CDE
February, 2003

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**Working Paper No. 114**

**Centre for Development Economics**
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# *Performance Evaluation of the New Connecticut Leading Employment Index Using Lead Profiles and BVAR Moddels*

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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 coincident index shows 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.

**JEL Classification:** C11, C32, E32, E37
**Keywords:** Business cycles, leading and coincident employment indexes, turning points, BVAR Models

## Acknowledgements

Anirvan Banerji is Director of Research,Economic Cycle Research Institute,New York, Pami Dua is Professor of Economics,Delhi School of Economics and Stephen M. Miller is Professor and Chair of Economics,University of Nevada, Las Vegas, USA. Funding for Anirvan Banerji's participation came from the Connecticut Center for Economic Analysis, the Connecticut Department of Labor, and the Connecticut Department of Economic and Community Development.

## 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, was the logical solution.

Past research has shown 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 makes 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 was 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.[1]

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.

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[1] 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.

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. However, our out-of-sample BVAR forecasting experiments 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 key to economic cycles is the concept of co-movements. 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 for relying not on a single series but on several series 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 cyclical peaks and troughs of each coincident series are first determined using the Bry-Boschan procedure (Bry and Boschan, 1971), which is an objective algorithmic formulation of the classical NBER procedure for picking cyclical turns. These turning points are listed in Table 1, along with the corresponding cyclical turns in the composite coincident index made up of the same indicators. 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 are those that 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 is then examined closely to check whether each component series is 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 is the final Connecticut employment cycle chronology (last column, Table 1). As Figure 1 shows quite clearly, cyclical turns in the coincident indicators included in the new coincident employment index conform quite well to this chronology. 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 are few and far between, because the average length of the cycle is about seven years. But the leading indicator approach is also suitable for 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 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 2, last column) was determined by the "clustering" procedure in the same way the employment cycle was determined, except that all the series are now in smoothed growth rate terms (Banerji, 1999). This growth rate cycle has 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) shows a small up-tick in 1992 but does not reach a trough until 1996 (Figure 1 and Table 1). 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 1).

Why do the two indexes differ so much? Since the components are exactly the same, 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) is 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 is necessarily lower 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 have had 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 been the decisive factor -- the DC method of trend adjustment procedure. In the DC method, the raw index, calculated by averaging the standardized components, has 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 is subtracted from the trend in the target series to produce the trend-adjustment factor, which is then added back to the monthly growth rate of the raw index. This trend-adjusted index is then cumulated and rebased to obtain the final index.

If a negative trend-adjustment factor that is added to slightly positive monthly growth rates in the raw index (which occurred during the "jobless recovery" of the early 1990s), then the resultant monthly trend is 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 quite 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 was the more traditional, and more robust, “clustering” procedure used for the new coincident index. It explicitly takes into account the consensus among the individual series, rather than emphasizing the coincident index alone. Therefore, our chronologies should be less sensitive 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 have slightly broader coverage and is slightly smoother as a result. Since data on the construction workweek starts only in 1982, it was 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 was used as a leading index component. It has a median lead of six months over the employment cycle (see Table A1 in the Appendix).

The other four leading indicator series were retained without any change. Of these, the Hartford help wanted advertising index has a median lead of 2.5 months over the employment cycle (Table A2). The short duration unemployment rate has a median lead of nine months over the employment cycle (Table A3). Initial claims for unemployment insurance has a median lead of six months over the employment cycle (Table A4). Finally, total housing permits has a median lead of 14 months over the employment cycle (Table A5).

One new series was added 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 this is 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 has a median lead of 14 months over the employment cycle (Table A6). 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.

Three other series were considered for inclusion but ultimately rejected. One was the Dun and Bradstreet employment optimism index for New England, which is quarterly, begins in 1989, and does not have a clear lead. The Dun and Bradstreet compilation of the number of business starts in the state was also considered, but this series starts only in 1996, and is very noisy. Finally, a standard leading indicator, the ratio of the help wanted advertising index to the number of unemployed, was also considered, but was not found to 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).

As Figure 3 shows, the old leading index possesses short leads at most turns. In fact, as Table 3 reports, the old leading index has 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 4 reports that the old leading index growth rate has a median lead of two months.

In contrast, the new leading employment index has a median lead of ten months over the employment cycle (Table 5, Figure 5), while its growth rate has a median lead of three months over the employment growth rate cycle (Table 6, Figure 6). Thus, it is 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 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 is 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 that the leads are significant. Some of the differences calculated 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 7 shows the lead profile of the new leading index against the Connecticut employment cycle, and is based on the leads shown in Table 5. The first bar represents a test of the null hypothesis that the new leading index's lead is zero months, against the alternative that it is greater than zero, i.e., at least one month. Analogously, the second bar represents another test, of the null hypothesis that the lead is one month, against the alternative that it is greater, i.e., at least two months.

As the figure shows, the confidence level remains above 95 percent for up to seven months, and above 90 percent for up to nine months.

Figure 8 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 6. In this case, the confidence level remains above 95 percent for up to one month, but falls rapidly for longer leads.

This technique can also test whether the new leading index has significantly longer leads than the old version. Figure 9 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 for up to two months, but drops thereafter.

Figure 10 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 gets above 57 percent, and is therefore statistically insignificant.

Thus, we can conclude that the new leading index has 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 has a statistically significant lead of two months, but its growth rate does not have 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.[2] We calculate forecasts using first the old indexes and then the new indexes.

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[2] 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.

Forecasting models are often formulated as 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 are poorly suited for forecasting, since projected future values of exogenous variables are required.

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 can be expressed as a VAR model and as 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.

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. An unrestricted VAR model (Sims 1980) is written as follows:

$y_t$ = $C + A(L)y_t + e_t$, where

$y$ = an (nx1) vector of variables being forecast;

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

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

$C$ = an (nx1) vector of constant terms; and

$e$ = 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 restrictions on these coefficients on the assumption that these are more likely to be near 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. This so called "Minnesota prior" was developed at the Federal Reserve Bank of Minneapolis and the University of Minnesota.

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:

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

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 have 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 $f(i, j) = 0.5$.[3] When $w = 0.2$, the standard deviation of the first own lag in each equation is 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, $f(i, j) = 0.5$ 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 contains a new trend adjustment procedure implemented by ECRI. The new leading index, on the other hand, contains one new variables – Moody's BAA corporate bond yield – and a modification of an old series – the adding of the

[3] 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.

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 and uses d = 1.0 rather than 2.0. Model 3 tightens the prior from Model 1 by using w = 0.1 rather than 0.2. Model 4 also tightens the prior from Model 1 and uses k = 0.4 rather than 0.5. Finally, Model 5 loosens the prior a bit from Model 1 and uses k = 0.6 rather than 0.5.

The variables are specified in levels rather than in differences because the Bayesian approach depends entirely on the likelihood function, which has 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).[4] 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.

*Forecast Accuracy*

We measure the out-of-sample forecast accuracy by the Theil U-statistics. 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 is defined as follows:

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

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

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 out perform the model forecasts. A U-statistic less than 1 demonstrates that the model's forecasts out perform the naive forecasts.

We generate the Theil U-statistics using the Kalman filter algorithm in RATS.[5] 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 the end of the forecast period is reached (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 periods.[6] That is, the average of U-statistics for all forecast periods is calculated for a given BVAR specification. The parameters in the prior are changed and a new set of U-statistics is generated. The combination of the parameters in the prior producing the lowest average U-statistic is identified.

*Out-of-Sample Forecasting Results*

Tables 7, 8, and 9 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

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[5] All statistical analysis was performed using RATS, version 4.31.

[6] Dua and Ray (1995, p. 170) and Curry, Divakar, Mathur, and Whiteman (1995, p. 191) each describe similar methods for selecting priors.

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, was frequently referred to as the "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.[7]

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 better forecasts of nonfarm employment than the old indexes and the naïve no-change forecasts throughout the 1990s (see Table 8). Similar findings for Model 2, however, do not occur for the coincident index and the unemployment rate forecasts (see Tables 7 and 9).

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 had, 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.

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[7] 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.

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.

It is notable that the new Connecticut leading employment index correctly predicted 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 ("A New System of Indicators for South Africa" 2002).

## 5. Conclusion

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

In addition, a new and improved Leading Employment Index was created, 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.

It is hoped, therefore, that the new index will 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.

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Tables and Graphs continued.

