.829	-4.654	5.548
3	34	10.065	0.870	-6.518	8.079	10.278	0.888	-7.007	8.005	9.672	0.836	-7.591	7.852
4	33	12.699	0.892	-9.173	10.345	12.384	0.869	-9.707	10.287	12.272	0.862	-10.537	10.648
5	32	15.664	0.915	-12.013	13.461	15.329	0.895	-12.699	13.129	15.102	0.882	-13.475	13.576
6	31	18.672	0.939	-15.089	16.132	18.634	0.937	-16.237	16.237	17.957	0.903	-16.649	16.649

Average		**11.666 0.914 -** **8.059 9.608**	**11.571 0.907 -** **8.626 9.491**	**11.142 0.866 -** **9.198 9.604**
		1991.01-1993.12	***1991.01-1993.12***	***1991.01-1993.12***
1	36	4.381 0.914 - 0.275 3.040	5.099 1.064 - 2.397 3.934	4.928 1.028 - 2.849 3.909
2	35	6.859 0.865 - 0.464 5.112	8.444 1.065 - 4.847 6.901	8.457 1.066 - 5.761 7.147
3	34	8.328 0.832 - 0.542 6.649	11.296 1.128 - 7.178 9.497	11.689 1.168 - 8.915 9.667
4	33	9.378 0.783 - 0.921 7.239	14.440 1.206 - 9.989 12.143	15.357 1.283 - 12.630 12.922
5	32	10.002 0.719 - 1.604 6.851	17.686 1.271 - 13.050 14.433	19.514 1.402 - 16.911 16.911
6	31	10.619 0.675 - 2.210 6.610	20.750 1.318 - 15.897 16.895	23.872 1.517 - 21.407 21.407
Average		**8.261 0.798 -** **1.003 5.917**	**12.953 1.175 -** **8.893 10.634**	**13.970 1.244 -** **11.412 11.994**

Table 4
Out-of-Sample Forecasts of the Unemployment Rate

Month-Ahead	N	Univariate Model RMSE	U	ME	MAE	VAR Model RMSE	U	ME	MAE	BVAR Model RMSE	U	ME	MAE
		1985.01-1987.12				***1985.01-1987.12***				***1985.01-1987.12***			
1	36	0.121	1.014	-0.058	0.090	0.134	1.124	-0.039	0.110	0.114	0.955	-0.033	0.089
2	35	0.189	1.033	-0.121	0.144	0.187	1.021	-0.064	0.150	0.166	0.906	-0.067	0.129
3	34	0.250	1.062	-0.186	0.195	0.234	0.993	-0.099	0.171	0.208	0.884	-0.107	0.145
4	33	0.323	1.071	-0.249	0.254	0.290	0.963	-0.116	0.216	0.264	0.874	-0.138	0.194
5	32	0.404	1.114	-0.327	0.330	0.338	0.931	-0.149	0.235	0.315	0.869	-0.182	0.222
6	31	0.503	1.164	-0.418	0.418	0.398	0.920	-0.194	0.271	0.379	0.877	-0.238	0.270
Average		**0.298**	**1.076**	**-0.227**	**0.239**	**0.264**	**0.992**	**-0.110**	**0.192**	**0.241**	**0.894**	**-0.128**	**0.175**
		1988.01-1990.12				***1988.01-1990.12***				***1988.01-1990.12***			
1	36	0.095	0.806	0.033	0.075	0.103	0.877	-0.003	0.076	0.079	0.670	-0.018	0.056
2	35	0.153	0.736	0.067	0.120	0.164	0.788	0.003	0.131	0.115	0.552	-0.024	0.089
3	34	0.211	0.701	0.108	0.171	0.211	0.700	0.032	0.164	0.145	0.481	-0.015	0.111
4	33	0.265	0.677	0.148	0.220	0.252	0.642	0.066	0.209	0.165	0.420	-0.004	0.135
5	32	0.316	0.657	0.194	0.266	0.282	0.585	0.095	0.238	0.180	0.374	0.014	0.148
6	31	0.368	0.644	0.239	0.306	0.313	0.547	0.121	0.268	0.193	0.337	0.037	0.161

Average		**0.235**	**0.704**	**0.221**	**0.690**	**0.146**	**0.472** -
		0.132	**0.193**	**0.052**	**0.181**	**0.002**	**0.117**
		1991.01-1993.12		***1991.01-1993.12***		***1991.01-1993.12***	
1	36	0.205	0.977	0.214	1.017	0.193	0.917
		0.064	0.145	0.060	0.162	0.039	0.142
2	35	0.329	0.966	0.348	1.023	0.309	0.908
		0.123	0.223	0.135	0.241	0.090	0.209
3	34	0.429	0.974	0.455	1.032	0.405	0.919
		0.178	0.308	0.201	0.314	0.146	0.279
4	33	0.534	0.992	0.562	1.045	0.500	0.930
		0.248	0.392	0.296	0.387	0.224	0.347
5	32	0.647	1.021	0.683	1.079	0.602	0.950
		0.332	0.495	0.412	0.493	0.322	0.426
6	31	0.779	1.055	0.822	1.113	0.722	0.978
		0.427	0.626	0.538	0.632	0.435	0.542
Average		**0.487**	**0.998**	**0.514**	**1.052**	**0.455**	**0.934**
		0.229	**0.365**	**0.274**	**0.372**	**0.209**	**0.324**

Table 1
Leads (-) and Lags(+) of Leading Indicators in Months at Employment Cycle Turns

Connecticut Employment Cycle Chronology **P** **T**	**Leading Employment Index** **P** **T**	**Average Workweek, Manufacturing** **P** **T**	**Short Duration Unemployment Rate (inverted)** **P** **T**	**Initial Claims - Unemployment Insurance (inverted)** **P** **T**	**Help Wa Index, Hartfor** **P** **T**
12/69 **10/71**	-11	-6	-11	-1	0
5/74 **11/75**	-8 - 7	-13 -6	-12 -7	-14 -6	-10 +1
2/80 **1/83**	-2 -4	-13 +1	-8 -3	-11 -4	-5 -4
3/88 **6/92**	0 -13	-2 -13	-5 -14	-5 -10	-12 -6
Mean Lead **Median Lead** **Standard Dev.**	-3 -9 -2 -9 4 4	-9 -6 -13 -6 6 6	-8 -9 -8 -9 4 5	-10 -5 -11 -5 5 4	-9 -2 -10 -2 4 3
Extra Cycles	6/80 7/81	2/76 9/76 4/84 7/86 10/91	8/80 7/81 12/85 6/86 2/93	1/77 2/78 6/80 5/81 9/84 10/85	

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