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**Performance Evaluation of the New Connecticut Leading Employment Index Using Lead Profiles and BVAR Models**

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## **Abstract**

Dua and Miller (1996) created leading and coincident employment indexes for the state of Connecticut, following Moore's (1981) work at the national level. The performance of the Dua-Miller indexes following the recession of the early 1990s fell short of expectations. This paper performs two tasks. First, it describes the process of revising the Connecticut Coincident and Leading Employment Indexes. Second, it analyzes the statistical properties and performance of the new indexes by comparing the lead profiles of the new and old indexes as well as their out-of-sample forecasting performance, using the Bayesian Vector Autoregressive (BVAR) method. The new indexes show improved performance in dating employment cycle chronologies. The lead profile test demonstrates that superiority in a rigorous, non-parametric statistic fashion. The mixed evidence on the BVAR forecasting experiments illustrates the truth in the Granger and Newbold (1986) caution that leading indexes properly predict cycle turning points and do not necessarily provide accurate forecasts except at turning points, a view that our results support.

**Journal of Economic Literature Classification:** C11, C43, C53, E32, E37

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# Performance Evaluation of the New Connecticut Leading Employment Index Using Lead Profiles and BVAR Models

## 1. Introduction

The original composite indexes of leading and coincident indicators for the U.S. economy, created more than three decades ago (Moore and Shiskin, 1967), were designed to move ahead of and in step with, respectively, the U.S. business cycle. In essence, they were meant to track cycles in aggregate economic activity. Moore (1981), who pioneered this work, recognized that employment has a cycle that is distinct from the business cycle. The creation of separate leading and coincident indexes of employment for the U.S. economy, analogous to the leading and coincident indexes for aggregate economic activity, provided the logical solution.

Past research showed that the employment cycle for an individual state or region differs from the national employment cycle (Guha and Banerji, 1998/1999). For this reason, it made sense to create separate leading and coincident employment indexes for various states, for which a fair variety of employment-related time series exist. Thus, Dua and Miller (1996) created leading and coincident employment indexes for the state of Connecticut, following Moore's work at the national level.

The performance of the Dua-Miller indexes following the recession of the early 1990s fell short of expectations. The leading employment index rose for more than four years before the coincident employment index followed suit, making for a lead that proved too long to be useful. The Economic Cycle Research Institute (ECRI), founded by Geoffrey Moore, was entrusted with the task of revamping the indexes in 2000.<sup>1</sup>

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<sup>1</sup> The Connecticut Center for Economic Analysis (CCEA) at the University of Connecticut, the Connecticut Department of Labor, and the Connecticut Department of Economic and Community Development funded the additional work with ECRI. The CCEA maintains the CCEA-ECRI Connecticut Coincident and Leading Employment Indexes. The monthly reports appear in the *Connecticut Economic Digest*, published by the Connecticut Department of Labor and the Connecticut Department of Economic and Community Development.

This paper performs two tasks. First, it describes the process of revising the Connecticut Coincident and Leading Employment Indexes (old indexes) into the CCEA-ECRI Connecticut Coincident and Leading Employment Indexes (new indexes). Second, it analyzes the statistical properties and performance of the new indexes by comparing the lead profiles of the new and old indexes as well as their out-of-sample forecasting performance, using the Bayesian Vector Autoregressive (BVAR) method.

Several conclusions emerge. First, the new coincident index shows improved performance in dating employment cycle chronologies. Second, the lead profile test demonstrates the superiority of the new leading index in a rigorous, non-parametric statistic fashion. Our out-of-sample BVAR forecasting experiments, however, produce mixed results. The mixed evidence on the BVAR forecasting experiments illustrates the truth in the Granger and Newbold (1986) warning that leading indexes properly predict cycle turning points and do not necessarily provide accurate forecasts of the cycle except near such turning points.

The paper unfolds as follows. Section 2 describes the process of construction of the new indexes and cyclical chronologies. In addition, this section performs non-parametric tests, generating lead profiles for the new leading index and comparing the lead profiles for the new and old leading indexes. Section 3 considers the BVAR forecasting experiment as an alternative to lead profiles. Section 4 concludes.

## **2. New Index Construction**

As noted above, the old indexes performed poorly during and after the recession in the early 1990s. These old indexes were constructed using the traditional Moore-Shiskin procedure, as described by the U. S. Department of Commerce (1977, 1984), which includes a final trend-

adjustment step to make the indexes match a specified trend. In fact, Dua and Miller consistently used the not-trend-adjusted indexes in their monthly analyses of the Connecticut economy.

### *Determining the Targets*

The first issue is whether the problem was with the leading index, or the coincident index, or both. In order to assess this, we need to first determine the appropriate benchmark, or target that answers the question of what the leading index is designed to predict.

The concept of co-movements provides the key to economic cycles. As Burns and Mitchell (1946) note in their classic definition, “a cycle consists of expansions occurring *at about the same time* in many economic activities, followed by similarly general recessions...” Specifically, the date of any cyclical peak chosen for our reference chronology, or benchmark, should use the dates when the peaks of several relevant coincident indicators cluster. The indicators should also reach a trough together, “at about the same time,” and the consensus of this cluster of dates should determine any trough date chosen for our reference chronology. This follows the traditional National Bureau of Economic Research (NBER) cyclical dating procedure that Geoffrey Moore helped establish.

Another reason to rely on several series and not just one is that “virtually all economic statistics are subject to error, and hence are often revised. Use of several measures necessitates an effort to determine what is the consensus among them, but it avoids some of the arbitrariness of deciding upon a single measure that perforce could be used only for a limited time with results that would be subject to revision every time the measure was revised” (Moore, 1982).

The determination of the consensus among the coincident indicator series relies on objective measurement tempered by experienced judgment. Thus, the Bry-Boschan procedure (Bry and Boschan, 1971), which is an objective algorithmic formulation of the classical NBER

procedure for picking cyclical turns, first determines the cyclical peaks and troughs of each coincident series. These coincident employment indicators (used in both the old and new coincident indexes) include total employment, total non-farm employment, total unemployment rate, and the insured unemployment rate.

Because the Burns and Mitchell (1946) definition of the cycle calls for expansions (and contractions) occurring “at about the same time,” the only turns that qualify for consideration must reflect a majority of the series, including, in particular, the coincident index. The clustering process involves finding the mode and median of the dates of each peak and trough, and then (subjectively) picking a date that matches both as closely as possible. Any potential pick receives close examination to determine whether each component series lies at least close to a local high or low on that date. In case of uncertainty, the turning points of the coincident index determine the best choice. The end result of this process becomes the final Connecticut employment cycle chronology (last column, Table A1). As Figure 1 shows clearly, cyclical turns in the coincident indicators included in the new coincident employment index conform well to this chronology.<sup>2</sup> Note that the procedure closely adheres to the method used to determine the official U.S. business cycle chronology.

Actual peaks and troughs in the employment cycle appear infrequently, because the average length of the cycle equals about seven years. But the leading indicator approach also suits the prediction of peaks and troughs in the *growth rate* of economic activity or employment (Layton and Moore, 1989). The growth rate of economic activity for most countries or sectors behaves in a cyclical manner, with the growth rates of the coincident indicators reaching peaks and troughs “at about the same time.” Moreover, peaks and troughs in the growth rates of the

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<sup>2</sup> These turning points are listed in Table A1, along with the corresponding cyclical turns in the composite coincident index made up of the same indicators.

corresponding leading indicators also lead the peaks and troughs in the growth rate of economic activity. Thus, a “growth rate cycle” defines an additional benchmark against which one can measure the performance of a leading index in growth rate terms. Therefore, the Connecticut *employment growth rate cycle* (Table A2, last column) emerged from the “clustering” procedure in the same way the employment cycle did, except that all series are now expressed in smoothed growth rate terms (Banerji, 1999). This growth rate cycle experiences an average duration of about four years. As Figure 2 shows, the growth rates of the four coincident indicators included in the new coincident index conform well to this chronology.

#### *Coincident Index: Diagnosing Discrepancies*

An examination of the old coincident index constructed by Dua and Miller, and its components, shows a notable discrepancy. Of the four components, three reach a cyclical trough in 1992, while one (total employment) rises slightly in 1992, but does not reach a trough until 1996 (Figure 1 and Table A1). In fact, the cyclical trough in the old coincident index does not occur until 1996, while the cyclical trough in the new coincident index occurs in 1992 (Table A1).

Why do the two indexes differ so much? Since the components do not change, the explanation must lie in the composite index construction procedure. The old coincident index uses the well-established Moore-Shiskin procedure, as described by the U. S. Department of Commerce (1977, 1984). The new coincident index, however, uses the method now in use at the Economic Cycle Research Institute (ECRI), which incorporates important changes to the Department of Commerce (DC) procedure, in line with the composite index procedure suggested by Boschan and Banerji (1990).

The issue of amplitude standardization (i.e., standardizing a cyclical indicator in terms of its own cyclical amplitude) proves central to composite index construction. Amplitude

standardization prevents the movements of the more cyclically volatile components from overwhelming the movements of the component series with shallower cycles, and determines the implicit weights imparted to the components.

In the DC method, the standardization factor (SF) calculates the average of the absolute month-to-month percent change in the component series. Standardization divides the month-to-month symmetric percent change in each series by this standardization factor. Such a standardization factor, however, necessarily reflects not only the cyclical component of the movement, but also the size of the trend, as well as the irregular component or noise. Therefore, in the DC method, if the cyclical components possess equal amplitude, the standardization factor necessarily equals a lower value for a lower-trend series or a smoother series.

Total employment appears slightly smoother in Figure 1 than the other three components, and may possess a relatively lower standardization factor in the DC method, and thus a higher effective weight, than it would otherwise have received. To that extent, its 1996 trough may exhibit too much influence on the timing of the old coincident index 1996 trough, as compared to the other three series, all of which trough in 1992. In the ECRI procedure, in contrast, the standardization factor equals the standard deviation of the smoothed, detrended series, and thus reflects only the cyclical component, unaffected by the size of the irregular component.

A more fundamental issue still exists in index construction that may have proved the decisive factor -- the DC method of trend adjustment procedure. In the DC method, the raw index, calculated by averaging the standardized components, experiences a trend growth rate different from the target trend growth rate between the initial and terminal peaks of a target series, say, nonfarm employment. The trend in the raw index gets subtracted from the trend in the target series to produce the trend-adjustment factor, which then gets added back to the

monthly growth rate of the raw index. This trend-adjusted index then cumulates and gets rebased to obtain the final index.

If a negative trend-adjustment factor affects a slightly positive monthly growth rates in the raw index (which occurred during the “jobless recovery” of the early 1990s), then the resultant monthly trend becomes slightly negative. In such a case, the cumulated final index possesses a downward drift, even if the raw index drifted up from a trough. The trough in such a final index would shift to a significantly later date than in the raw index. In this case, the trough in the raw old coincident index occurred in June 1992, but in the final old coincident index, obtained after trend adjustment, that trough shifted to January 1996. Thus, the old coincident index conforms fairly well to the new employment cycle chronology, except at that trough. The old coincident index growth rate conforms well, in any case, with the new employment growth rate chronology.

Finally, Dua and Miller (1996), in fact, chose the Connecticut employment cycle chronology on the basis of the turning points of the old coincident index without trend adjustment, as selected by the Bry-Boschan procedure. They realized that some problem existed with the trend-adjusted series, since three of the components troughed in 1992.

The solution followed the more traditional, and more robust, “clustering” procedure used for the new coincident index. It explicitly incorporates the consensus among the individual series, rather than emphasizing the coincident index alone. Therefore, our chronologies should exhibit less sensitivity to future data revisions or to the vagaries of any composite index construction procedure.

### *The Leading Employment Index*

Having revamped the coincident index and the old employment cycle chronology, we now turn our attention to the leading index. The components of the old leading index include the average weekly hours in manufacturing, the help wanted advertising index, the short-duration unemployment rate (inverted), the initial claims for unemployment insurance (inverted), and total housing permits. In the end, we replaced only one of the existing components, the average manufacturing workweek, with a close substitute, the average workweek for manufacturing and construction.