**Table 1:**
**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 2:**
**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 3:**
**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** | **overall** | **peaks** |
| | | | **Average** | -7 | -5 | -3 |
| | | | **Median** | -8.0 | -6.0 | -3.0 |
| | | | **Percent Lead** | 100 | 93 | 83 |
| | | | **Std. Deviation** | 3.1 | 3.6 | 3.0 |

**Table 4: Connecticut Leading Employment Index, Growth Rate (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** | **overall** | **peaks** |
| | | | **Average** | -4 | -2 | 0 |
| | | | **Median** | -3.5 | -2.0 | -1.0 |
| | | | **Percent Lead** | 94 | 83 | 71 |
| | | | **Std. Deviation** | 2.7 | 4.3 | 5.3 |

**Table 5:**
**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** | **overall** | **peaks** |
| | | | **Average** | -10 | -9 | -7 |
| | | | **Median** | -11.0 | -10.0 | -7.0 |
| | | | **Percent Lead** | 100 | 93 | 83 |
| | | | **Std. Deviation** | 3.1 | 4.9 | 7.0 |

Table 6

**Connecticut Leading Employment Index, Growth Rate (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 | overall | peaks |
| | | | Average | -5 | -2 | 0 |
| | | | Median | -4.5 | -3.0 | -1.0 |
| | | | Percent Lead | 100 | 83 | 64 |
| | | | Std. Deviation | 2.4 | 5.0 | 5.8 |

## Table 7
## 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 |
| **1985-1987** | 1.2159 | 0.7617 | 0.9342 | 0.7210 | 1.2142 | 0.7642 | 1.1941 | 0.7516 | 1.2237 | 0.7671 |
| **1988-1990** | 1.6225 | 0.7833 | 1.1082 | 0.6629 | 1.7910 | 0.8781 | 1.6354 | 0.7959 | 1.6025 | 0.7737 |
| **1991-1993** | 1.3581* | 1.7123 | 1.0180* | 1.3872 | 1.5349* | 1.6810 | 1.3579* | 1.3631 | 1.3544* | 1.7119 |
| **1994-1996** | 0.9191* | 1.7236 | 1.5891 | 1.4510 | 2.7805 | 2.0399 | 2.5446 | 1.7599 | 2.4650 | 1.6896 |
| **1997-1999** | 0.6262* | 1.3527 | 0.5956* | 1.3543 | 0.7150* | 1.1833 | 0.6337* | 1.2985 | 0.6181* | 1.3896 |
| **1998-2000** | 0.6743* | 1.6456 | 0.7158* | 1.5861 | 0.7369* | 1.5136 | 0.6736* | 1.6013 | 0.6755* | 1.6752 |
| **Average U** | 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≠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 8**

**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 |
| 1985-1987 | 1.0148 | 0.6548 | 0.9533 | 0.6307 | 0.9724 | 0.6550 | 1.0073 | 0.6562 | 1.0157 | 0.6529 |
| 1988-1990 | 1.3949 | 0.8910 | 1.1112 | 0.8495 | 1.4673 | 0.9702 | 1.4008 | 0.9026 | 1.3864 | 0.8828 |
| 1991-1993 | 1.2642* | 1.5353 | 0.9149* | 1.3318 | 1.3799* | 1.4249 | 1.2952* | 1.5191 | 1.2337* | 1.5366 |
| 1994-1996 | 1.1474 | 0.8993 | 0.9160* | 0.9186 | 1.1761 | 0.9184 | 1.1612 | 0.9084 | 1.1273 | 0.8928 |
| 1997-1999 | 0.7353 | 0.7082 | 0.6104* | 0.7269 | 0.8017 | 0.6101 | 0.7379 | 0.6836 | 0.7314 | 0.7240 |
| 1998-2000 | 0.7937* | 0.7995 | 0.6593* | 0.8119 | 0.8785 | 0.6934 | 0.7992 | 0.7733 | 0.7879* | 0.8157 |
| Average U | 1.0584 | 0.9147 | 0.8609** | 0.8782** | 1.1127 | 0.8787 | 1.0669 | 0.9072 | 1.0471 | 0.9175 |

**Note:** See Table 7.

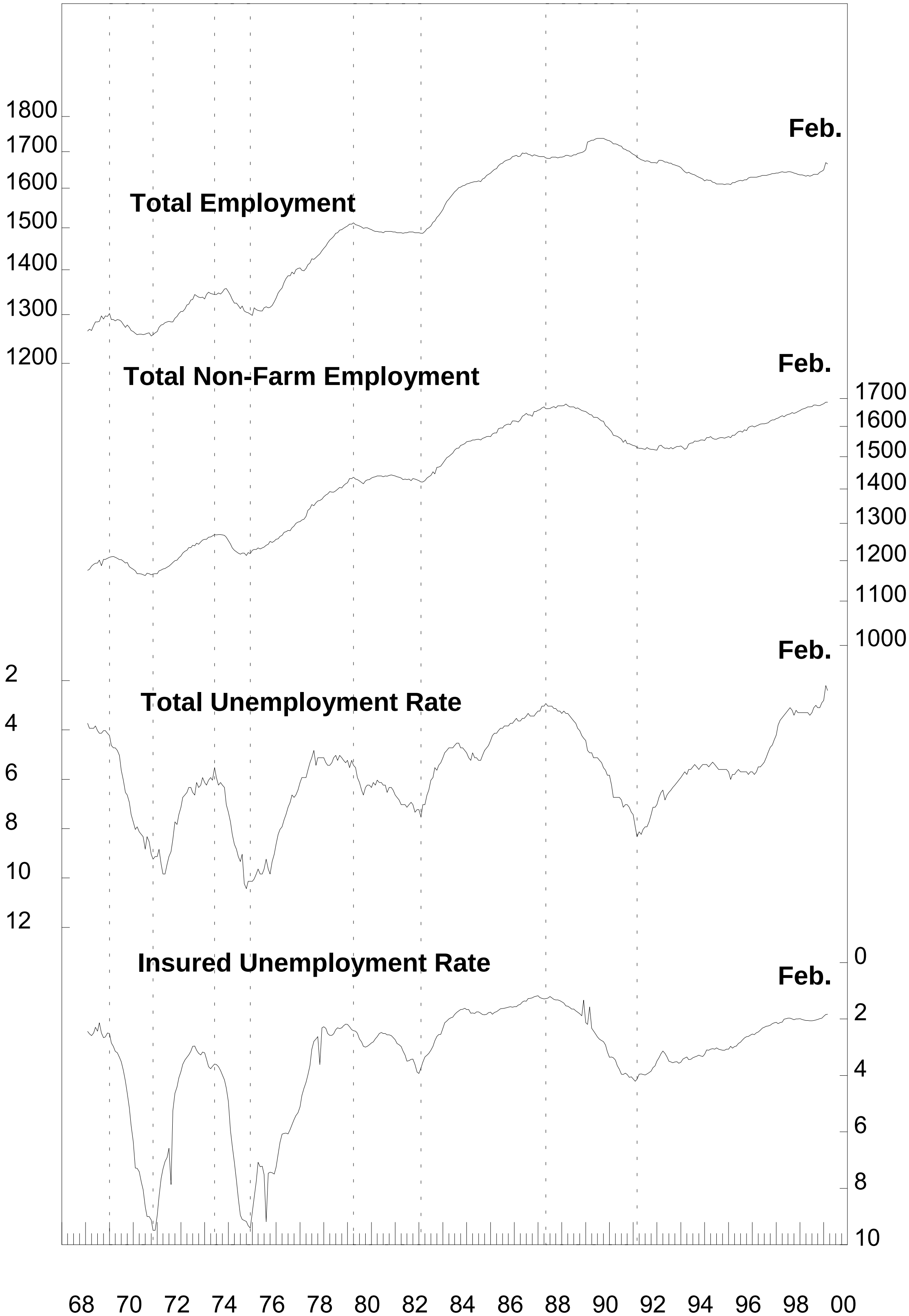
## Table 9

### 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** |
| **1985-1987** | 1.1658 | 0.7080 | 0.8026* | 0.8764 | 1.1738 | 0.6768 | 1.1651 | 0.6711 | 1.1417 | 0.6784 |
| **1988-1990** | 1.1526 | 0.5581 | 0.7856 | 0.7375 | 1.2657 | 0.6853 | 1.1819 | 0.5789 | 1.1230 | 0.5435 |
| **1991-1993** | 1.2625 | 1.0418 | 1.0503 | 0.9422 | 1.3247 | 1.0539 | 1.2847 | 1.0393 | 1.0215* | 1.0497 |
| **1994-1996** | 2.9329 | 1.4952 | 1.9754 | 1.1102 | 3.2577 | 1.7592 | 2.9702 | 1.4841 | 2.8810 | 1.5007 |
| **1997-1999** | 0.6617* | 1.0004 | 0.7194* | 1.0130 | 0.6763* | 0.9410 | 0.6568* | 0.9972 | 0.6672* | 0.9999 |
| **1998-2000** | 0.7742* | 1.4205 | 0.9204* | 1.4309 | 0.7740* | 1.2997 | 0.7702* | 1.4168 | 0.7800* | 1.4165 |
| ***Average U*** | 1.3250 | 1.0373 | 1.0423** | 1.0184** | 1.4120 | 1.0693 | 1.3382 | 1.0312 | 1.2691 | 1.0315 |

