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ABSTRACT

Procedures for tracking and forecasting economic conditions in regional economies have evolved significantly over the last 30 years. Much of this evolution has followed developments in macroeconomics, where techniques for tracking/forecasting key economic variables have tended to originate. This technique adoption and adaptation process continues today, as developments in the modeling of cointegrated macroeconomic time series have begun to appear in the regional modeling and forecasting literature. This paper presents an effort at modeling a segment of a regional economy using the cointegration testing procedures suggested by Johansen and Jusilius (1990) to develop a forecasting model for manufacturing employment in Milwaukee, WI. The paper demonstrates how Vector Error Correction (VEC) modeling can lead to gains in the accuracy of local manufacturing employment forecasts relative to more traditional VAR models in either levels or first-differenced form. In the process, it demonstrates procedures for developing a relatively simple VEC model that reveals something about the structure of the local manufacturing sector, including possible linkages to the national

economy. This information can assist local policy makers in anticipating and adapting to business cycle-related fluctuations in this critical sector of the local economy.

Introduction

Procedures for tracking and forecasting economic conditions in regional economics have evolved significantly over the last 30 years. Much of this evolution has followed developments in macroeconomics, where techniques for tracking/forecasting key economic variables have tended to originate. For example, the techniques originally used to construct national index numbers such as the leading indicators have been adapted to regional and local economies. Regional structural econometric models have been constructed using national models as templates. More recently, both standard and Bayesian variants of vector autoregressive (VAR and BVAR) models first used to examine the macro economy have been applied to regional and local economies.

This technique adoption and adaptation process continues today, as developments in the modeling of cointegrated macroeconomic time series have begun to appear in the regional modeling and forecasting literature. This is not surprising; regional modelers tend to be faced with a more limited set of available data series that are often subject to greater measurement error. Cointegration modeling offers at least the possibility of getting significant structural information and predictive ability out of relatively modest sized models. It also offers an opportunity to explore linkages between national and regional economies.

The use of cointegration analysis at the regional level is itself an on-going evolutionary process. The first generation of cointegration-based regional analysis made use of the two-step Engle-Granger (1987) approach to estimation and forecasting of cointegrated series. A second generation of models has incorporated the more sophisticated multi-variate approach to cointegration developed originally by Johansen (1988).

This paper presents a third-generation effort at modeling a regional economy. It employs the next level of cointegration testing procedures suggested by Johansen and Jusilius (1990) to develop a forecasting model for manufacturing employment in Milwaukee WI. It is the first installment in a series of high frequency time-series models that will be used to analyze and forecast economic conditions in the metro area. The paper demonstrates how Vector Error Correction (VEC) modeling can lead to gains in the accuracy of local manufacturing employment forecasts relative to more traditional VAR models in either levels or first-differenced form. In the process, it demonstrates procedures for developing a relatively simple VEC model that can still reveal something about the structure of the local manufacturing sector, including possible linkages to the national economy. This information can assist local policy makers in anticipating and adapting to business cycle-related fluctuations in this critical sector of the local economy.

The rest of this paper is organized as follows. The next section provides an overview of relevant cointegrated time-series modeling procedures. The third section presents a review of recent regional forecasting literature that incorporates various cointegrated time-series procedures. In the fourth section a forecasting model for the manufacturing sector of the metro Milwaukee area is developed. This is based on a combination of a priori reasoning, cointegration analysis, and related testing procedures. The fifth section contains evidence on the forecasting performance of this model. Concluding comments are offered in the final section.

Overview of Cointegrated Time Series Modeling

The following sketch of the vector error-correction (VEC) framework developed by Johansen (1988) and extended by Johansen and Juselius (1990) is offered as background for what comes later. It is also contrasted, where appropriate, with the earlier approach developed by Engle and Granger (1987).

To begin, say a group of variables has been identified that are thought to reflect the economic conditions in a region which is to be modeled. If there are p of these variables, they can be written as X_t a $p \times 1$ vector of time series. If the selection of X_t is guided by economic theory, there is likely to be some structural relation(s) among these series, although the specifics of the relation(s) are not likely to be fully known.

The hope is to capture the essence of the relation(s) in a quantitative model that can be used to forecast the components of X_t that are of interest to policy makers.