While the new workweek series does not differ substantially from the old one, it does, in fact, incorporate slightly broader coverage and proves slightly smoother as a result. Since data on the construction workweek starts only in 1982, it became more feasible to incorporate that data now than when Dua and Miller (1996) did their study. In effect, we spliced the manufacturing workweek series (from its start date to 1981) with the manufacturing and construction workweek series, which starts in 1982. The resultant spliced series entered as a leading index component. It exhibits a median lead of six months over the employment cycle (see Table A3 in the Appendix).<sup>3</sup>

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<sup>3</sup> We retained the other four leading indicator series without any change. Of these, the Hartford help wanted advertising index experiences a median lead of 2.5 months over the employment cycle (Table A4). The short duration unemployment rate exhibits a median lead of nine months over the employment cycle (Table A5). Initial claims for unemployment insurance displays a median lead of six months over the employment cycle (Table A6). Finally, total housing permits reveals a median lead of 14 months over the employment cycle (Table A7). We also added one new series to the mix – Moody’s BAA corporate bond yield. Interest rates, when used on an inverted basis, act as long leading indicators at the national level. In fact, Cullity and Moore (1990) used bond prices (the inverse of bond yields) as a component of their U.S. long leading index. Though not a state-level series, the rationale for using the same series as a leading indicator at the state level is just as strong as it is at the national level. More generally, national economic conditions certainly impinge upon the state outlook. This series evidences a median lead of 14 months over the employment cycle (Table A8). More generally, as Figures A1 and A2 show, all the leading series show good leads over the employment cycle. Also, as Figures A3 and A4 show, the growth rates of these series lead the employment growth rate cycles. We considered three other series for inclusion, but ultimately rejected them. The Dun and Bradstreet quarterly employment optimism index for New England begins in 1989, and does not exhibit a clear lead. We also examined the Dun and Bradstreet compilation of the number of business starts in the state, but this series starts only in 1996, and proves noisy. Finally, we explored a standard leading indicator,

As Figure 3 shows, the old leading index possesses short leads at most turns. In fact, as Table 1a reports, the old leading index experiences a median lead of six months. As Figure 4 shows, the growth rate of the old leading index possesses short leads over the employment growth rate cycle. Table 2a reports that the old leading index growth rate exhibits a median lead of two months.

In contrast, the new leading employment index shows a median lead of ten months over the employment cycle (Table 1b, Figure 5), while its growth rate displays a median lead of three months over the employment growth rate cycle (Table 2b, Figure 6). Thus, it provides an improvement over the old leading index.

The improvement in the leading index reflects, in part, its expanded list of components. The enhanced composite index procedure probably also contributes to that improvement. Cullity and Banerji (1996) show that the ECRI procedure empirically dominates both the Conference Board procedure (a variant of the DC method used by Dua and Miller) and the procedure used by the Organization for Economic Cooperation and Development (OECD).

#### *Lead Profiles: Testing for the Statistical Significance of Cyclical Leads*

Statistical evaluation of a leading index challenges the researcher. Granger and Newbold (1986) note that a leading index “is intended only to forecast the timing of turning points and not the size of the forthcoming downswing or upswing nor to be a general indicator of the economy at times other than near turning points. Because of this, evaluation of (a leading index) by standard statistical techniques is not easy.” (p. 295). In particular, the leading index covers a small number of cycles. Thus, evaluating its cyclical leads at turning points by parametric statistical methods

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the ratio of the help wanted advertising index to the number of unemployed, but it did not lead. Thus, the components of the new leading index include the average weekly hours in manufacturing and construction, the help wanted advertising index, the short-duration unemployment rate (inverted), the initial claims for unemployment insurance (inverted), total housing permits, and Moody’s BAA corporate bond yields (inverted).

proves difficult. Assuming heroically that the probability distribution of the leads exhibits a standard functional form also precludes the use of parametric tests of statistical significance. The solution uses a non-standard statistical technique – a series of non-parametric statistical tests that yield the lead profile (Banerji, 2000).

Since the leads in question differ in timing at cyclical turns (e.g., between a pair of indicators), the appropriate nonparametric tests apply matched pairs of samples. The Randomization test (Fisher, 1935) for matched pairs provides the most appropriate test to assess the significance of leads within this class of problems. This test owns a power-efficiency of 100 percent, since it uses all information in the sample (Siegel, 1956).

The procedure that determines the lead profile follows several steps. First, calculate the difference in timing at turning points (i.e., leads of one indicator over another, or leads over the business cycle turning points). We test the null hypothesis that those do not differ significantly against the alternative hypothesis of significant leads. Some calculated differences may exceed, others may fall below, zero. If the null hypothesis is true, then positive differences should occur just as frequently as negative differences, and vice versa. So given  $N$  differences from  $N$  pairs of observations, each difference possesses a 50-50 chance that it is positive or negative. Thus, the observed set of differences constitutes just one of  $2^N$  equally probable outcomes under the null hypothesis. Also, under the null hypothesis, the sum of the positive differences should, on average, equal the sum of the negative differences. So, the expected sum of the positive and negative differences should equal zero. If the alternative hypothesis is true and the leads significantly exceed zero, then the sum should also exceed zero.

Second, sum the differences, assigning positive signs to each difference; then switch the signs systematically, one-by-one, to generate all outcomes that generate sums equal to or higher

than that observed. Given  $R$  such outcomes, then the probability of the observed (or more extreme) outcome under the null hypothesis equals  $(R/2^N)$ . In other words, we can reject the null hypothesis at the  $x$ -percent confidence level, where  $x = 100[1-(R/2^N)]$ .

So far, the discussion considers the confidence level such that we can reject the null hypothesis (“leads not significantly different from zero”) in favor of the alternative hypothesis (“leads significantly greater than zero months”). Now, we can also determine how much greater than zero months the leads prove significant (e.g., leads significantly greater than one, two, three, or more months). To accomplish that task, subtract one, two, three, or more months from each of the timing differences at turning points (already calculated in the first step of the Randomization test). Then, as before, find the confidence level such that we reject the null hypothesis in favor of the alternative hypothesis that the timing differences at turning points significantly exceed one, two, three, or more months. We call this full set of confidence levels a “lead profile”.

The lead profile concentrates on the magnitude of leads and tests whether the lead of one time series significantly exceeds that of another at turning points, which does precisely what a leading index should do, according to Granger and Newbold (1986). The lead profile appears graphically as a bar chart or “lead-profile chart”. Figure 7a shows the lead profile of the new leading index against the Connecticut employment cycle, based on the leads shown in Table 1b. The first bar represents a test of the null hypothesis that the new leading index’s lead equals zero months, against the alternative that it exceeds zero, i.e., at least one month. Analogously, the second bar represents another test, of the null hypothesis that the lead equals one month, against the alternative that it exceeds at least two months. As the figure shows, the confidence level remains above 95 percent (black bars) for up to seven months, and above 90 percent (gray hatched bars) for up to nine months.

Figure 7b shows the lead profile of the new leading index growth rate against the Connecticut employment growth rate cycle, based on the leads shown in Table 2b. In this case, the confidence level remains above 95 percent (black bar) for up to one month, but falls rapidly for longer leads.

This technique can also test whether the new leading index possesses significantly longer leads than the old version. Figure 7c shows the lead profile of the new leading index against the old leading employment index. In this case, the confidence level remains above 90 percent (gray hatched bars) for up to two months, but drops thereafter.

Figure 7d shows the lead profile of the new leading index growth rate against the old leading employment index growth rate. In this case, the confidence level never exceeds 57 percent, and therefore proves statistically insignificant (white bars).

Thus, we can conclude that the new leading index displays a statistically significant lead of seven to nine months, depending on the level of significance. Its growth rate, however, has a statistically significant lead of only a month over the employment growth rate cycle. Compared with the old version, the new leading index experiences a statistically significant lead of two months, but its growth rate does not possess a significant lead over the growth rate of the old version.

### **3. BVAR Forecasting: Review**

Having evaluated the leading indexes using a non-standard statistical technique, in line with Granger and Newbold's admonition, we now revert to more standard statistical techniques, designed to test the leading indexes using their complete histories, not just their performance near turning points. To evaluate the old and new Connecticut coincident and leading employment indexes, we perform out-of-sample forecasting tests on a system of four variables – nonfarm employment, the

total unemployment rate, the coincident employment index and the leading employment index.<sup>4</sup> We calculate forecasts using first the old indexes and then the new indexes.

Forecasting models often employ simultaneous equations structural models. Two problems exist with structural models, however. First, proper identification of individual equations in the system requires the correct number of excluded variables from an equation in the model. As argued by Cooley and LeRoy (1985), such exclusions often possess little theoretical justification. Second, structural models prove poorly suited for forecasting, since forecasts require projected future values of exogenous variables.

A vector autoregressive (VAR) model offers an alternative approach, particularly useful for forecasting purposes. Although the approach is "atheoretical," a VAR model approximates the reduced form of a structural system of simultaneous equations. As shown by Zellner (1979), and Zellner and Palm (1974), any linear structural model theoretically reduces to a VAR moving average (VARMA) model, whose coefficients combine the structural coefficients. Under some conditions, a VARMA model reduces to a VAR model or a VMA model. A VAR model can also approximate the reduced form of a simultaneous structural model. Thus, a VAR model does not totally differ from a large-scale structural model. Rather given the correct restrictions on the parameters of the VAR model, they reflect mirror images of each other. Those observations loom as especially important for regional modeling, since data limitations prohibit the use of large structural models.

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<sup>4</sup> Dua and Miller (1996) examine the forecasting performance of the old Connecticut leading employment index in vector autoregressive (VAR) and Bayesian VAR models to forecast the coincident employment index, non-farm employment, and the total unemployment rate. The Bayesian VAR model provided marginally better forecasts. The next section compares the forecast performance of the new leading index using only the Bayesian VAR model.

The VAR technique uses regularities in the historical data on the forecasted variables. Economic theory only selects the economic variables to include in the model. We can write an unrestricted VAR model (Sims 1980) as follows:

$$y_t = C + A(L)y_t + e_t, \text{ where}$$

$$y = \text{an (nx1) vector of variables being forecast;}$$

$$A(L) = \text{an (nxn) polynomial matrix in the back-shift operator } L \\ \text{with lag length } p,$$

$$= A_1L + A_2L^2 + \dots + A_pL^p;$$

$$C = \text{an (nx1) vector of constant terms; and}$$

$$e = \text{an (nx1) vector of white noise error terms.}$$

The model uses the same lag length for all variables. One serious drawback exists -- overparameterization produces multicollinearity and loss of degrees of freedom that can lead to inefficient estimates and large out-of-sample forecasting errors. One solution excludes insignificant variables/lags based on statistical tests.

An alternative approach to overcome overparameterization uses a Bayesian VAR model as described in Litterman (1981), Doan, Litterman and Sims (1984), Todd (1984), Litterman (1986), and Spencer (1993). Instead of eliminating longer lags and/or less important variables, the Bayesian technique imposes coefficient restrictions on the assumption that some coefficients more likely equal zero than the coefficients on shorter lags and/or more important variables. If, however, strong effects do occur from longer lags and/or less important variables, the data can override this assumption. The restrictions specify normal prior distributions with means zero and small standard deviations for all coefficients with decreasing standard deviations on increasing lags, except for the

coefficient on the first own lag of a variable that is given a mean of unity. The Federal Reserve Bank of Minneapolis and the University of Minnesota developed this so called "Minnesota prior."

The standard deviation of the prior distribution for lag  $m$  of variable  $j$  in equation  $i$  for all  $i, j$ , and  $m$  --  $S(i, j, m)$  -- equals the following specification:

$$\begin{aligned} S(i, j, m) &= \{wg(m)f(i, j)\}s_i/s_j; \\ f(i, j) &= 1, \quad \text{if } i = j; \\ &= k \quad \text{otherwise } (0 < k < 1); \text{ and} \\ g(m) &= m^{-d}, d > 0. \end{aligned}$$

The term  $s_i$  equals 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  $w$  measures 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 equals the function  $g(m)$ , assumed to possess a harmonic shape with decay factor  $d$ . The tightness of variable  $j$  relative to variable  $i$  in equation  $i$  equals the function  $f(i, j)$ .

To illustrate, we use the specification of Model 1 below:  $w = 0.2$ ;  $d = 2.0$ ; and  $f(i, j) = 0.5$ .<sup>5</sup> When  $w = 0.2$ , the standard deviation of the first own lag in each equation equals 0.2, since  $g(1) = f(i, j) = s_i/s_j = 1.0$ . The standard deviation of all other lags equals  $0.2[s_i/s_j\{g(m)f(i, j)\}]$ . For  $m = 1, 2, 3, 4$ , and  $d = 2.0$ ,  $g(m) = 1.0, 0.25, 0.11, 0.06$ , respectively, showing the decreasing influence of longer lags. The value of  $f(i, j)$  determines the importance of variable  $j$  relative to variable  $i$  in the equation for variable  $i$ , higher values implying greater interaction. For instance,

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<sup>5</sup> Dua and Miller (1996) use those parameter values for the BVAR model that they use in their forecasting experiment. We adopt the same specification in our Model 1.