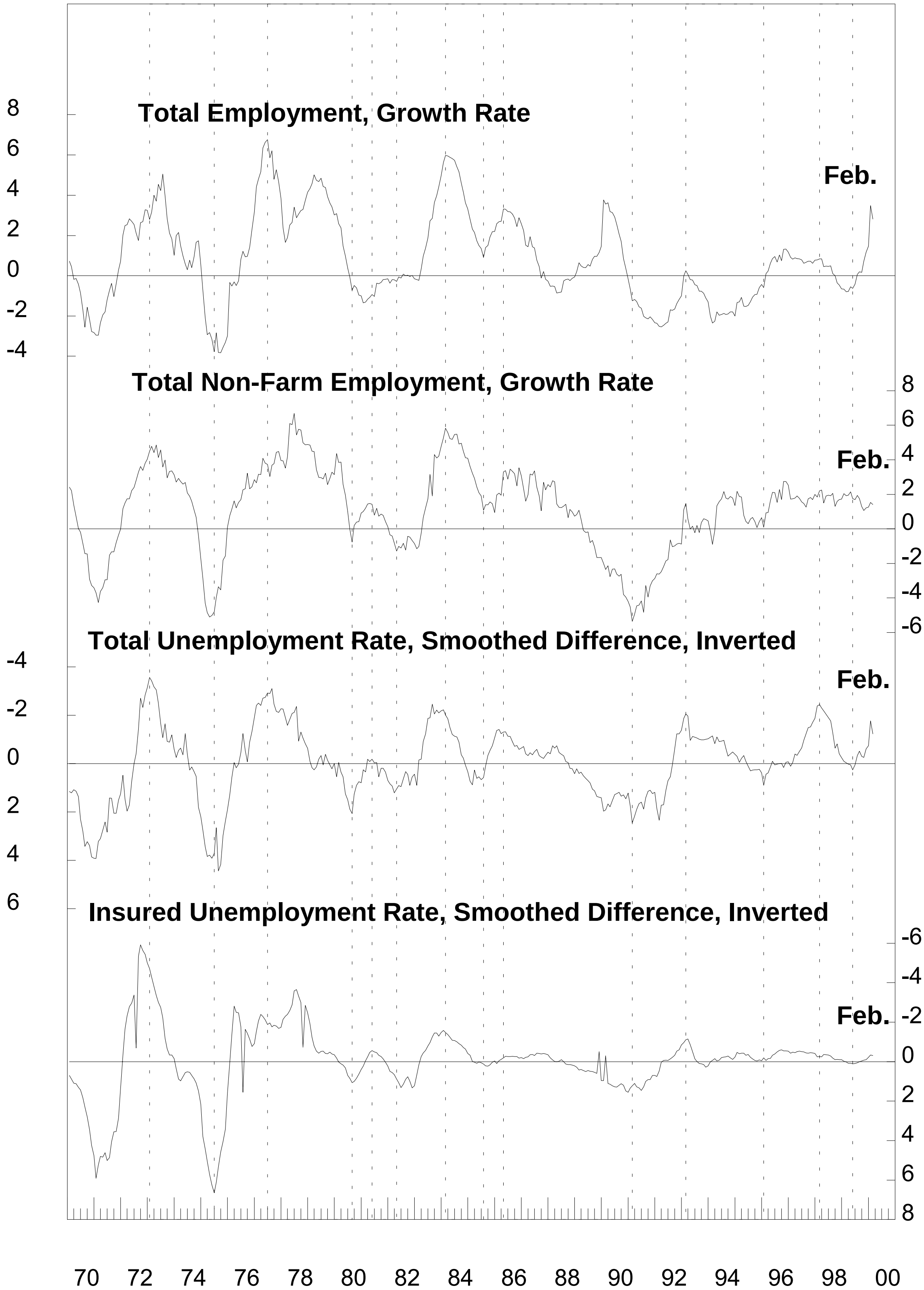
Note: **See Table 7.**

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



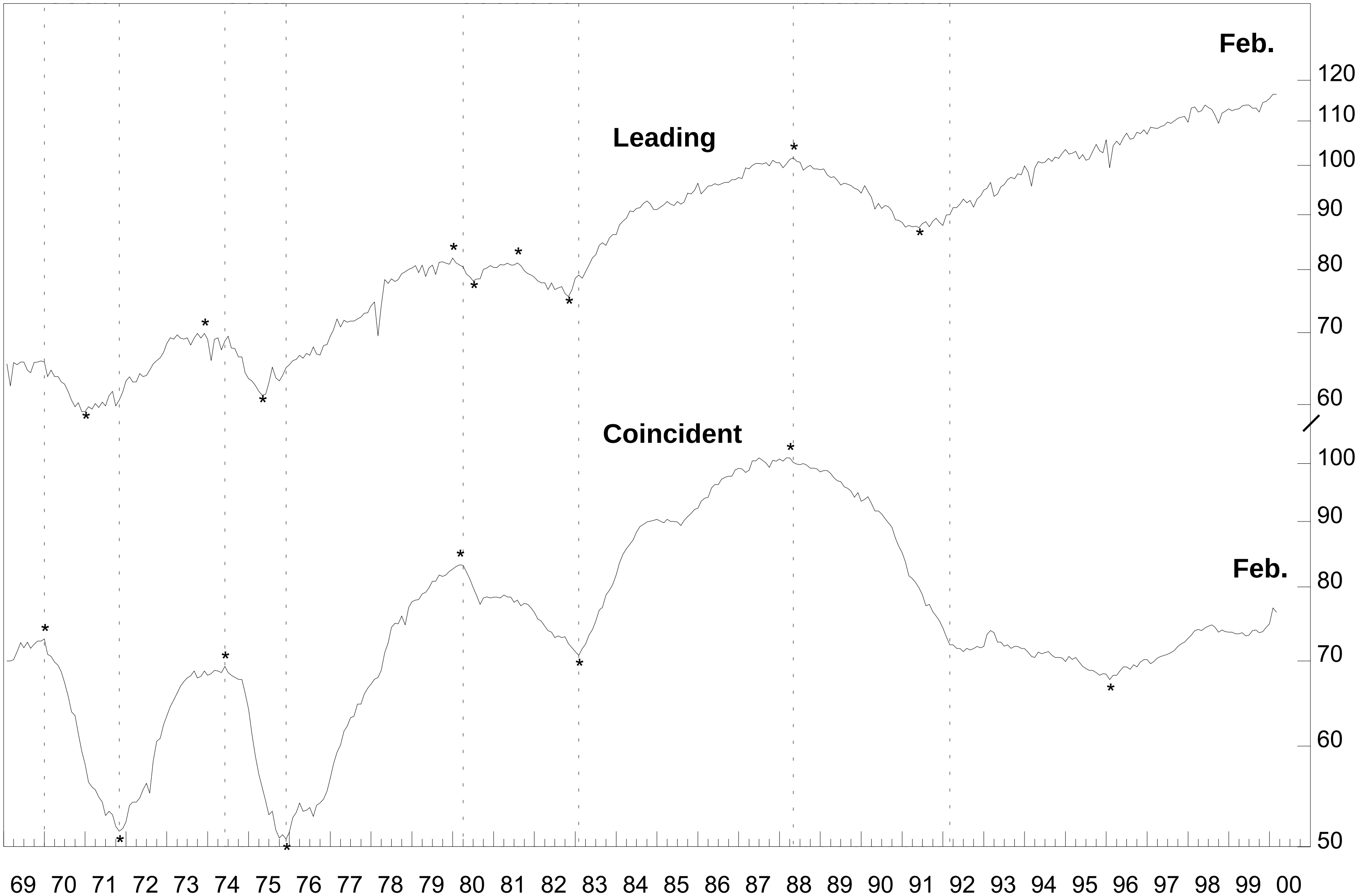

Shaded areas represent cyclical downturns in the Connecticut employment cycle.