The simplest multi-variate empirical model for these series would be a conventional p-equation VAR model of lag k, which can be specified as,

(1)

$$X_t = \mu + \Gamma_1 X_{t-1} + \Gamma_2 X_{t-2} + \ldots + \Gamma_k X_{t-2} + \varepsilon_t.$$

However, such a model is only appropriate if each of the series in X_t is integrated to order zero, $I(0)$, meaning that each series is stationary.

A problem emerges, if, as is often the case with regional economic data, some elements of X_t are integrated to order one, $I(1)$. Each data series that is $I(1)$ contains a stochastic trend that can be eliminated by first differencing, thereby making the series stationary.(n1) The existence of these stochastic trends calls for an adjustment in modeling strategy. Because they ignore the effects of integration, models such as Equation (1) have been referred to as "spurious regressions" by Granger and Newbold (1974). These regression models cannot be used to draw statistical inferences or to make reliable forecasts of variables of interest.(n2)

A popular alternative specification is to rewrite Equation (1) in first-differenced form, which focuses exclusively on the short-run relations among the series. This is proper if there is no connection among the stochastic trends in the respective elements of X_t, If there is one or more such connection, a complication emerges because these series will be cointegrated. Cointegrated series are ones that tend to "hang together" in the sense that they don't tend to drift too far apart over time because there is one or more underlying long-run relationship tying them together.(n3) A shock may cause cointegrated series to temporarily move apart, but they eventually move back in line as the underlying long-run relationships among the series reassert themselves.

The problem with using the first-differenced form of Equation (1) in the presence of cointegration is that differencing results in the loss of the information about the underlying long-term relationship that ties the cointegrated series together. This causes the first-differenced VAR model to be mis-specified. As a result, forecasts from this model may tend to drift away from the actual values because the tying forces are ignored.

To avoid this problem the information regarding the long-run stationary component of the data must be retrieved and incorporated into the short-run, first-differenced model. This is done by rewriting Equation (1) as a VEC model,

(2)

$$\Delta X_t = \mu + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \ldots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \varepsilon_t,$$

where the matrix Γ reflects the short-run aspects of the relationship between the elements of X_t and the matrix Π captures the long-run information.(n4)

Recall that in a multi-variate model there can be one or more cointegrating relations, depending on the number of linear combinations of X_t that are stationary. The number of cointegrating relations (and thus the informational content of Π) can be determined by the rank of Π, which is denoted r. Knowing r helps determine the proper empirical specification. If $r = p$, so that Π has full rank, it can be concluded that X_t is a stationary process. This could happen, but it tends to be unusual in sets of economic time series. At the other extreme, we might have $r = 0$, so the rank of Π is zero. This implies that the elements of X_t are not cointegrated, and thus no stationary long-run relationship exists. As a result, the conventional VAR model in first-differenced form shown in Equation (1) is an appropriate specification.

A final possibility is that $0 < r < p$, which implies that there are r cointegrating vectors and p-r stochastic trends among the elements of X_t If this occurs, Π can be decomposed into two $p \times r$ matrices, α and β, where $\Pi = \alpha\beta'$. Matrix a contains the weights or speeds of adjustment (the error-correction coefficients) that force the series back toward their underlying equilibrium relations, and matrix β contains the cointegrating vectors that summarize the underlying long-run relations.

The number of cointegrating relations can be determined using either of two tests. Both are based on the null hypothesis that there are $r = n$ cointegrating relations, where $0 </= n </= p$. The two tests differ in the way the alternative hypothesis is formulated. One test (the trace test) assumes the alternative is $r \leq n$. The other test (the maximal eigenvalue test) assumes a more restricted alternative hypothesis, that there is one cointegrating vector more than that hypothesized by the null. Because of this difference in approach, the two are often used as complementary tests.(n5)

Johansen and Juselius (1990) also developed likelihood-ratio procedures for testing restrictions on the elements of α and β that are useful for model specification. For example, it is possible to test hypotheses regarding the values of β, which can be useful in evaluating the long-run relation. It is also possible to test whether any of the series in X_t are weakly exogenous. In general terms, a variable in a cointegrated system that is weakly exogenous can appear in the cointegrating relation, but need not have a separate equation in the overall system.(n6) Thus, the presence of weakly exogenous variables permits reduction of the dimension of the empirical model. Weak exogeneity can be evaluated by testing the j statistical significance of the weight associated with the stationary part of X_j in the equation for X_i.(n7)