$f(i, j) = 0.5$  implies that relative to variable  $i$ , variable  $j$  has a weight of 50 percent. A tighter prior occurs by decreasing  $w$ , increasing  $d$ , and/or decreasing  $k$ .

The BVAR method uses Theil's (1971) mixed estimation technique that supplements data with prior information on the distributions of the coefficients. With each restriction, the number of observations and degrees of freedom artificially increase by one. Thus, the loss of degrees of freedom due to overparameterization does not affect the BVAR model as severely.

#### **4. BVAR Forecasting Experiment: Old Versus New Indexes**

As noted above, we follow Dua and Miller (1996) and adopt a simple four-variable BVAR system to compare the forecasting performance of the old and new Connecticut leading employment indexes. The BVAR system includes the coincident and leading indexes along with total non-farm employment and the total unemployment rate. The coincident index measures the employment cycle in Connecticut. In addition, it includes both non-farm employment and the total unemployment rate. Non-farm employment comes from the employer survey while the total unemployment rate comes from the household survey. That is, in addition to forecasting the coincident index, we also forecast one variable each from the employer and household surveys of employment.

As noted above, the new coincident index contains the same variables as the old index, but includes a new trend adjustment procedure implemented by ECRI. The new leading index, on the other hand, contains one new variable – Moody's BAA corporate bond yield – and a modification of an old series – the adding of the average workweek of construction workers to the average workweek of manufacturing production workers.

### *Alternative Forecasting Models*

We report the forecast performance of five slightly different multivariate BVAR models (Models 1 to 5). All models include the same four variables – the Connecticut coincident and leading employment indexes, non-farm employment, and the total unemployment rate. Model 1 adopts the same parameters for the BVAR model (i.e.,  $w = 0.2$ ,  $d = 2.0$ , and  $k = 0.5$ ) as employed in Dua and Miller (1996). Model 2 tightens the prior a bit, using  $d = 1.0$  rather than 2.0. Model 3 tightens the prior from Model 1, using  $w = 0.1$  rather than 0.2. Model 4 also tightens the prior from Model 1, using  $k = 0.4$  rather than 0.5. Finally, Model 5 loosens the prior a bit from Model 1, using  $k = 0.6$  rather than 0.5.

We specify the variables in levels rather than in differences because the Bayesian approach depends entirely on the likelihood function, which possesses the same shape regardless of the presence of non-stationarity (Sims et al. 1990). Furthermore, Sims et al. (1990) note that, "Bayesian inference need take no special account of non-stationarity." (p. 136).<sup>6</sup> The models include twelve lags of each variable. Thus, each model possesses 49 parameters, including the constant.

The out-of-sample forecast periods include the same three periods examined by Dua and Miller (1996) -- 1985-1987, 1988-1990, and 1991-1993 – plus the continuation of consecutive three-year periods through the 1990s – 1994-1996 and 1997-1999 – as well as one over-lapping three-year period – 1998-2000 – that takes us to the end of our sample.

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<sup>6</sup> See, also, Sims (1988) for a discussion on Bayesian skepticism on unit-root econometrics.

### *Forecast Accuracy*

We measure the out-of-sample forecast accuracy by the Theil U-statistic. 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 Theil U-statistic equals the following:

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

Thus, the U-statistic measures the ratio of the root mean square error (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 outperform the model forecasts. A U-statistic less than 1 demonstrates that the model's forecasts outperform the naive forecasts.

We generate the Theil U-statistics using the Kalman filter algorithm in RATS.<sup>7</sup> The forecasting method proceeds as follows. For example, take the forecasts of the 1985-1987 period. We estimate the model from 1970:1 to 1984:12 and then forecast six-months ahead (i.e., 1985:1 to 1985:6). We add one observation to the sample, which now becomes 1970:1 to 1985:1, re-estimate the model, and forecast six months ahead again. The process continues until we reach the end of the forecast period (i.e., 1987:12). Based on the out-of-sample forecasts, we compute the Theil U-statistics for 1- through 6-month-ahead forecasts. Finally, we report the average Theil U-statistics over the forecast horizon (i.e., 1985:1 to 1987:12).

We also identify the “optimal” Bayesian priors for the multivariate BVAR models by comparing the average Theil U-statistics for out-of-sample forecasts for all sample forecast

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<sup>7</sup> All statistical analysis was performed using RATS, version 4.31.

periods.<sup>8</sup> That is, we calculate the average of U-statistics for all forecast periods for a given BVAR specification. We change the parameters in the prior and generate a new set of U-statistics. We identify the combination of the parameters in the prior producing the lowest average U-statistic.

### *Out-of-Sample Forecasting Results*

Tables 3a, 3b, and 3c report the U-statistics for the Connecticut coincident employment index, Connecticut non-farm employment, and the Connecticut unemployment rate, respectively, for Models 1 to 5 over the six out-of-sample forecast periods for the old and new indexes.

Several patterns emerge. First, the forecast performance for the beginning and middle of the expansion in the 1990s – 1991 to 1993 and 1994 to 1996 – does not surpass the performance of the naïve, no-change forecast (i.e., the Theil U-statistics exceed one) with one exception noted in the next paragraph. That observation generally holds for both the old and new indexes of the forecasts of the coincident index, nonfarm employment, and the unemployment rate. The 1990s experience, especially during the early years, a so-called “jobless recovery” in Connecticut. That is, the recovery does not exhibit its usual robustness with respect to job growth. That unusual experience with the 1990s recovery may explain the poorer forecasting performance for both the old and new indexes.<sup>9</sup>

Model 2 provides the “optimal” Bayesian priors, defined as the minimum average Theil U-statistic over all forecast periods, for the coincident index, nonfarm employment, and the unemployment rate for both the old and new indexes. For Model 2, the new indexes produce

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<sup>8</sup> Dua and Ray (1995, p. 170) and Curry, Divakar, Mathur, and Whiteman (1995, p. 191) each describe similar methods for selecting priors.

<sup>9</sup> Dua and Miller (1996) also find that the forecast performance of the univariate model exceeded that of the BVAR model during the 1991 to 1993 period. The BVAR model did better than the univariate model during the 1985 to 1987 and 1988 to 1990 periods, however.

better forecasts of nonfarm employment than the old indexes and the naïve no-change forecasts throughout the 1990s (see Table 3b). Similar findings for Model 2, however, do not occur for the coincident index and the unemployment rate forecasts (see Tables 3a and 3c).

Second, the new indexes outperform the old indexes as well as the naïve, no-change forecast during most of the recent periods – 1997 to 1999 and 1998 to 2000 -- across all models examined. Moreover, the old indexes generally do not outperform the naïve, no-change forecast for the coincident index and the unemployment rate.

Third, the new indexes generally do not outperform the naïve, no-change forecasts during the two early periods – 1985 to 1987 and 1988 to 1990. The old indexes, on the other hand, do outperform the naïve, no-change forecasts during these periods.

In sum, the forecasting results provide mixed signals. Both indexes do not perform well during the jobless recovery of the early- and mid-1990s. The new index provides superior forecasting performance during the end of the 1990s while the old index provides superior performance during the end of the 1980s.

The superiority of the naïve, no-change forecasts during the 1991 to 1996 period probably reflects the significant structural change experienced by the Connecticut economy. The end of the Cold War saw big cuts in defense spending, which caused shrinkage in Connecticut's dependence on defense outlays. The financial services sector (i.e., Finance, Insurance, and Real Estate -- FIRE) underwent significant downsizing and reorganization of operations and functions that especially affected employment trends in the state. Foxwoods Casino began operations in the early 1990s and provided an unexpected boost to the overall economy.

Thus, during the structural change, the performance of the old indexes, based on data prior to the structural change, broke down. The new indexes, based on data that included the

structural changes in the early- and mid-1990s, better tracked the Connecticut employment cycle by the late 1990s.

The new Connecticut leading employment index did correctly predict turning points in the employment cycle, even during the significant structural change experienced by Connecticut during the early- and mid-1990s. Such performance may reflect the hallmark of good leading indexes. For example, the South African Long Leading Index, which ECRI developed in collaboration with the South African Reserve Bank, correctly predicted turning points, even through the intense structural change immediately after the end of apartheid (Economic Cycle Research Institute, 2002).

## **5. Conclusion**

The re-examination of the Dua-Miller composite indexes yielded several improvements. First, we created a new Coincident Employment Index, which conforms better to the movements of its components, using an improved composite index construction method. Second, we identified a revised employment cycle chronology, using a more robust procedure. Third, we sketched a new employment growth rate chronology, also using the same robust procedure.

In addition, we produced a new and improved Leading Employment Index, using a slightly expanded list of components, as well as an improved composite index construction procedure. This new leading index shows significantly improved leads over the Connecticut employment cycle, while its growth rate shows slightly improved leads over the Connecticut employment growth rate cycle.

The new index will hopefully provide substantial advance warning of downswings and upswings in the Connecticut employment cycle, along with early signals of accelerations and

retardations in job growth. It should therefore provide both policy makers and businesses with a sound basis for advance planning.

Finally, we also analyzed the performance of the new leading index in two ways – lead profiles and BVAR out-of-sample forecasting. First, lead profiles possess a major advantage in that explicit statistical inferences emerge about the significance of leads at turning points without assumptions about the probability distribution of leads or restrictions on sample size. Such statistical inferences can compare the leads of a given cyclical indicator to a reference cycle, such as a set of business cycle turning points, or the leads of one cyclical indicator to another, to assess whether one owns significantly longer leads than the other. Moreover, lead profiles provide convenient pictures (bar charts) for easy and effective visual appraisal of the significance of lead lengths. We find that the lead profile of the new leading index outperforms the old leading index, increasing the lead by two months. No significant improvement, however, occurs for the leading index growth rate.

Second, we also performed out-of-sample forecasting experiments for the old and new Connecticut coincident and leading employment indexes. While the coincident and leading employment indexes are designed first and foremost to identify turning points in the employment cycle, Dua and Miller (1996) report forecasting experiments, suggesting that a BVAR model generally performs better than a set of other possible alternative models. Our findings support the dominance of the new indexes only for the most recent forecast periods – 1997 to 1999 and 1998 to 2000. The old indexes perform better than the new indexes for the early sample periods – 1985 to 1987 and 1988 to 1990. Interestingly, neither set of indexes does better than a naïve, no-change forecast during the jobless recovery during the early and mid-1990s – 1991 to 1993 and 1994 to 1996.

In sum, our findings provide a contrast between “more-standard” BVAR forecasting experiments and “less-standard” lead profiles for turning point prediction. The comparison highlights the suitability of the techniques themselves for evaluating leading indexes. Our results support the admonition of Granger and Newbold (1986) that because leading indexes are designed to predict cyclical turning points and not to provide accurate forecasts away from turning points, standard statistical techniques may prove unsuitable.

Certainly, in terms of turning-point prediction, the new Connecticut leading employment index outperforms the old index and the naïve, no-change forecast, which by definition cannot predict turning points. The lead profile test demonstrates that superiority in a rigorous, non-parametric statistic fashion. The mixed evidence on the BVAR forecasting experiments illustrates the truth in the Granger and Newbold (1986) admonition.

## References

- Banerji A. 1999. The three P's: simple tools for monitoring economic cycles. *Business Economics*, 34: 72-76.
- Banerji A. 2000. “The Lead Profile and Other Non-parametric Tools to Evaluate a Survey Series.” In *Use of Survey Data for Industry, Research and Economic Policy*, Oppenlander KH, Poser G, Schips B (eds); Ashgate: Aldershot, England.
- Boschan C, Banerji A. 1990. A reassessment of composite indexes. In *Analyzing Modern Business Cycles*, Klein PA (ed); ME Sharpe: Armonk, NY:
- Bry G, Boschan C. 1971. *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs*. National Bureau of Economic Research: New York.
- Burns AF, Mitchell WC. 1946. *Measuring Business Cycles*. National Bureau of Economic Research: New York.
- Cooley TF, LeRoy SF. 1985. Atheoretical macroeconomics: A critique. *Journal of Monetary Economics* 16: 283-308.
- Cullity JP, Banerji A. 1996. Procedures for constructing composite indexes: A reassessment. Presented at the Meeting on OECD Leading Indicators, 17-18 October, Paris.