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



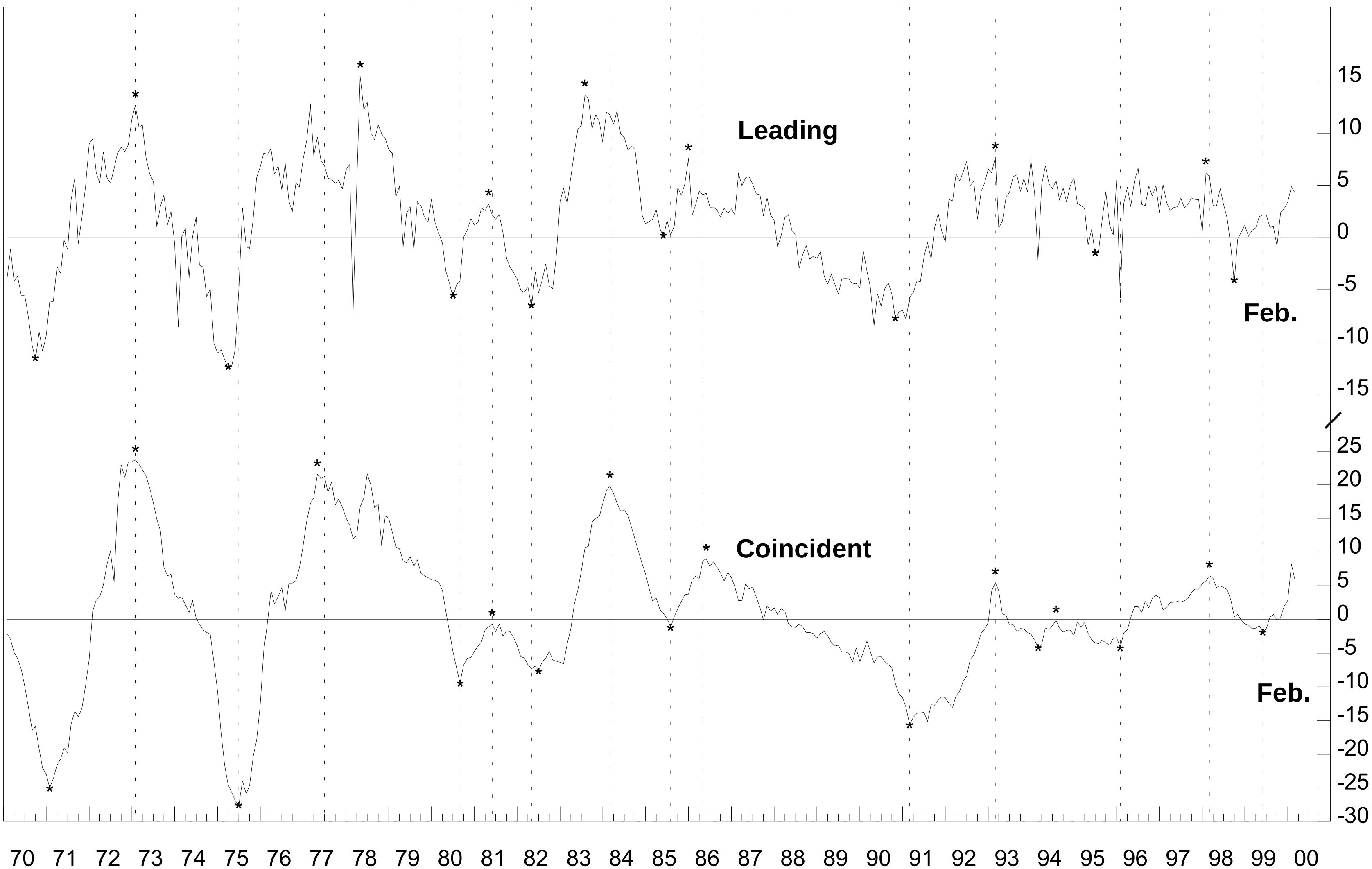

Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.

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



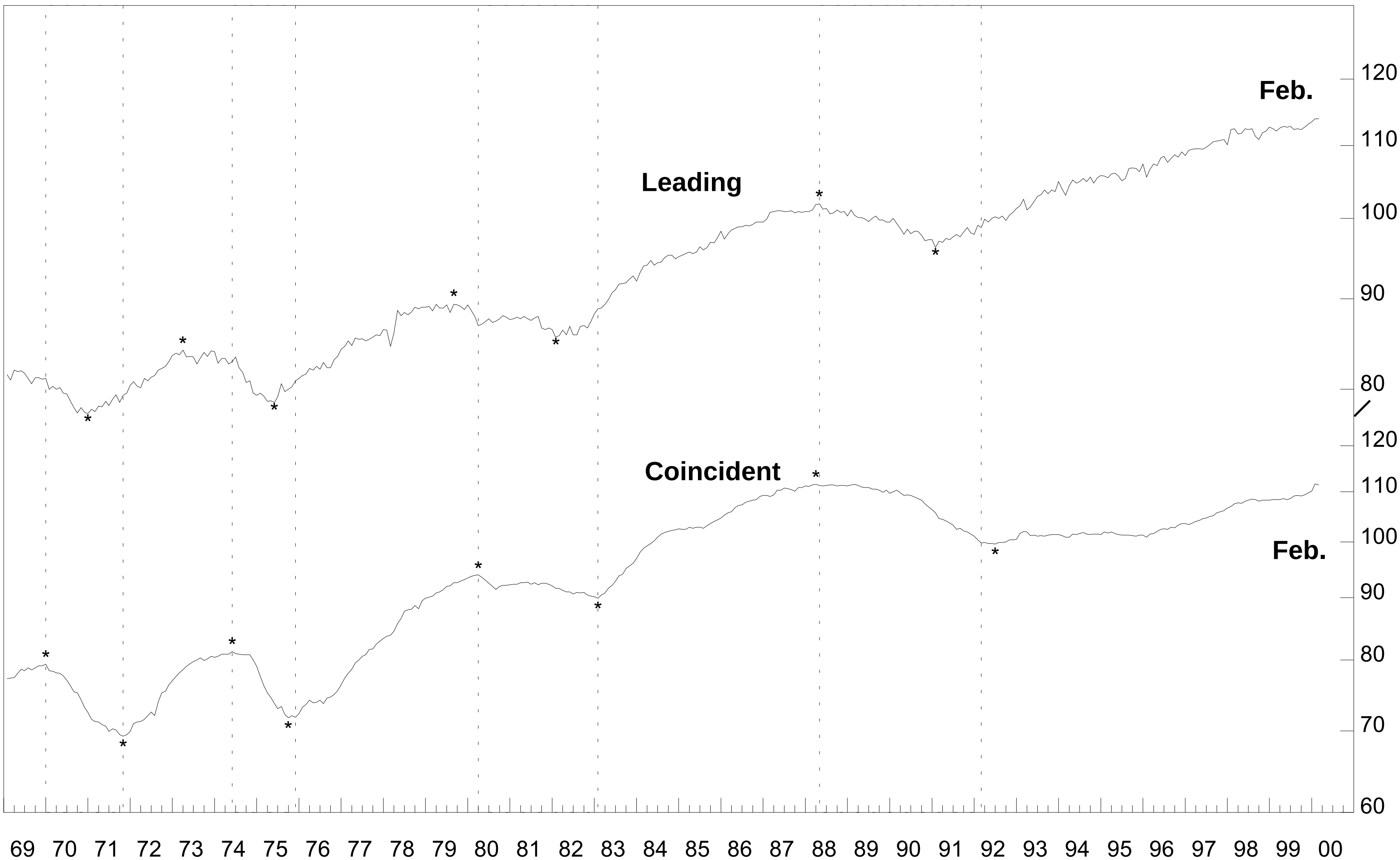

Shaded areas represent cyclical downturns in the Connecticut employment cycle.

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



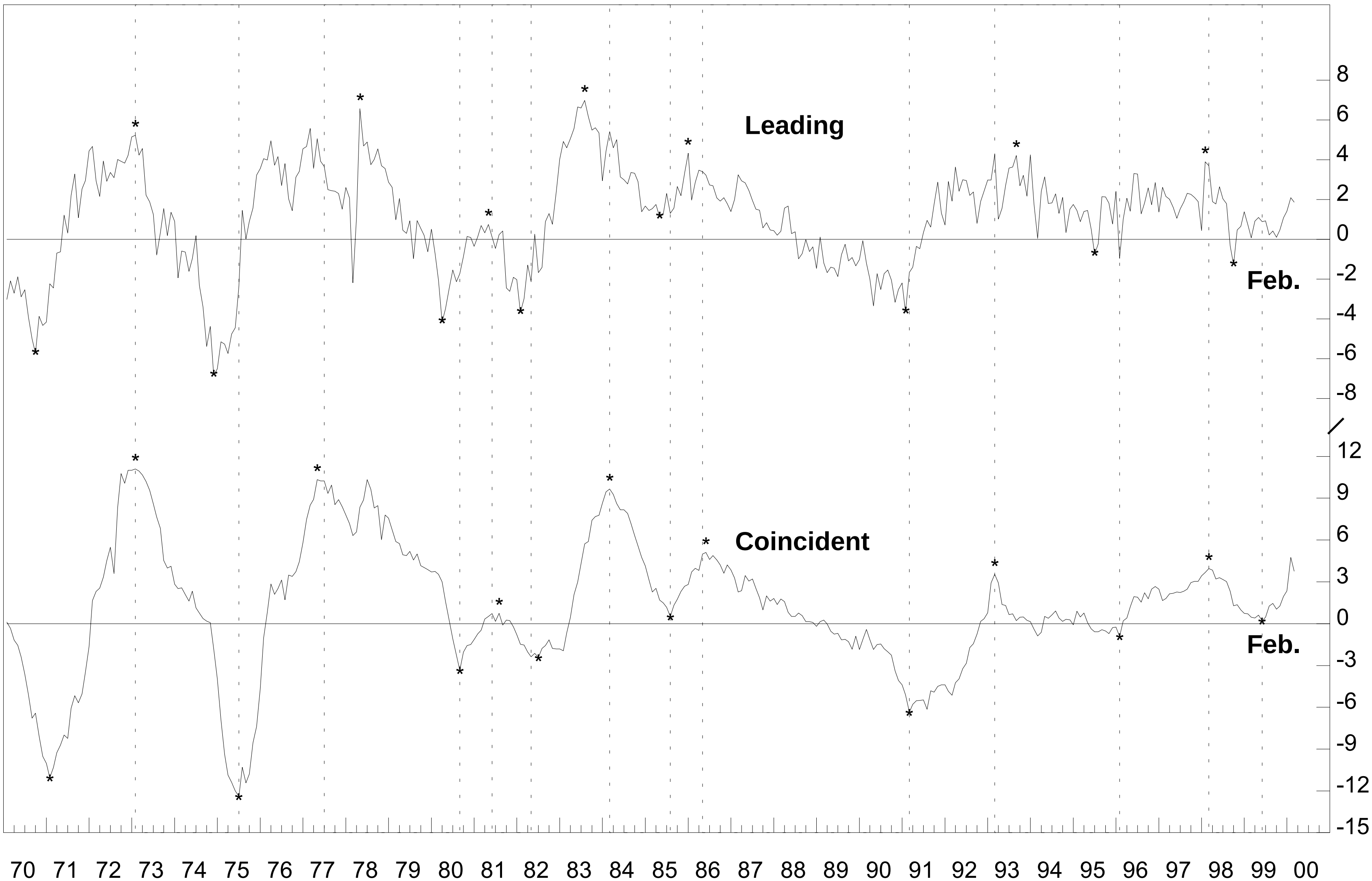

Shaded areas represent cyclical downturns in the Connecticut employment growth rate cycle.