Causality and the associated testing procedures are also useful concepts that come into play when developing forecasting models of cointegrated time series.(n8) The causality issue is inherent in the modeling of cointegrated data series because cointegration implies causality in at least one direction. However, cointegration tests cannot be used to determine the direction in which causality flows. This requires Granger-noncausality tests, as well as tests of significance of the elements of Π.(n9) Noncausality tests provide related, but distinct information from the exogeneity tests. Establishing weak exogeneity justifies the VEC estimation procedure and makes statistical inference possible based on the estimated long-run relation(s). Establishing Granger-noncausality justifies forecasting a particular time series, X_i, conditional on future values of another series, X_j provided X_j is not Granger-caused by X_i.(n10)

These modeling and testing procedures collectively offer a more flexible and sophisticated approach to modeling cointegrated series than the earlier method proposed by Engle and Granger (1987). The advantages are readily apparent. For example, Engle and Granger suggest testing for cointegration by running an OLS regression on the levels or logarithms of a number of $I(1)$ variables, obtaining the residuals, and applying the Dicky-Fuller unit root test to the residuals.(n11) This procedure does not provide a mechanism for determining the number of cointegrating relations, and is based on arbitrary normalization rules. In contrast, Johansen and Juselius provide a multi-variate maximum likelihood approach that permits the determination of the number of cointegrating vectors and does not depend on the normalization choice.

Another advantage of the latter procedure relates to drawing statistical inference on the parameters of the cointegrating relation. Engle and Granger suggest estimating the cointegrating regression by OLS. This makes any attempt to test hypotheses on the parameters of the cointegrating relation problematic because the resulting estimated standard errors are "unreliable."(n12) This problem does not arise in the Johansen maximum likelihood framework.

These advantages clearly make the Johansen and Juselius framework the preferred approach to regional time-series forecasting. Thus, it can help to meet the long-standing need of regional policy makers for forecasting models that are useful for anticipating and responding to business cycle-related and other types of economic shocks. In the section below, a model of Milwaukee manufacturing employment is developed using the step-by-step procedure just described. But first, a sample of the previous work that utilizes cointegration analysis to forecast at a regional level is reviewed in order to provide a context for this modeling effort.

Evolution of Cointegration Modeling at the Regional Level

There is extensive literature dealing with the development of short-term forecasting models at the regional level. Here the focus is exclusively on the work that attempts to incorporate information about the longer-term relations that cointegration analysis reveals.

The early work in this area attempted to establish the applicability and relevance of cointegration models at the regional level. Representative of this work are two efforts by LeSage that concentrated strictly on regional economies in isolation, and had only limited interest in developing models with at least a loosely specified theoretical underpinning. In each case, the focus was a forecasting experiment comparing VEC models based on cointegration relations with more traditional alternative modeling procedures.

In his first work, LeSage (1990a) modeled several broad sectors for eight metro areas in Ohio. He demonstrated that, where they could be appropriately applied, VEC models produced superior forecasts compared to those of standard VAR, BVAR, and recursive autoregressive models. Further, these gains in forecasting performance tended to improve with longer forecasting horizons. Thus, cointegrating relations, if present, were shown to improve forecasting ability as Engle and Granger (1987) had suggested.

In his subsequent work, LeSage (1990b) conducted a more elaborate forecasting experiment using employment data for over fifty Ohio industries. Here he added structure by focusing on three series (total man-hours of employment, nominal wages, and prices) that can be at least loosely tied together in a labor market model specified in terms of nominal wages. A discouraging aspect of this work was that he was only able to find limited evidence of cointegration among the strictly local data series. This suggested that an error-correction specification was only appropriate for a limited number of industries.

A short time later, Shoesmith (1992) used the Engle-Granger approach to analyze whether state-level employment was cointegrated with either national employment or broad regional employment. In general, he found very little evidence of cointegration. He did find, however, that national employment tended to "cause" state employment. While not offering much encouragement about the use of VEC modeling at the state level, Shoesmith's analysis did reveal something about the probable underlying structural relationships--one supporting a "top-down" view of state economies where national employment affects state employment over time, but with long-run responses that are not uniform.