- Cullity JP, Moore GH. 1990. Long-leading and short-leading indexes. In *Leading Indicators for the 1990s*, Moore GH (ed); Dow Jones Irwin: Homewood, IL:.
- Curry DJ, Divakar S, Mathur SK, Whiteman CH. 1995. BVAR as a category management tool: An illustration and comparison with alternative techniques. *Journal of Forecasting* 14: 181-199.
- Doan TA, Litterman RB, Sims CA. 1984. Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews* 3: 1-100.
- Dua P, Miller, SM. 1996. Forecasting and analyzing activity with coincident and leading indexes: The case of Connecticut. *Journal of Forecasting* 15: 509-526.
- Dua P, Ray, SC. 1995. A BVAR model for the Connecticut economy. *Journal of Forecasting* 14: 167-80.
- Economic Cycle Research Institute. 2002. A new system of indicators for South Africa. *International Cyclical Outlook*, 7, 3 (March), 3-4.
- Fisher, RA. 1935. *The Design of Experiments*. Oliver & Boyd: Edinburgh.
- Guha D, Banerji, A. 1998/1999. Testing for regional cycles: A Markov-switching approach. *Journal of Economic and Social Measurement* 25: 163-182.
- Granger CWJ, Newbold, P. 1986. *Forecasting Economic Time Series*, 2nd edn. Academic Press: San Diego, CA.
- Layton AP, Moore, GH. 1989. Leading indicators for the service sector” *Journal of Business and Economic Statistics* 7: 379-386.
- Litterman RB. 1986. Forecasting with Bayesian vector autoregressions - Five years of experience. *Journal of Business and Economic Statistics* 4: 25-38.
- Litterman RB. 1981. A Bayesian procedure for forecasting with vector autoregressions. Federal Reserve Bank of Minneapolis, Working Paper.
- Moore GH. 1982. Business cycles. In *Encyclopedia of Economics*, Greenwald D (ed). McGraw-Hill: New York.
- Moore GH. 1981. A new leading index of employment and unemployment” *Monthly Labor Review* 104: 44-47.
- Moore GH, Shiskin J. 1967. *Indicators of Business Expansions and Contractions*. National Bureau of Economic Research: New York.
- Siegel S. 1956. *Nonparametric Statistics for the Behavioral Sciences*. McGraw Hill: New York:

- Sims CA. 1988. Bayesian skepticism on unit root econometrics. *Journal of Economic Dynamics and Control* 12: 463-74.
- Sims CA. 1980. Macroeconomics and reality. *Econometrica* 48: 1-48.
- Sims CA, Stock JH, Watson, MW. 1990. "Inference in linear time series models with some unit roots. *Econometrica* 58: 113-144.
- Spencer DE. 1993. Developing a Bayesian vector autoregression forecasting model. *International Journal of Forecasting* 9: 407-421.
- Theil H. 1971. *Principles of Econometrics*. John Wiley: New York.
- Todd RM. 1984. Improving economic forecasting with Bayesian vector autoregression. Federal Reserve Bank of Minneapolis *Quarterly Review* Fall: 18-29.
- US Department of Commerce. 1977. Composite indexes of leading, lagging and coincident indicators: A brief explanation of their construction. In *Handbook of Cyclical Indicators, A Supplement to the Business Conditions Digest*. Bureau of Economic Analysis: Washington, DC, (May), 73-76.
- US Department of Commerce. 1984. Composite indexes of leading, lagging and coincident indicators: A brief explanation of their construction." In *Handbook of Cyclical Indicators, A Supplement to the Business Conditions Digest*. Bureau of Economic Analysis: Washington, DC, (May), 65-70.
- Zellner A. 1979. Statistical analysis of econometric models. *Journal of the American Statistical Association* 74: 628-643.
- Zellner A, Palm F. 1974. Time series analysis and simultaneous equation econometric models. *Journal of Econometrics* 2: 17-54.

Table 1a:					
Connecticut Leading Employment Index (Old) Lead/Lag					
Connecticut Employment Cycle		Connecticut Leading Employment Index (Old)		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971		12/1970		-10	
	05/1974		11/1973		-6
11/1975		04/1975		-7	
	03/1980		12/1979		-3
		06/1980		extra	
			07/1981		extra
01/1983		10/1982		-3	
	04/1988		04/1988		0
02/1992		05/1991		-9	
				troughs	peaks
				overall	
Average				-7	-3
				-5	
Median				-8.0	-3.0
				-6.0	
Percent Lead				100	83
				93	
Std. Deviation				3.1	3.0
				3.6	

Table 1b:					
Connecticut Leading Employment Index (New) Lead/Lag					
Connecticut Employment Cycle		Connecticut Leading Employment Index (New)		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971		12/1970		-10	
	05/1974		03/1973		-14
11/1975		05/1975		-6	
	03/1980		08/1979		-7
01/1983		01/1982		-12	
	04/1988		04/1988		0
02/1992		01/1991		-13	
				troughs	peaks
				overall	
Average				-10	-7
				-9	
Median				-11.0	-7.0
				-10.0	
Percent Lead				100	83
				93	
Std. Deviation				3.1	7.0
				4.9	

Table 2a:					
Connecticut Leading Employment Index, (Old) Lead/Lag					
Connecticut Employment Growth Rate Cycle		Connecticut Leading Employment Index Growth Rate (Old)		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
01/1971		09/1970		-4	
	01/1973		01/1973		0
06/1975		03/1975		-3	
	06/1977		04/1978		10
08/1980		06/1980		-2	
	05/1981		04/1981		-1
04/1982		04/1982		0	
	02/1984		07/1983		-7
07/1985		05/1985		-2	
	04/1986		12/1985		-4
02/1991		10/1990		-4	
	02/1993		02/1993		0
01/1996		06/1995		-7	
	02/1998		01/1998		-1
05/1999		09/1998		-8	
				troughs	peaks
				overall	
Average				-4	0
Median				-3.5	-1.0
Percent Lead				94	71
Std. Deviation				2.7	5.3
					4.3

Table 2b					
Connecticut Leading Employment Index, (New) Lead/Lag					
Connecticut Employment Growth Rate Cycle		Connecticut Leading Employment Index, Growth Rate (New)		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
01/1971		09/1970		-4	
	01/1973		01/1973		0
06/1975		11/1974		-7	
	06/1977		04/1978		10
08/1980		03/1980		-5	
	05/1981		04/1981		-1
04/1982		01/1982		-3	
	02/1984		07/1983		-7
07/1985		04/1985		-3	
	04/1986		12/1985		-4
02/1991		01/1991		-1	
	02/1993		08/1993		6
01/1996		06/1995		-7	
	02/1998		01/1998		-1
05/1999		09/1998		-8	
				troughs	peaks
				overall	
Average				-5	0
Median				-4.5	-1.0
Percent Lead				100	64
Std. Deviation				2.4	5.8
					5.0

**Table 3a****Connecticut Coincident Index: Average U-Statistics for One- through Six-Months-Ahead Forecasts**

MODELS	Model 1		Model 2		Model 3		Model 4		Model 5	
	w=0.2 ; d=2 ; k=0.5		w=0.2 ; d=1 ; k=0.5		w=0.1 ; d=2 ; k=0.5		w=0.2 ; d=2 ; k=0.4		w=0.2 ; d=2 ; k=0.6	
	NEW	OLD	NEW	OLD	NEW	OLD	NEW	OLD	NEW	OLD
<b>1985-1987</b>	1.2159	0.7617	0.9342	0.7210	1.2142	0.7642	1.1941	0.7516	1.2237	0.7671
<b>1988-1990</b>	1.6225	0.7833	1.1082	0.6629	1.7910	0.8781	1.6354	0.7959	1.6025	0.7737
<b>1991-1993</b>	1.3581*	1.7123	1.0180*	1.3872	1.5349*	1.6810	1.3579*	1.3631	1.3544*	1.7119
<b>1994-1996</b>	0.9191*	1.7236	1.5891	1.4510	2.7805	2.0399	2.5446	1.7599	2.4650	1.6896
<b>1997-1999</b>	0.6262*	1.3527	0.5956*	1.3543	0.7150*	1.1833	0.6337*	1.2985	0.6181*	1.3896
<b>1998-2000</b>	0.6743*	1.6456	0.7158*	1.5861	0.7369*	1.5136	0.6736*	1.6013	0.6755*	1.6752
<b>Average U</b>	1.0694	1.3299	0.9935**	1.1938**	1.4621	1.3434	1.3399	1.2617	1.3232	1.3345

**Note:** The models are estimated with lag length=12. The forecasts are for one- through six-months-ahead and are calculated as rolling forecasts i.e., one extra observation is added after each forecast is made until the end of our sample is reached. In each model, 'w' refers to overall tightness, 'd' is the decay parameter for lags, and 'k' is the interaction parameter which is constant for all combinations of i and j,  $i \neq j$ , thus implying a symmetric interaction function,  $f(i,j)$ . 'New' refers to the forecasts made on the basis of new indexes and 'Old' refers to forecasts on the basis of the previous indexes. An asterisk denotes the time periods for which the out-of-sample forecasts using the new indexes are more accurate. 'Average U' in the last row denotes the average of the U-statistics across all the time periods. Two asterisks denote the minimum 'Average U' for each of the 'New' and 'Old' models.

**Table 3b****Connecticut Nonfarm Employment: Average U-Statistics for One- through Six-Months-Ahead Forecasts**

MODELS	Model 1		Model 2		Model 3		Model 4		Model 5	
	w=0.2 ; d=2 ; k=0.5		w=0.2 ; d=1 ; k=0.5		w=0.1 ; d=2 ; k=0.5		w=0.2 ; d=2 ; k=0.4		w=0.2 ; d=2 ; k=0.6	
	NEW	OLD	NEW	OLD	NEW	OLD	NEW	OLD	NEW	OLD
<b>1985-1987</b>	1.0148	0.6548	0.9533	0.6307	0.9724	0.6550	1.0073	0.6562	1.0157	0.6529
<b>1988-1990</b>	1.3949	0.8910	1.1112	0.8495	1.4673	0.9702	1.4008	0.9026	1.3864	0.8828
<b>1991-1993</b>	1.2642*	1.5353	0.9149*	1.3318	1.3799*	1.4249	1.2952*	1.5191	1.2337*	1.5366
<b>1994-1996</b>	1.1474	0.8993	0.9160*	0.9186	1.1761	0.9184	1.1612	0.9084	1.1273	0.8928
<b>1997-1999</b>	0.7353	0.7082	0.6104*	0.7269	0.8017	0.6101	0.7379	0.6836	0.7314	0.7240
<b>1998-2000</b>	0.7937*	0.7995	0.6593*	0.8119	0.8785	0.6934	0.7992	0.7733	0.7879*	0.8157
<b>Average U</b>	1.0584	0.9147	0.8609**	0.8782**	1.1127	0.8787	1.0669	0.9072	1.0471	0.9175