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



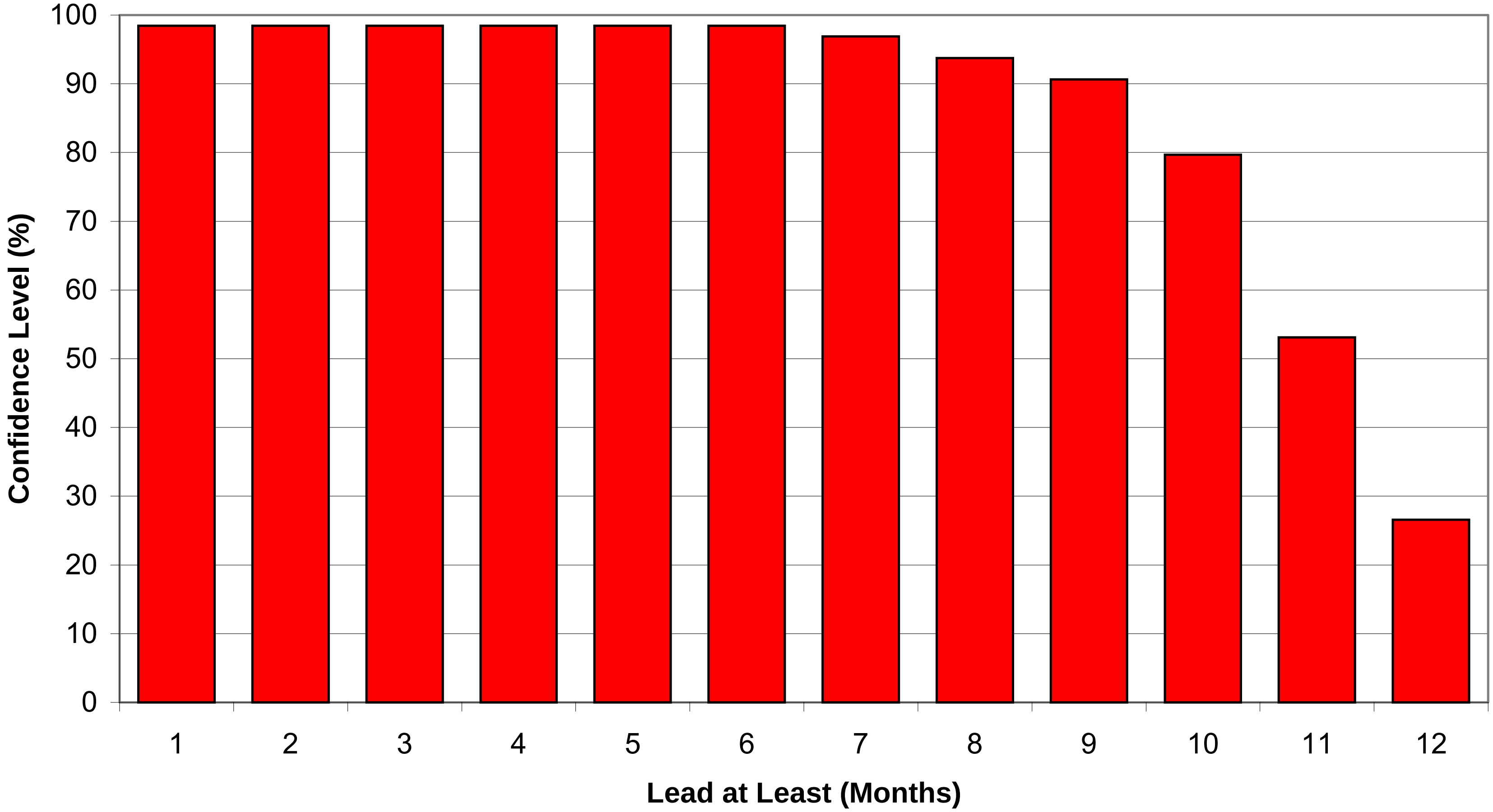

Shaded areas represent cyclical downturns in the Connecticut employment cycle.