Despite the general lack of evidence of cointegration, Shoesmith concluded that definite gains could be realized by testing to probe the nature of the underlying relations among the regional time series of interest. Testing for cointegration and causality provided useful insights for his model specification. In more recent work, Shoesmith (1995) presented one of the first attempts to use Johansen's multi-variate test of cointegration in developing forecasting models for regional economies. For each of four state economies, he considered a five-equation model with a fairly solid theoretical underpinning. The specification included a mix of local and national variables. This offered the possibility of discovering more complicated cointegrative relations and of clarifying the nature of any structural links between the national and regional economies.

A discouraging aspect of this empirical analysis was that Shoesmith found only limited evidence of cointegration among the local and national data series, suggesting once again that VEC modeling may have limited applicability at the regional level. Where cointegration was present, however, the multi-variate VEC-type models outperformed the VAR-type models for both long- and short-term horizons. This was particularly true when the cointegrating relation had a firm theoretical interpretation. The implication is a mixed blessing: VEC modeling at the regional level looks promising where applicable, but its applicability appears somewhat limited.

Phillips and Chang (1995) recently built upon the work of Shoesmith. In an attempt to address the repeated problem of finding little evidence of cointegration at the regional level, they developed a model of the Texas economy that was based on a plausible underlying theoretical structure. They had in mind a local labor market in which Texas labor demand was driven in part by migration across regions, which, in turn, was tied to relative wages. Phillips and Chang expected to find a long-run relation between Texas relative employment and Texas relative wages, where each is defined as the ratio of the Texas variable to the corresponding national variable. They believed this would improve the chances of finding cointegration at the regional level, which would offer the opportunity to exploit the potential gains from using VEC modeling.

The general framework settled upon by Phillips and Chang was a four-variable model that included equations for 1) the relative wage, 2) Texas employment, and 3) U.S. employment, with the fourth equation reflecting a Texas leading indicator variable that was added to capture short-run cyclical shocks. Using this model, they undertook a series of statistical tests, the most critical of which for the current discussion were multi-variate Johansen tests of cointegration. They were able to establish successfully that, in Texas, there was cointegration among the four variables in their model, and that there was only one cointegration vector. This provided the justification to use a VEC form of their model to forecast Texas employment, and to compare the forecasts with a Texas variant of a LeSage-style export-base model. They established that the model which exploited the cointegrating relation produced superior results.

The latter work of Shoesmith, and that of Phillips and Chang are promising because they illustrate how cointegration analyses can be used for regional model specification, estimation, and inference. They also suggest that more effective forecasting may result from using this framework when cointegrating relations can be established. The goal here is to expand upon this: to develop a regional model that has a cointegrating relation that can aid in the forecasting process. The goal is also to take the specification testing one step further by evaluating exogeneity and temporal causality. This will make it possible to generate more efficient estimates of this regional model, thereby giving policy makers more reliable information for decision making.

Modeling the Metro Milwaukee Labor Market in Manufacturing

The goal is to develop a fairly simple VEC model that can legitimately be used for forecasting manufacturing employment in the Milwaukee metro area. This interest in manufacturing employment is straightforward: Manufacturing is a base industrial sector that, historically, has paid higher, family-supporting wages. As a traditional Midwestern industrial city, Milwaukee is more dependent on this sector than many other cities. The sector tends to be highly cyclical, and has endured a painful restructuring in response to a substantial external shock (discussed below). It has also enjoyed a resurgence in the 1990s that has contributed to the improved economic conditions in the metro area. Thus, a relatively simple model that can help local policy makers better track and anticipate changes in metro manufacturing employment should be a welcome policy too].

Of course, a key necessary condition for a VEC model is to establish a cointegrating relation between local manufacturing employment and other relevant data series. As noted in the previous section, there has been only limited success at establishing cointegrating relations at the regional level. Here, the attempt to establish such a relation for metro Milwaukee manufacturing employment drew upon the experience of others, economic theory, and a bit of preliminary experimentation. The general model specification and refinement process is described next.