**Note:** See Table 3a.

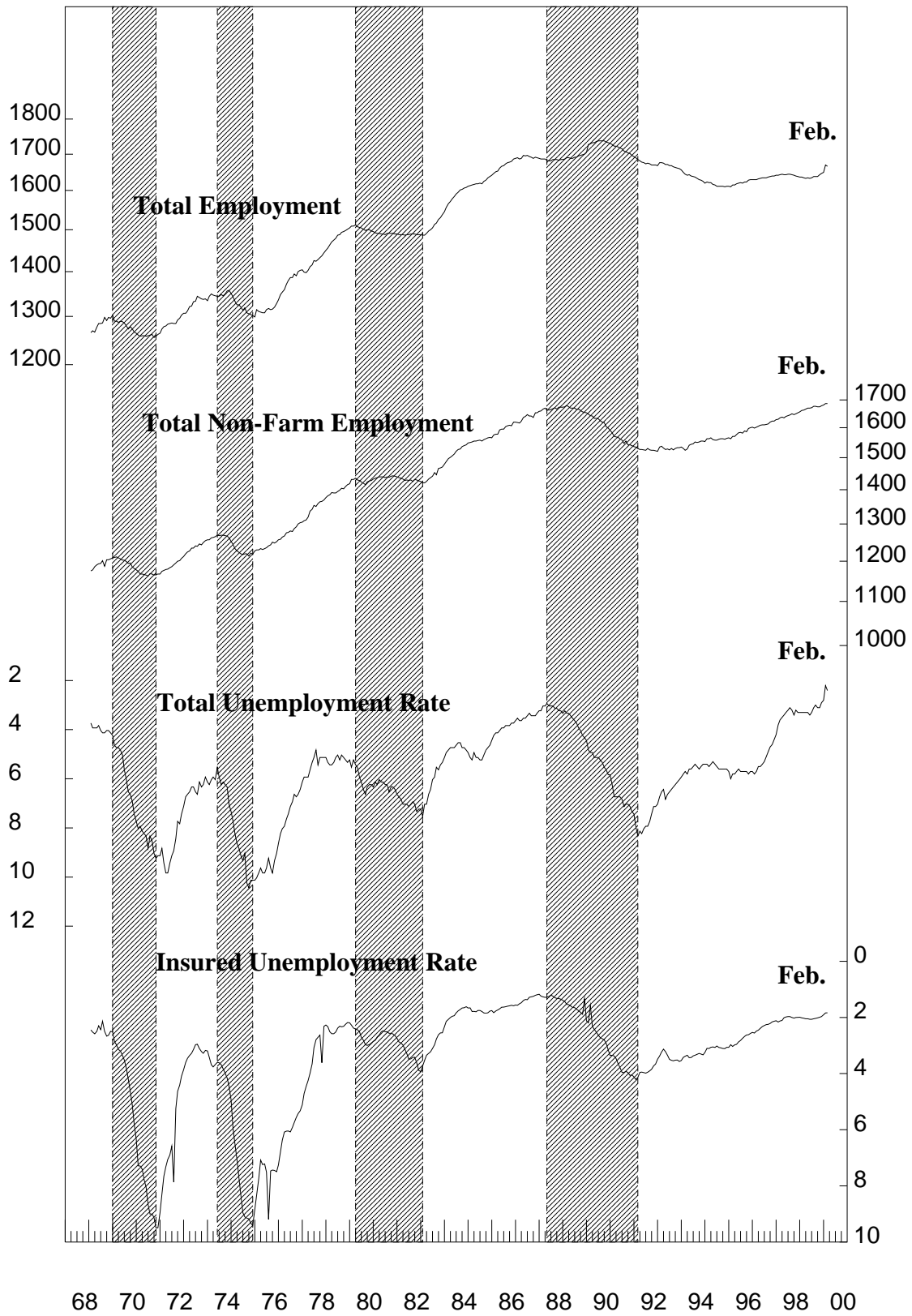
Table 3c

## Connecticut Unemployment Rate: Average U-Statistics for One- through Six-Months-Ahead Forecasts

MODEL	Model 1		Model 2		Model 3		Model 4		Model 5	
	w=0.2 ; d=2 ; k=0.5		w=0.2 ; d=1 ; k=0.5		w=0.1 ; d=2 ; k=0.5		w=0.2 ; d=2 ; k=0.4		w=0.2 ; d=2 ; k=0.6	
	NEW	OLD	NEW	OLD	NEW	OLD	NEW	OLD	NEW	OLD
<b>1985-1987</b>	1.1658	0.7080	0.8026*	0.8764	1.1738	0.6768	1.1651	0.6711	1.1417	0.6784
<b>1988-1990</b>	1.1526	0.5581	0.7856	0.7375	1.2657	0.6853	1.1819	0.5789	1.1230	0.5435
<b>1991-1993</b>	1.2625	1.0418	1.0503	0.9422	1.3247	1.0539	1.2847	1.0393	1.0215*	1.0497
<b>1994-1996</b>	2.9329	1.4952	1.9754	1.1102	3.2577	1.7592	2.9702	1.4841	2.8810	1.5007
<b>1997-1999</b>	0.6617*	1.0004	0.7194*	1.0130	0.6763*	0.9410	0.6568*	0.9972	0.6672*	0.9999
<b>1998-2000</b>	0.7742*	1.4205	0.9204*	1.4309	0.7740*	1.2997	0.7702*	1.4168	0.7800*	1.4165
<b>Average U</b>	1.3250	1.0373	1.0423**	1.0184**	1.4120	1.0693	1.3382	1.0312	1.2691	1.0315

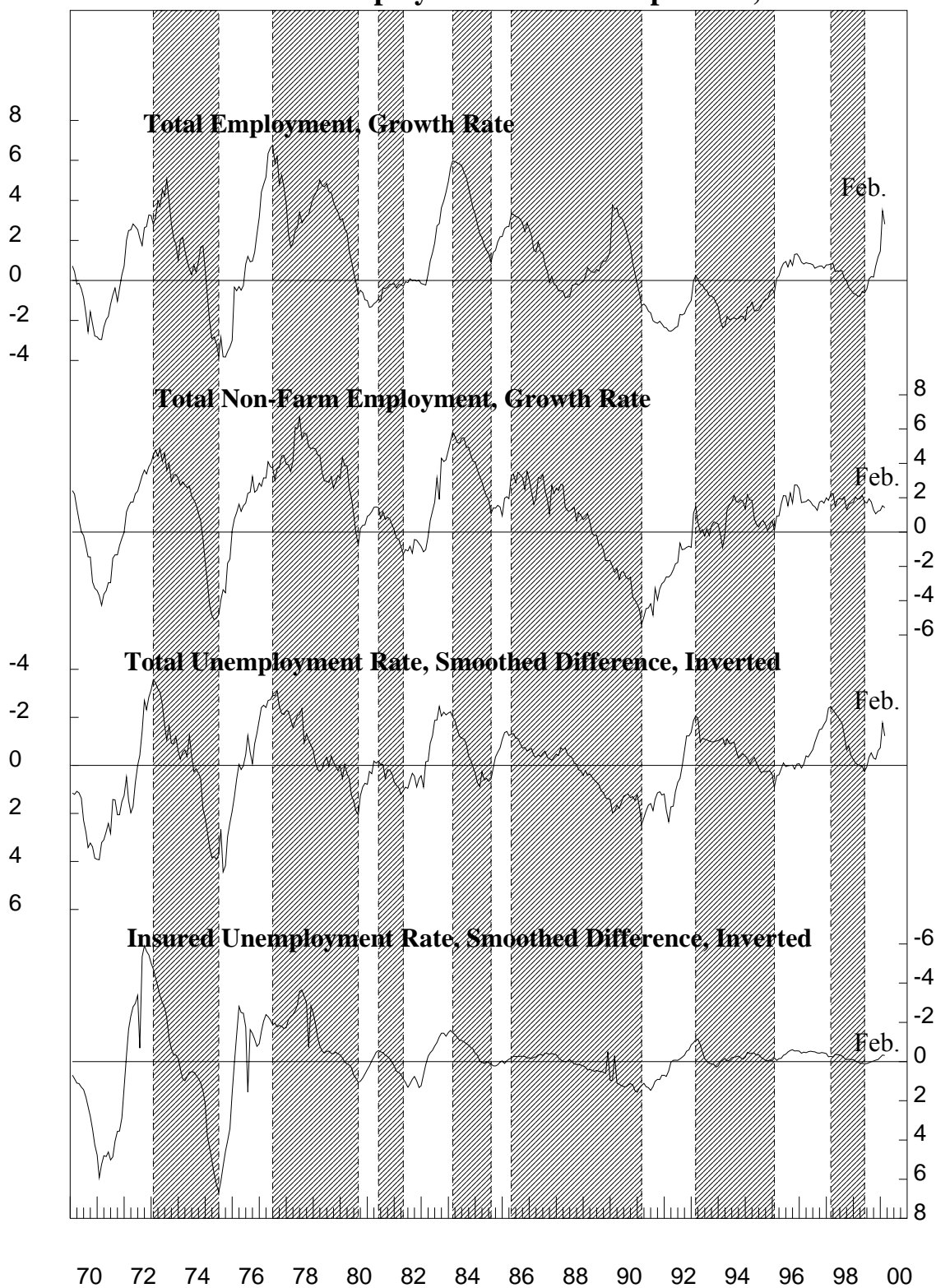
Note: See Table 3a.

**Figure 1:**  
**Connecticut Coincident Employment Index Components**



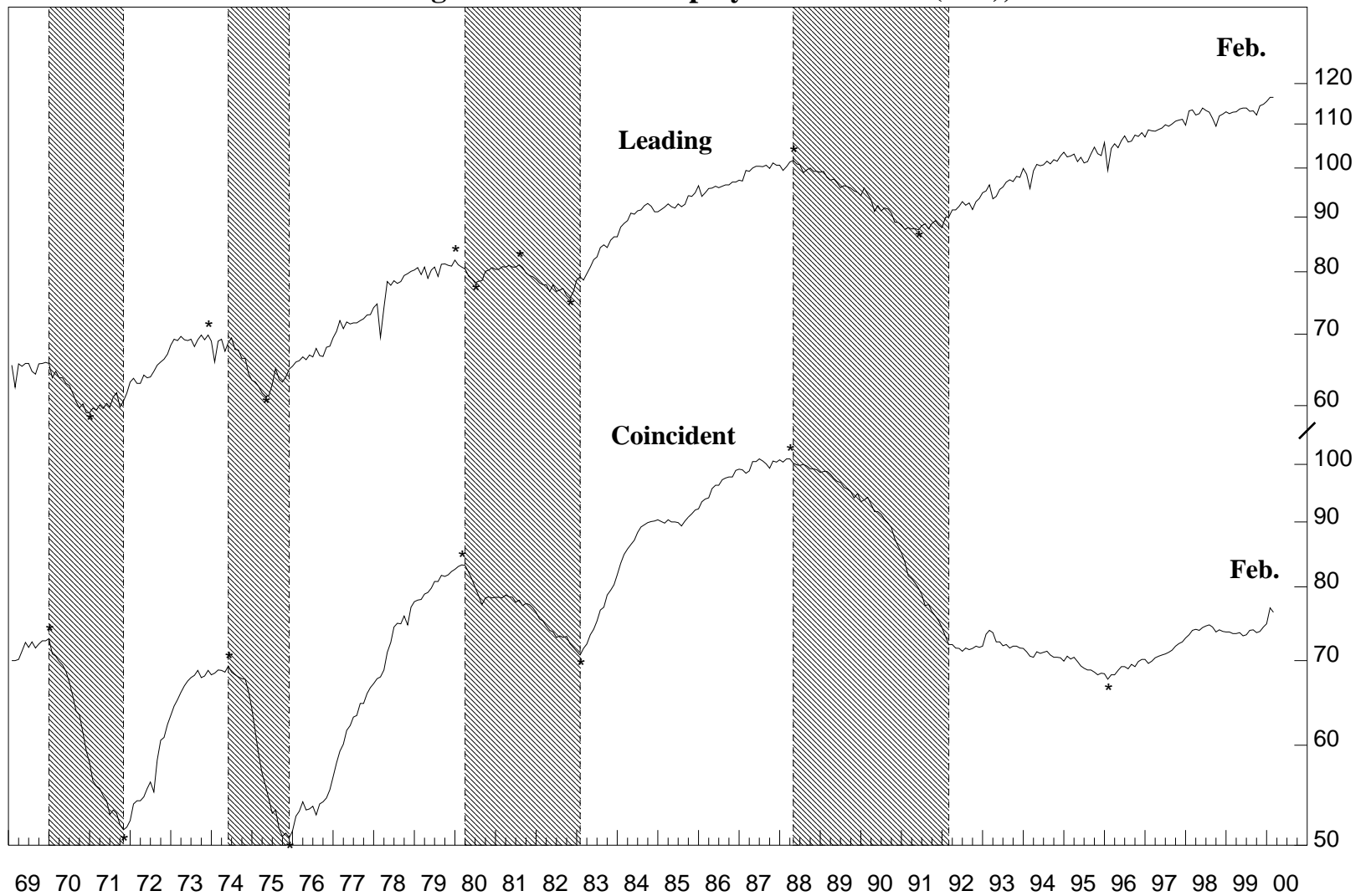
Shaded areas represent cyclical downturns in the Connecticut employment cycle.