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




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

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



## Figure 8:
## Lead Profile of Connecticut Leading Employment Index, Growth Rate

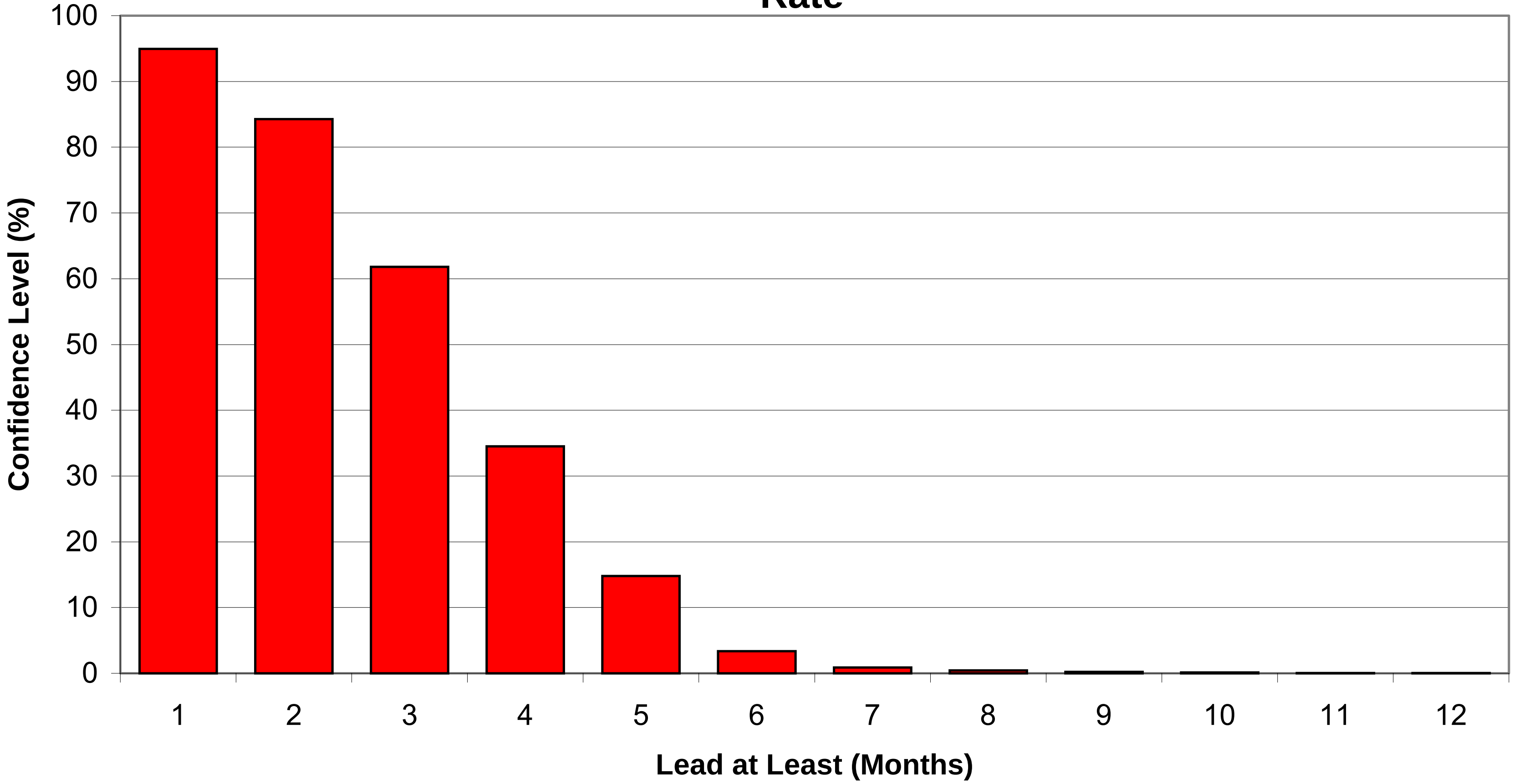


**Figure 9:**
**Lead Profile of New vs. Old Leading Employment Index**

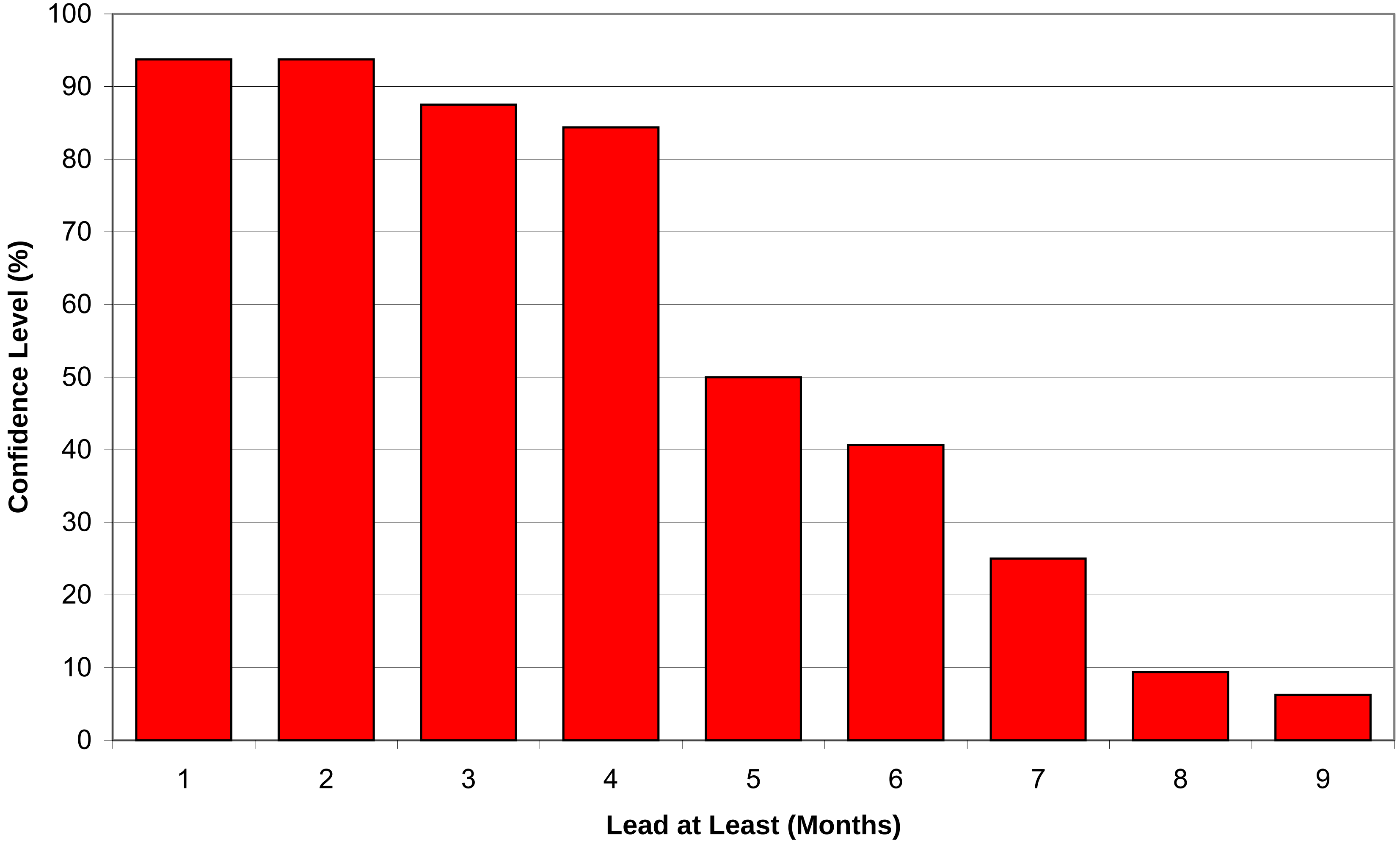


**Figure 10:**
**Lead Profile of New vs. Old Leading Employment Index Growth Rates**

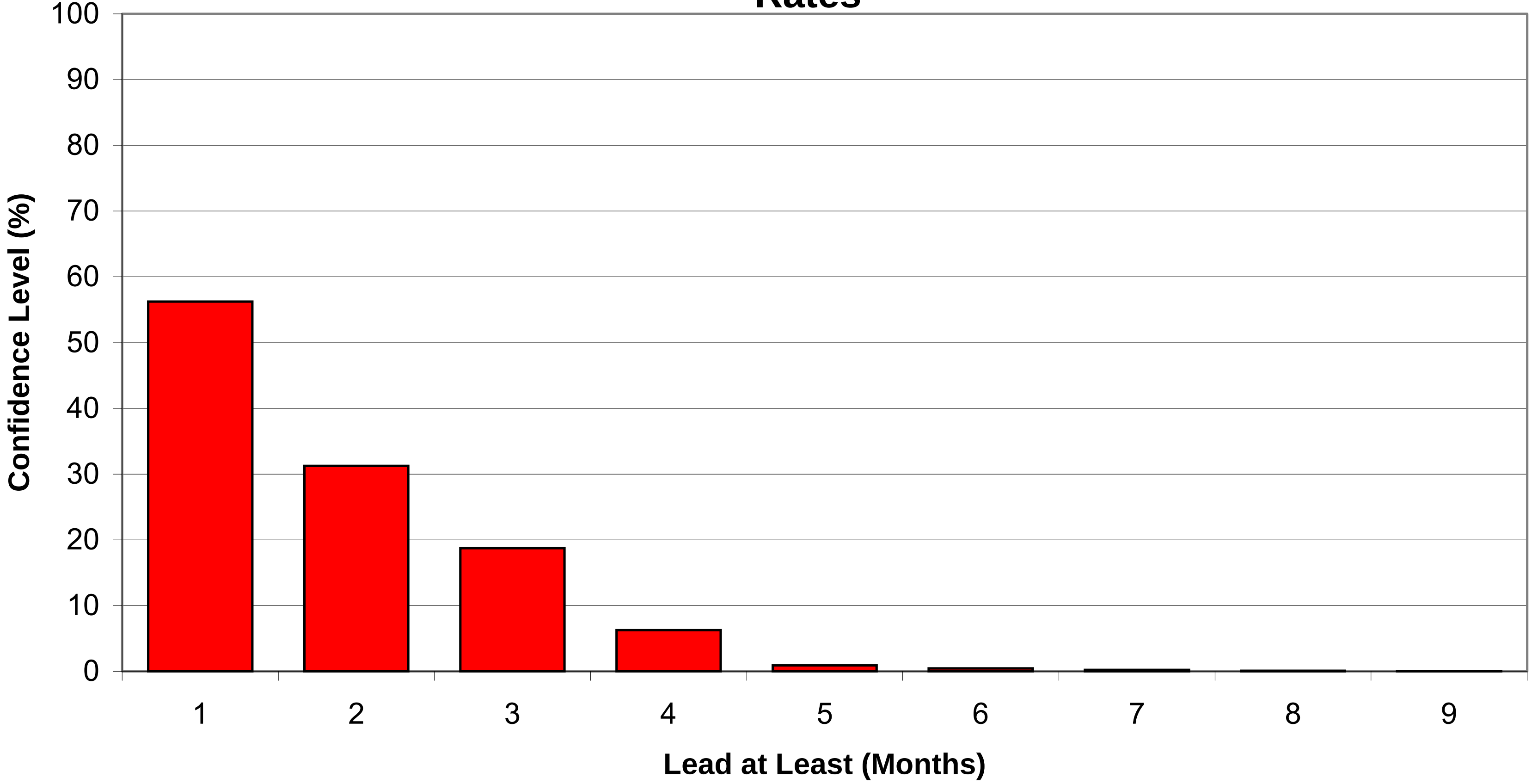


**Table A1:**
**Average Weekly Hours of Manufacturing & Construction Lead/Lag**

| 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** | **overall** | **peaks** |
| | | | **Average** | -3 | -4 | -5 |
| | | | **Median** | -5.5 | -6.0 | -13.0 |
| | | | **Percent Lead** | 75 | 71 | 67 |
| | | | **Std. Deviation** | 6.4 | 9.7 | 14.7 |

**Table A2:**
**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 | overall | peaks |
| | | | Average | 0 | -4 | -7 |
| | | | Median | -1.0 | -2.5 | -8.0 |
| | | | Percent Lead | 63 | 81 | 100 |
| | | | Std. Deviation | 3.1 | 4.9 | 4.3 |

**Table A3:**
**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 |
| | | 06/1986 | | extra | | |
| | 04/1988 | | 10/1987 | | | -6 |
| 02/1992 | | 04/1991 | | -10 | | |
| | | | | **troughs** | **overall** | **peaks** |
| | | | **Average** | -8 | -8 | -9 |
| | | | **Median** | -8.5 | -9.0 | -9.0 |
| | | | **Percent Lead** | 100 | 100 | 100 |
| | | | **Std. Deviation** | 3.6 | 3.1 | 3.0 |

**Table A4:**
**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 |
| | | 10/1985 | | extra | | |
| | 04/1988 | | 10/1987 | | | -6 |
| 02/1992 | | 08/1991 | | -6 | | |
| | | | | **troughs** | **overall** | **peaks** |
| | | | **Average** | -4 | -7 | -11 |
| | | | **Median** | -5.0 | -6.0 | -12.0 |
| | | | **Percent Lead** | 100 | 100 | 100 |
| | | | **Std. Deviation** | 2.4 | 4.5 | 4.2 |