**Figure 2:**  
**Connecticut Coincident Employment Index Components, Growth Rates (%)**



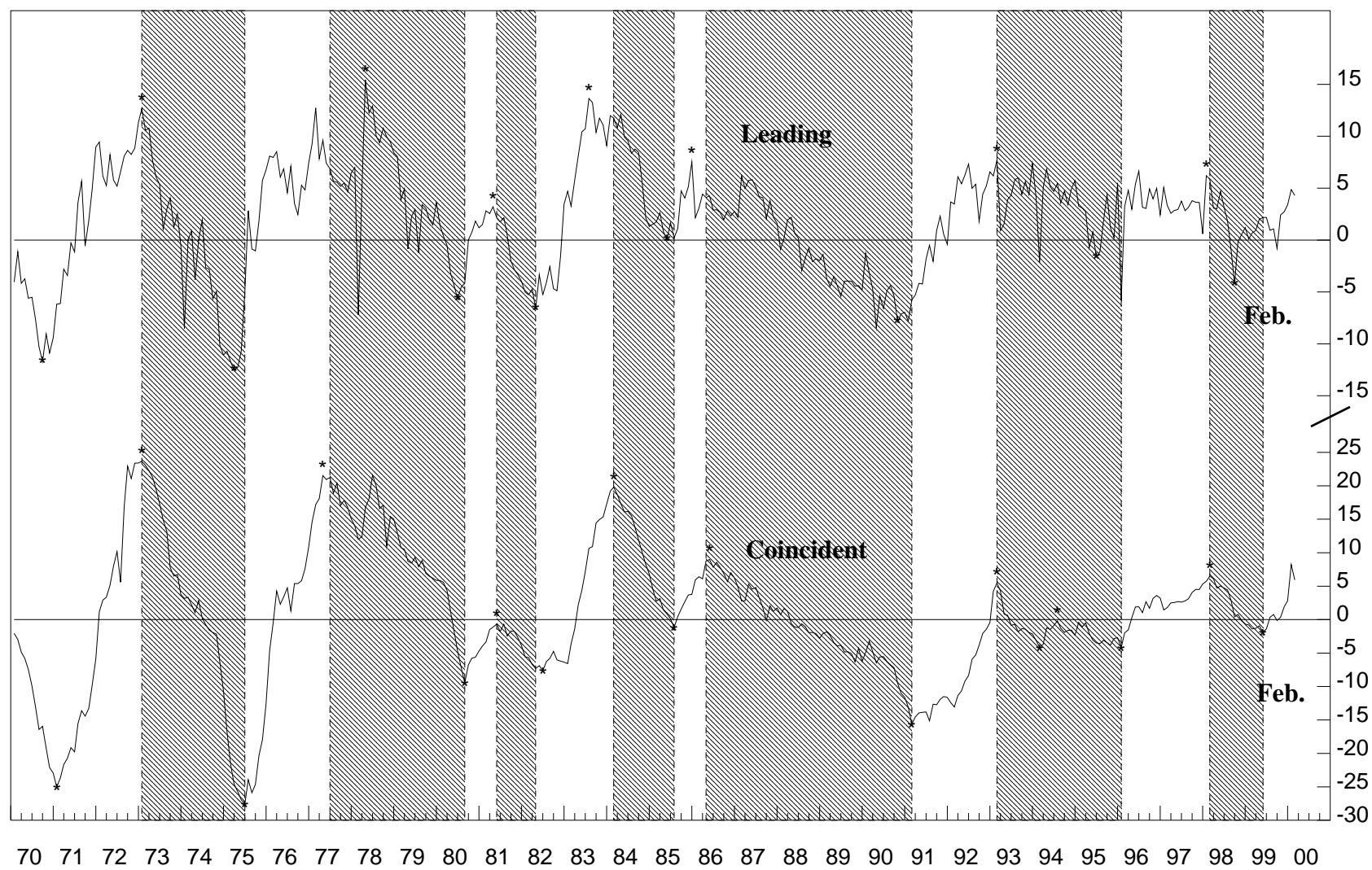
Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.

**Figure 3:**  
**Connecticut Leading & Coincident Employment Indexes (Old), 1992=100**



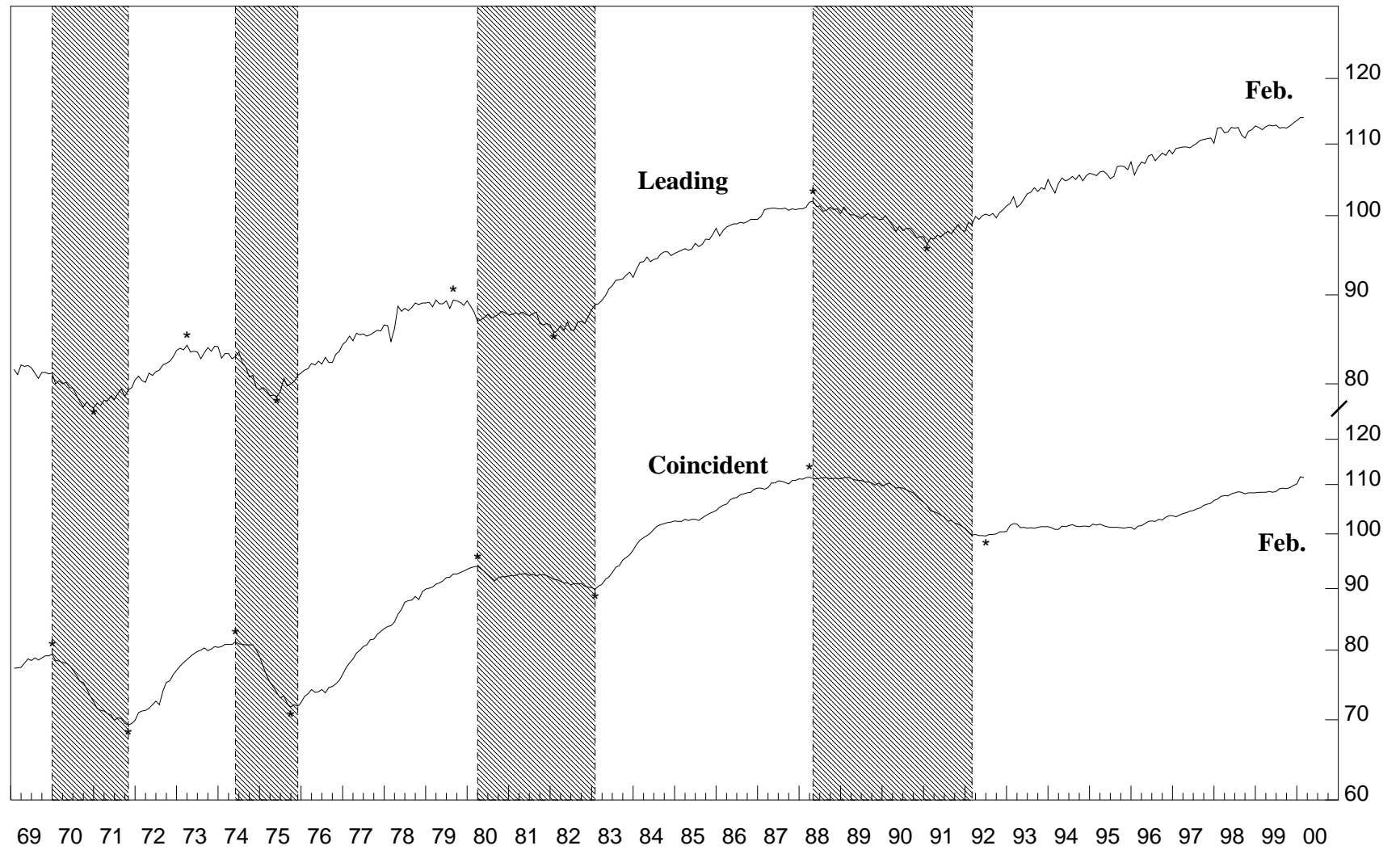
Shaded areas represent cyclical downturns in the Connecticut employment cycle.

**Figure 4:**  
**Connecticut Leading & Coincident Employment Indexes (Old), Growth Rates (%)**



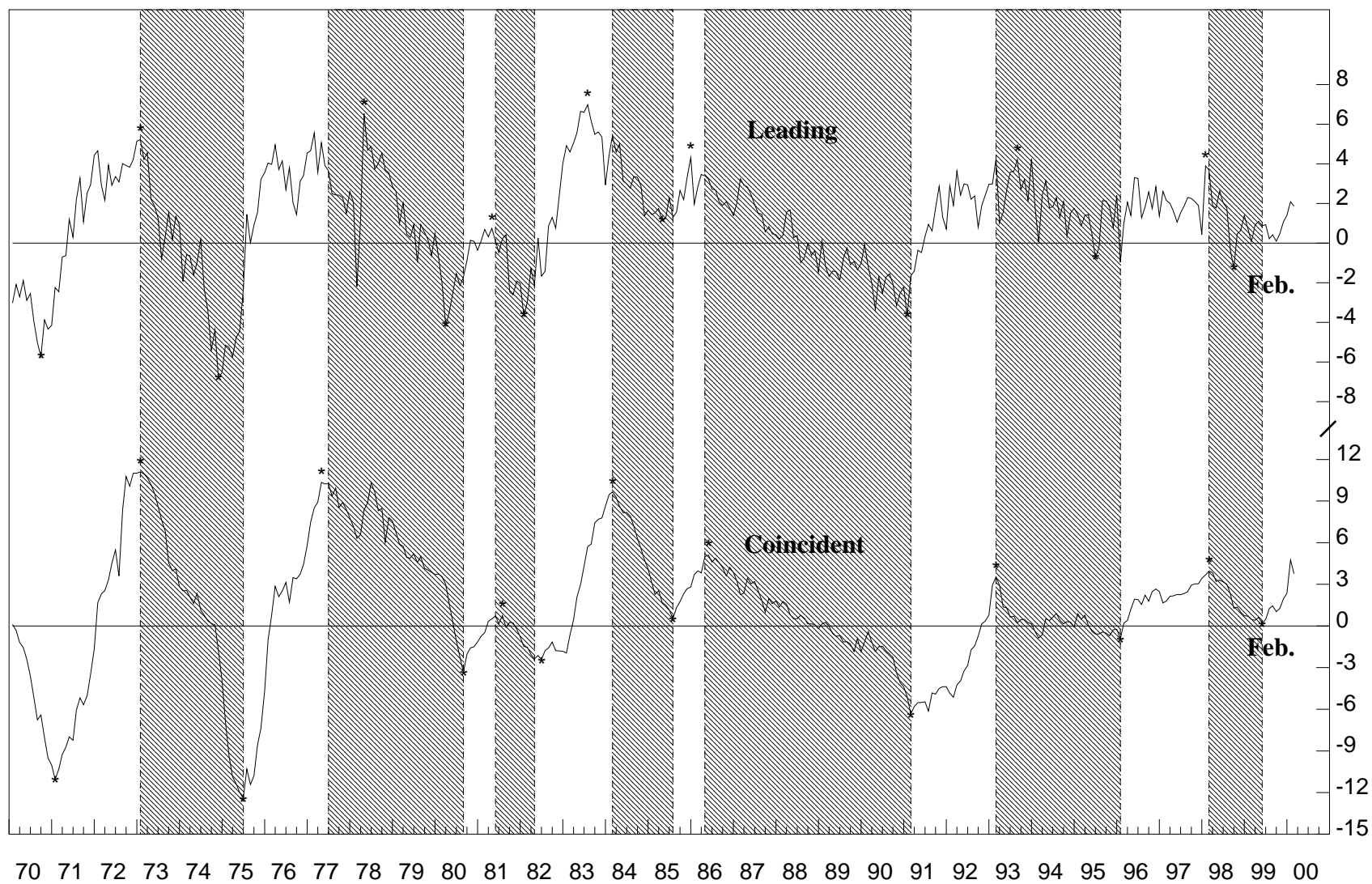
Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.

**Figure 5:**  
**Connecticut Leading & Coincident Employment Indexes (New), 1992=100**



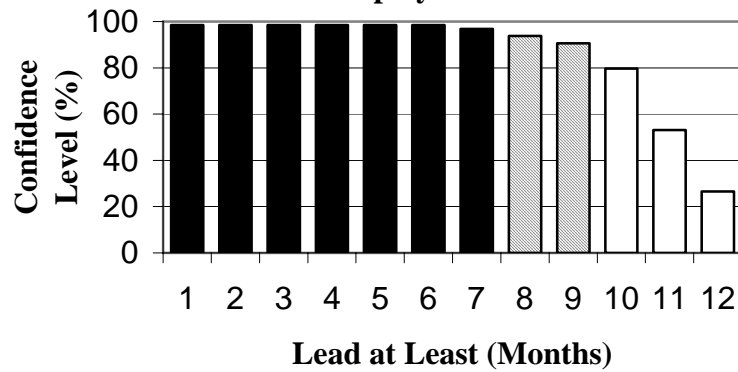
Shaded areas represent cyclical downturns in the Connecticut employment cycle.

**Figure 6:**  
**Connecticut Leading & Coincident Employment Indexes (New), Growth Rates (%)**

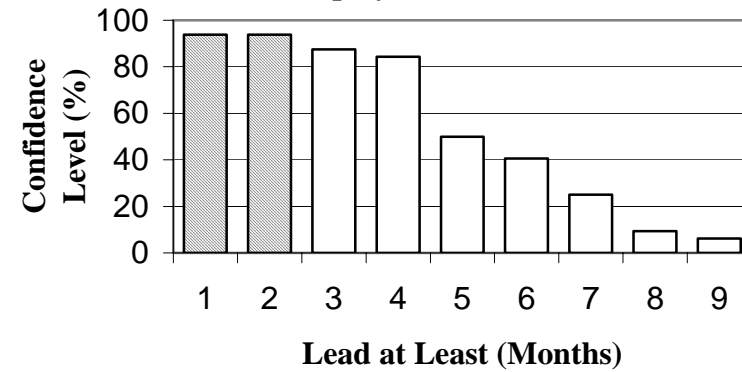


Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.