**Table A5:**
**Total Housing Permits Lead/Lag**

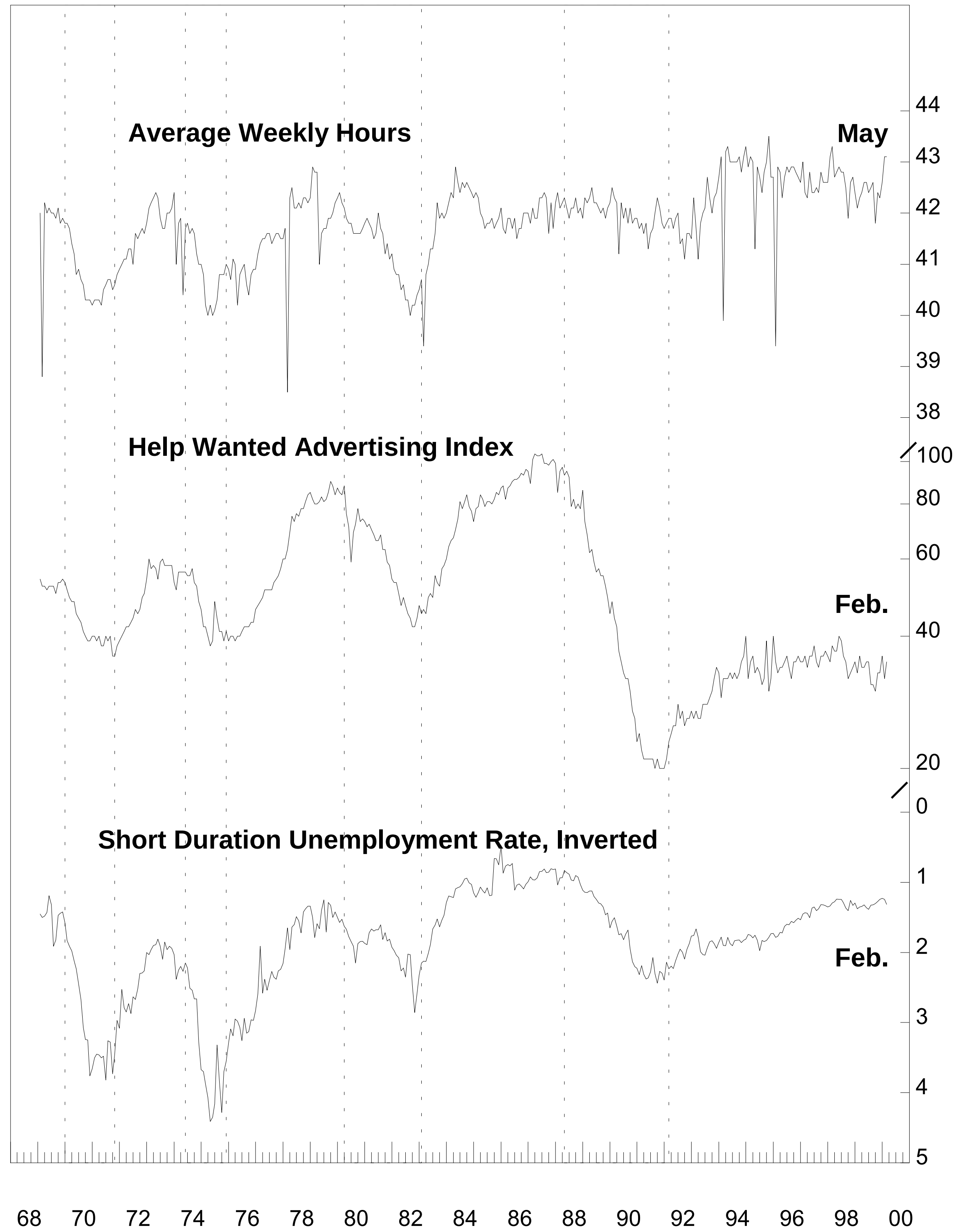
| Connecticut Employment Cycle | | Total Housing Permits | | Lead(-) / | Lag(+) |
|---|---|---|---|---|---|
| **Troughs** | **Peaks** | **Troughs** | **Peaks** | **Troughs** | **Peaks** |
| 10/1971 | | 01/1970 | | -21 | |
| | 05/1974 | | 01/1973 | | -16 |
| 11/1975 | | 09/1974 | | -14 | |
| | | | 12/1976 | | extra |
| | | 02/1978 | | extra | |
| | 03/1980 | | 08/1978 | | -19 |
| | | 03/1980 | | extra | |
| | | | 10/1980 | | extra |
| 01/1983 | | 01/1982 | | -12 | |
| | 04/1988 | | 02/1987 | | -14 |
| 02/1992 | | 01/1991 | | -13 | |

| | troughs | overall | peaks |
|---|---|---|---|
| **Average** | -15 | -16 | -16 |
| **Median** | -13.5 | -14.0 | -16.0 |
| **Percent Lead** | 100 | 100 | 100 |
| **Std. Deviation** | 4.1 | 3.3 | 2.5 |

**Table A6:**
**Moody's BAA Corporate Bond Yields Lead/Lag**

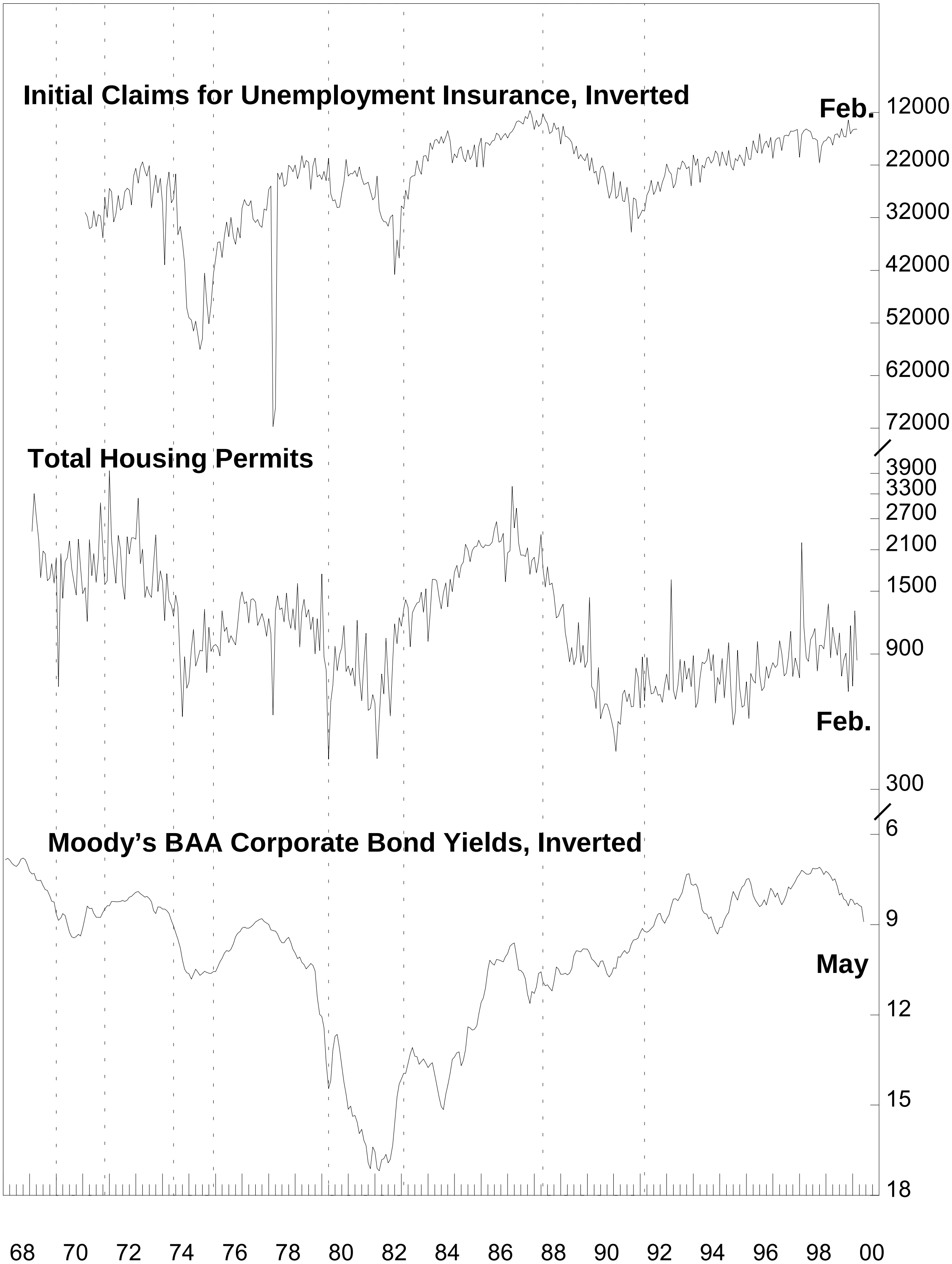
| Connecticut Employment Cycle | | Moody's BAA Corporate Bond Yields | | Lead(-) / Lag(+) | | |
|---|---|---|---|---|---|---|
| **Troughs** | **Peaks** | **Troughs** | **Peaks** | **Troughs** | | **Peaks** |
| 10/1971 | | 08/1970 | | -14 | | |
| | 05/1974 | | 01/1973 | | | -16 |
| 11/1975 | | 01/1975 | | -10 | | |
| | 03/1980 | | 09/1977 | | | -30 |
| 01/1983 | | 02/1982 | | -11 | | |
| | | | 05/1983 | | | extra |
| | | 07/1984 | | extra | | |
| | 04/1988 | | 03/1987 | | | -13 |
| | | 10/1987 | | extra | | |
| | | | 11/1989 | | | extra |
| 02/1992 | | 10/1990 | | -16 | | |
| | | | | **troughs** | | **peaks** |
| | | | | | **overall** | |
| | | | **Average** | -13 | | -20 |
| | | | | | -16 | |
| | | | **Median** | -12.5 | | -16.0 |
| | | | | | -14.0 | |
| | | | **Percent Lead** | 100 | | 100 |
| | | | | | 100 | |
| | | | **Std. Deviation** | 2.8 | | 9.1 |
| | | | | | 6.7 | |