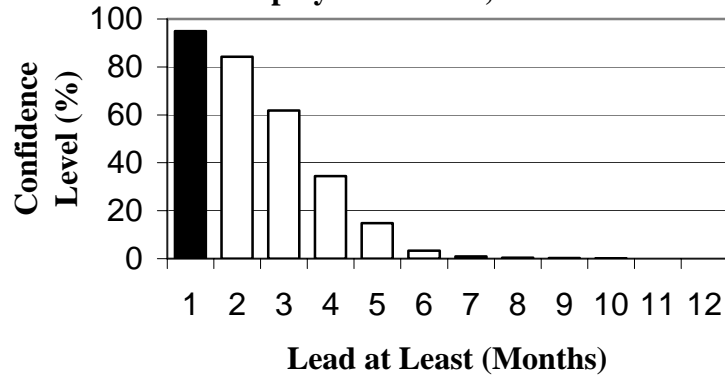
**Figure 7a:**  
**Lead Profile of New Connecticut Leading**  
**Employment Index**



**Figure 7c:**  
**Lead Profile of New vs. Old Leading**  
**Employment Index**



**Figure 7b:**  
**Lead Profile of New Connecticut Leading**  
**Employment Index, Growth Rate**



**Figure 7d:**  
**Lead Profile of New vs. Old Leading**  
**Employment Index, Growth Rate**

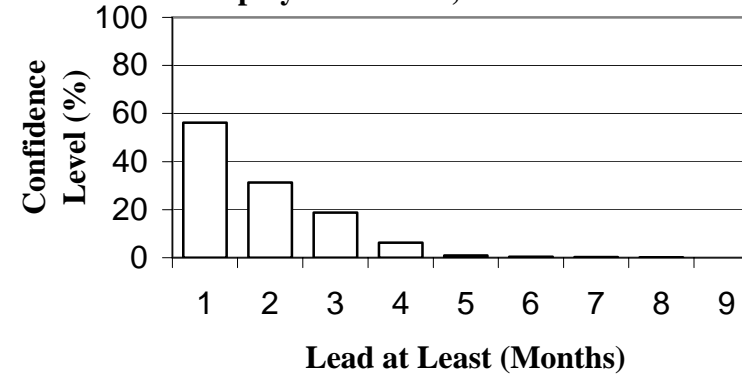


Table A1:								
Clustering of Cyclical Turns, Coincident Employment Indicators								
Connecticut Coincident Employment Index (Old)	Connecticut Coincident Employment Index (New)	Insured Unemployment Rate	Total Employment	Total Non-Farm Employment	Total Unemployment Rate	Mode	Median	Final Chronology
Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak
12/1969	12/1969	07/1969	12/1969	02/1970		-	12/1969	12/1969
10/1971	10/1971	10/1971	02/1971	06/1971	04/1972	-	06,10/1971	10/1971
05/1974	05/1974	07/1973	11/1974	08/1974	05/1974	-	05,08/1974	05/1974
11/1975	09/1975	11/1975	12/1975	09/1975	09/1975	09/1975	09,11/1975	11/1975
02/1980	03/1980	11/1979	03/1980	10/1981	08/1979	-	11/79, 03/80	03/1980
01/1983	01/1983	12/1982	02/1983	02/1983	01/1983	02/1983	01,02/1983	01/1983
					08/1984			
					07/1985			
03/1988	03/1988	12/1987	06/1987	02/1989	04/1988	-	12/87, 04/88	04/1988
			06/1988					
			09/1990					
01/1996	06/1992	01/1992	01/1996	12/1992	02/1992	-	02,06/1992	02/1992
					04/1995			
					01/1996			

Table A2:								
Clustering of Cyclical Turns, Coincident Employment Indicators, Growth Rates								
Connecticut Coincident Employment Index Growth Rate (Old)	Connecticut Coincident Employment Index Growth Rate (New)	Insured Unemployment Rate Smoothed Difference	Total Employment Growth Rate	Total Non-Farm Employment Growth Rate	Total Unemployment Rate Smoothed Difference	Mode	Median	Final Chronology
Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak	Trough Peak
01/1971	01/1971	01/1971	02/1971	02/1971	01/1971	01,02/1971	01,02/1971	01/1971
01/1973	01/1973	09/1972	07/1973	04/1973	01/1973	-	01,04/1973	01/1973
06/1975	06/1975	06/1975	09/1975	04/1975	08/1975	-	06,08/1975	06/1975
04/1977	04/1977	07/1978	06/1977	06/1978	08/1977	-	08/77,06/78	06/1977
			02/1978					
			03/1979					
08/1980	08/1980	08/1980	01/1981	08/1980	08/1980	08/1980	08/1980	08/1980
05/1981	07/1981	05/1981		04/1981	05/1981	05/1981	05/1981	05/1981
06/1982	06/1982	11/1982		04/1982	03/1982	-	04/1982	04/1982
02/1984	02/1984	01/1984	02/1984	02/1984	08/1983	02/1984	01,02/1984	02/1984
07/1985	07/1985	09/1985	07/1985	12/1985	02/1985	-	07,09/1985	07/1985
05/1986	05/1986	07/1987	04/1986	11/1986	02/1986	-	04,11/1986	04/1986
			04/1988		10/1987			
			01/1990		04/1988			
02/1991	02/1991	12/1990	03/1992	02/1991	02/1991	02/1991	02/1991	02/1991
02/1993	02/1993	03/1993	02/1993	01/1995	02/1993	02/1993	02,03/1993	02/1993
02/1994	02/1994	11/1993	02/1994					
07/1994	07/1994	01/1995						
01/1996	01/1996	10/1995		10/1995	01/1996	10/1995	10/1995	01/1996
		09/1996	11/1996	10/1996				
				08/1997				
02/1998	02/1998			03/1998	02/1998	-	02,03/1998	02/1998
05/1999	05/1999	05/1999	02/1999		05/1999	05/1999	05/1999	05/1999

Table A3:					
Average Weekly Hours of Manufacturing & Construction Lead/Lag					
Connecticut Employment Cycle		Average Weekly Hours of Manufacturing and Construction		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971		04/1971		-6	
	05/1974		04/1973		-13
11/1975		05/1975		-6	
	03/1980		01/1979		-14
01/1983		08/1982		-5	
			04/1984		extra
		07/1986		extra	
	04/1988		04/1989		12
02/1992		09/1992		7	
				troughs	peaks
				overall	
Average				-3	-5
Median				-4	
Percent Lead				-5.5	-13.0
Std. Deviation				-6.0	
				75	67
				71	
				6.4	14.7
				9.7	

Table A4:					
Help Wanted Advertising Index Lead/Lag					
Connecticut Employment Cycle		Help Wanted Advertising Index		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
	12/1969		11/1969		-1
10/1971		10/1971		0	
	05/1974		07/1973		-10
11/1975		03/1976		4	
	03/1980		09/1979		-6
01/1983		10/1982		-3	
	04/1988		06/1987		-10
02/1992		12/1991		-2	
				troughs	peaks
				overall	
Average				0	-7
Median				-1.0	-8.0
Percent Lead				-2.5	
Std. Deviation				63	100
				81	
				3.1	4.3
				4.9	

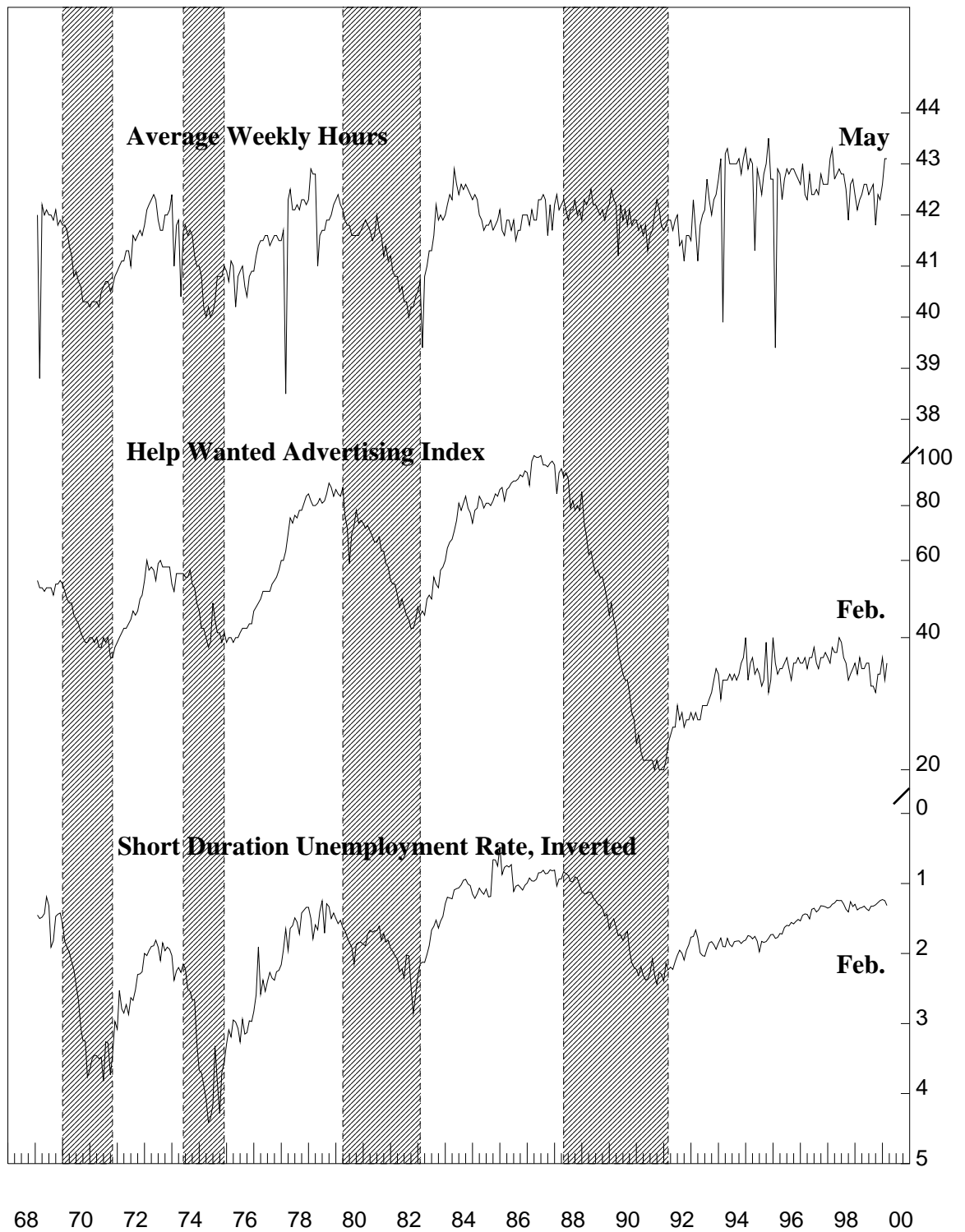
Table A5:					
Short Duration Unemployment Rate Lead/Lag					
Connecticut Employment Cycle		Short Duration Unemployment Rate		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971		11/1970		-11	
	05/1974		05/1973		-12
11/1975		04/1975		-7	
	03/1980		06/1979		-9
		08/1980		extra	
			07/1981		extra
01/1983		10/1982		-3	
			12/1985		extra
	04/1988	06/1986		extra	
			10/1987		-6
02/1992		04/1991		-10	
				troughs	peaks
				overall	
Average				-8	-9
					-8
Median				-8.5	-9.0
					-9.0
Percent Lead				100	100
					100
Std. Deviation				3.6	3.0
					3.1

Table A6:					
Initial Claims for Unemployment Insurance Lead/Lag					
Connecticut Employment Cycle		Initial Claims for Unemployment Insurance		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971		09/1971		-1	
	05/1974		03/1973		-14
11/1975		05/1975		-6	
			01/1977		extra
		02/1978		extra	
	03/1980		03/1979		-12
01/1983		09/1982		-4	
			09/1984		extra
	04/1988	10/1985		extra	
			10/1987		-6
02/1992		08/1991		-6	
				troughs	peaks
				overall	
Average				-4	-11
					-7
Median				-5.0	-12.0
					-6.0
Percent Lead				100	100
					100
Std. Deviation				2.4	4.2
					4.5

Table A7:					
Total Housing Permits Lead/Lag					
Connecticut Employment Cycle		Total Housing Permits		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971	05/1974	01/1970		-21	
			01/1973		-16
11/1975		09/1974		-14	
			12/1976		extra
	03/1980	02/1978		extra	
			08/1978		-19
		03/1980		extra	
	04/1988		10/1980		extra
01/1983		01/1982		-12	
			02/1987		-14
02/1992		01/1991		-13	
				troughs	peaks
				overall	
				Average	-15 -16
				Median	-13.5 -16.0
				Percent Lead	100 100
				Std. Deviation	4.1 2.5
					3.3

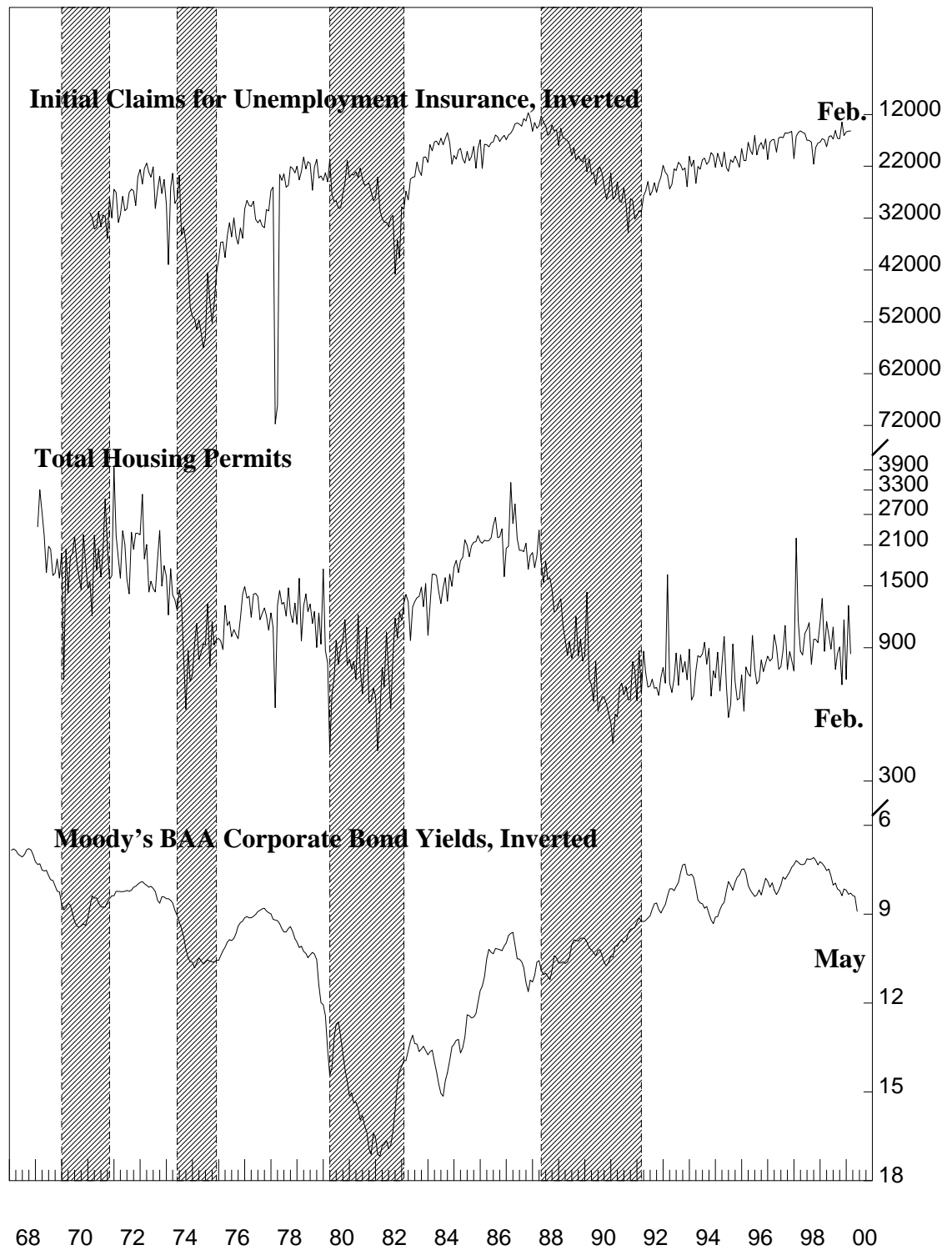
Table A8:					
Moody's BAA Corporate Bond Yields Lead/Lag					
Connecticut Employment Cycle		Moody's BAA Corporate Bond Yields		Lead(-) / Lag(+)	
Troughs	Peaks	Troughs	Peaks	Troughs	Peaks
10/1971	05/1974	08/1970		-14	
			01/1973		-16
11/1975	03/1980	01/1975		-10	
			09/1977		-30
01/1983	04/1988	02/1982		-11	
			05/1983		extra
		07/1984		extra	
			03/1987		-13
		10/1987		extra	
			11/1989		extra
02/1992		10/1990		-16	
				troughs	peaks
				overall	
				Average	-13 -20
				Median	-12.5 -16.0
				Percent Lead	100 100
				Std. Deviation	2.8 9.1
					6.7

**Figure A1:  
Connecticut Leading Employment Index Components**



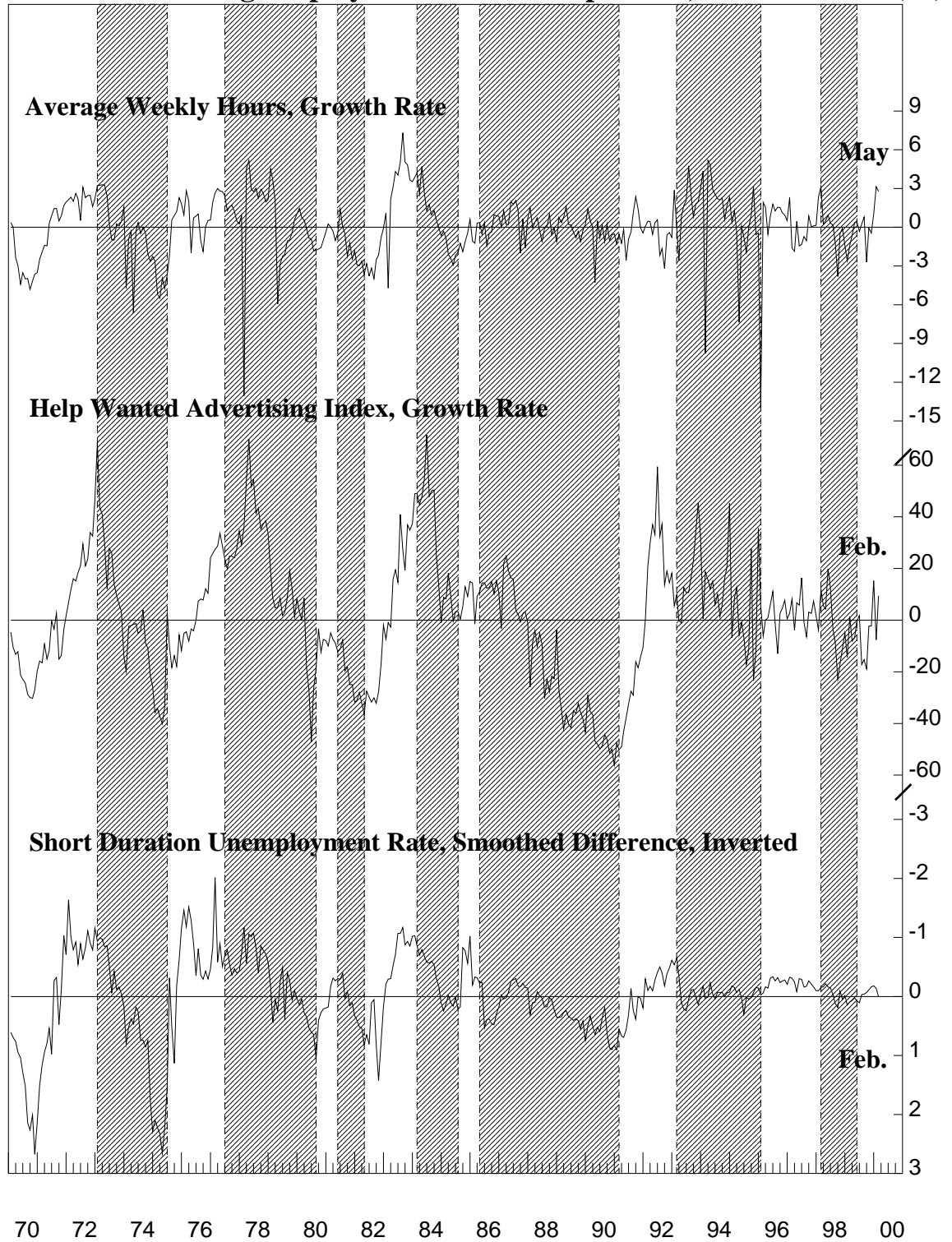
Shaded areas represent cyclical downturns in the Connecticut employment cycle.

**Figure A2:  
Connecticut Leading Employment Index Components**



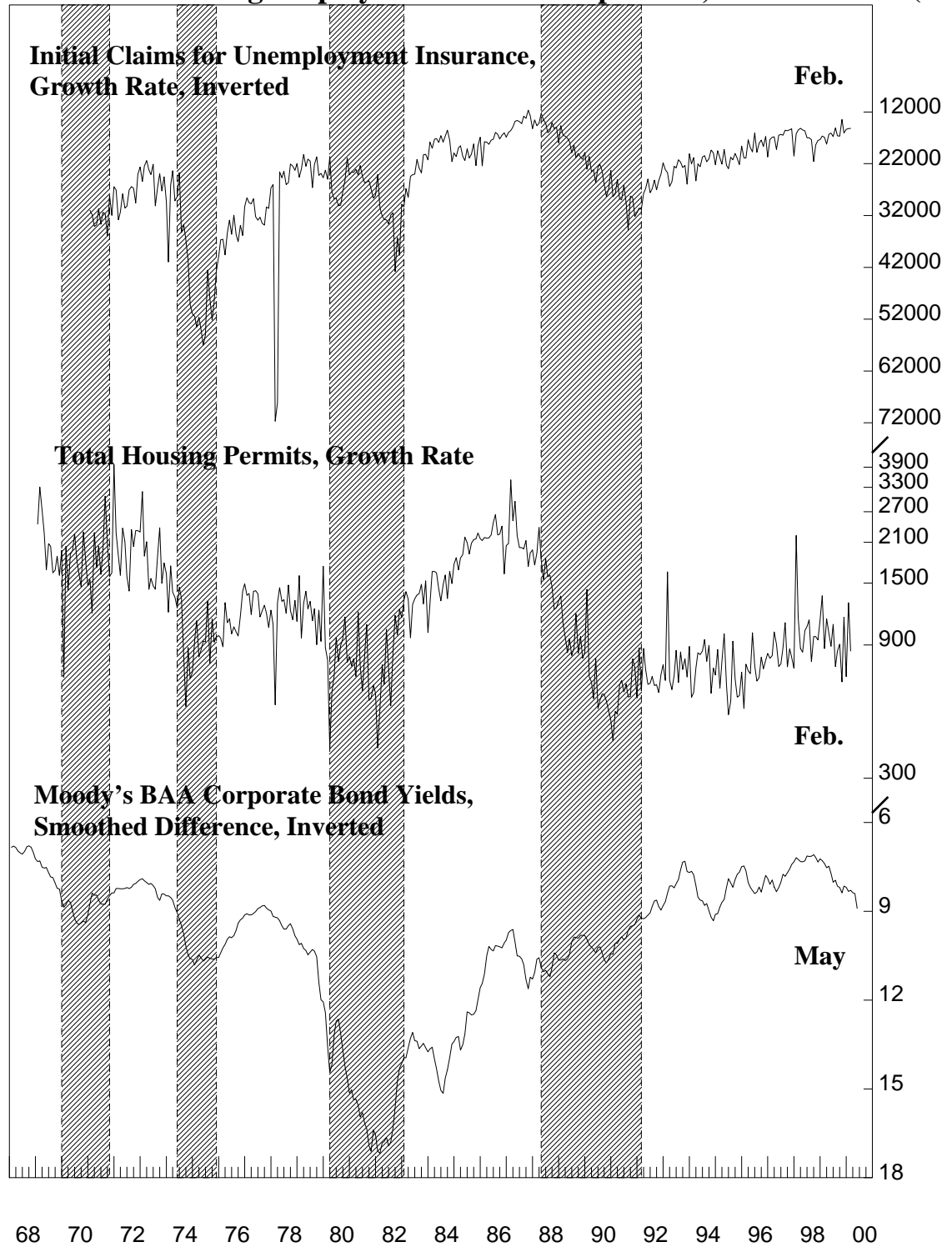
Shaded areas represent cyclical downturns in the Connecticut employment cycle.

**Figure A3:**  
**Connecticut Leading Employment Index Components, Growth Rates (%)**



Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.

**Figure A4:**  
**Connecticut Leading Employment Index Components, Growth Rates (%)**



Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.