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



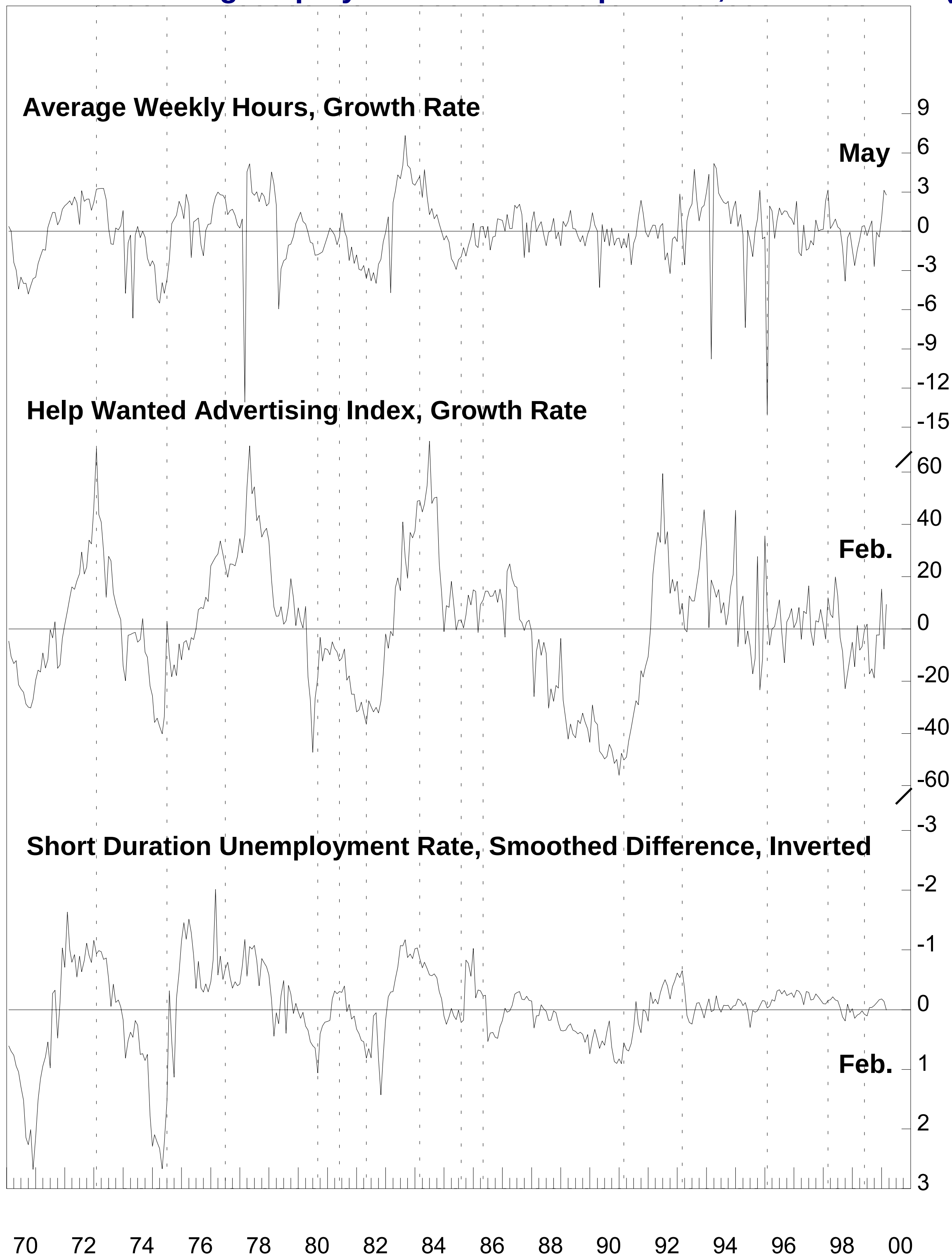

Shaded areas represent cyclical downturns in the Connecticut employment cycle.

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



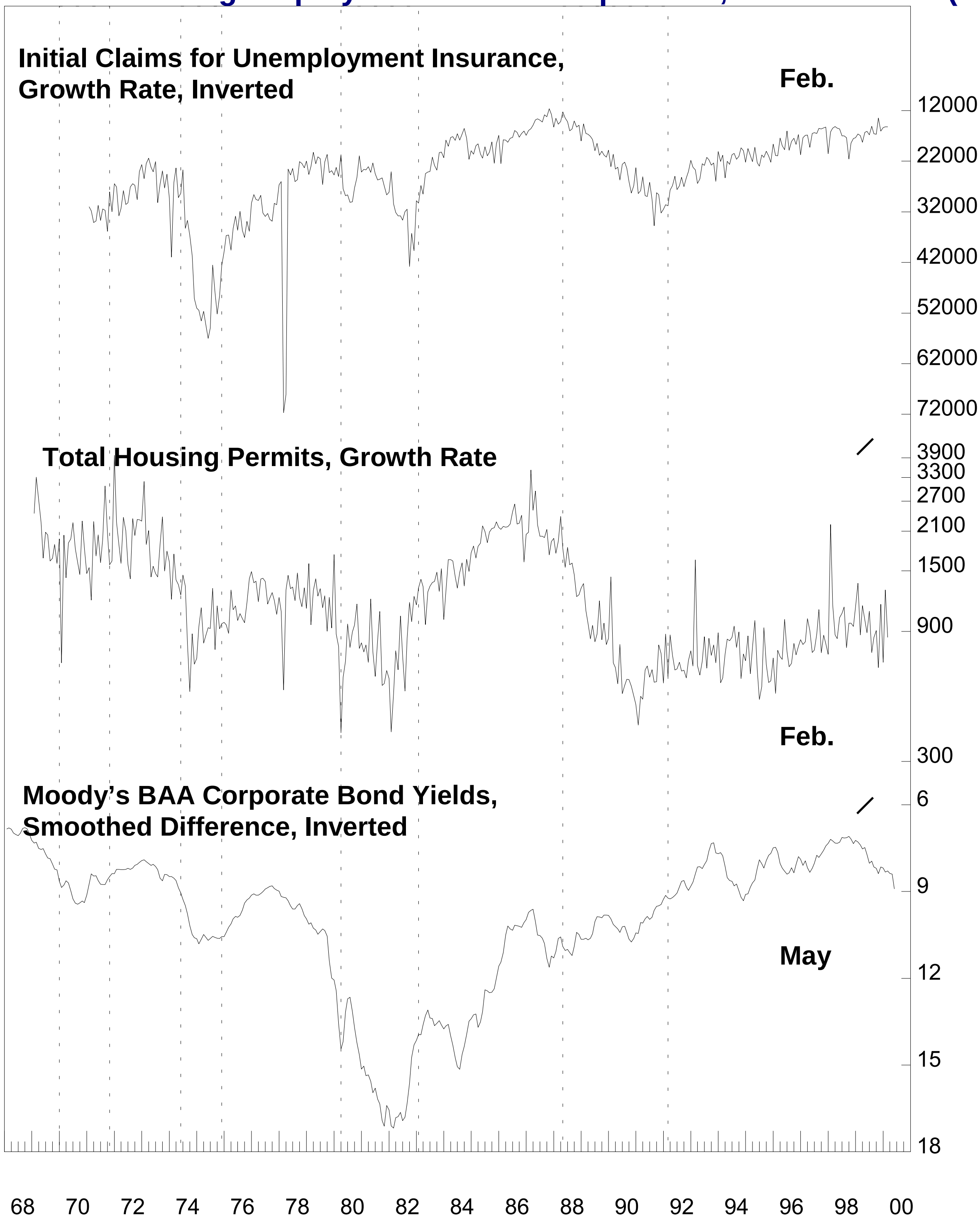

Shaded areas represent cyclical downturns in the Connecticut employment cycle.

**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.

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