Since the interest here is in forecasting manufacturing employment, a labor market is considered in nominal wages. This means focusing on local manufacturing employment and on nominal wages in manufacturing. Given the prominence of the relative wage and labor migration theories, and the success at establishing a cointegrating relation enjoyed by Phillips and Chang, U.S. manufacturing wage rate was also included in the model." Wages were chosen as the focus, since these price signals tend to be a primary transmission mechanism for labor market adjustment. This should establish a linkage to the national economy, while keeping the model specification parsimonious. However, by incorporating the two wages as separate influences, rather than as a single relative wage variable, a bit more flexibility remains. In effect, the two wage effects on local employment are not constrained to be of the exact same magnitude but of opposite sign, as is the case with the relative wage specification. In fact, this restriction can be tested.

Moving beyond the labor market itself, control for short-run business cycle effects seemed appropriate. The success Phillips and Chang had with a leading indicator, combined with its ready availability, prompted the incorporation of a local leading indicator to capture short-run business cycle effects.(n14)

To complete the model, several additional variables believed to be appropriate were added. Because the model is specified in nominal wages, the rate of change of the U.S. Consumer Price Index (CPI) was included to control for inflation. In addition, centered seasonal dummy variables were explicitly incorporated into the model instead of working with seasonally adjusted data.(n15) Lastly, a binary variable was introduced to control for a structural change that occurred in the local manufacturing sector. Along with much of the rest of the "rustbelt," Milwaukee went through a significant structural change in the early 1980s. The time frame was readily apparent in the historical manufacturing employment data.(n16) This restructuring dummy reflects the period between October 1981 and March 1983.

The local data used in this analysis pertain to the Milwaukee MSA, which is made up of Milwaukee County and the three suburban counties that ring the central city area. All labor market data come from the Bureau of Labor Statistics. The Local Leading Indicator is constructed in Milwaukee. The data cover the period 1972.01 through 1995.12, In our analysis, data for 1972.01 through 1993.12 is used for model estimation and diagnostic purposes, and the 1994-95 data are reserved for forecasting experiments. The variable definitions and notation used throughout are as follows:

LEMP	Natural Log of Milwaukee Manufacturing Employment
LWAGE	Natural Log of Milwaukee Manufacturing Nominal Wage Rate, which is average weekly earnings divided by the average work week
LUSWAGE	Natural Log of U.S. Manufacturing Nominal Wage Rate
LCPI	Natural Log of U.S. Consumer Price Index
LNLEAD	Natural Log of Metro Milwaukee Leading Indicator
DUMMY	A binary variable to reflect the major restructuring in local manufacturing during the early 1980s. It equals 1 from 1981.10 through 1983.3, and 0 otherwise
D()	The Difference Operator
(-n)	The Lag Operator, showing a lag of n periods

Given these time series, a variety of empirical model specifications could be chosen. A VAR or a VEC model could be specified with as many as five endogenous variables (LEMP, LWAGE, LUSWAGE, LCPI and LNLEAD). Each equation would be estimated in first-differenced form, and would contain: 1) lags of the left-hand-side variable, 2) lagged first-differences of the other four variables, and 3) the seasonal and structural change dummy variables. The VEC specification would also include lagged levels of the 5 endogenous variables as error-correction terms.

A slightly simpler model, one that treats CPI inflation as a purely exogenous conditioning variable, is used to begin." Thus, there is no CPI equation and the remaining four equations include current and lagged first-differences of CPl, but not its lagged level. Given this initial structure, the objective is to conduct a series of tests to determine, first, if a VEC model structure can be used, and second, whether it is possible to reduce the size of the model due to exogeneity considerations.

Following the approach described in the second section, tests were conducted to determine whether or not the series are $\mathrm{I}(1)$ and to determine the appropriate lag length, k. A variety of approaches are available for both of these steps. It was established that all series were $\mathrm{I}(1)$ through a combination of visually inspecting data plots and conducting likelihood-based Chi Square tests.(n18) For the choice of the lag-length the suggestion of Johansen and Juselius (1990) was followed. The shortest lag that resulted in uncorrelated residuals was chosen. In this situation, this proved to be a lag of 10 months.

Using $\mathrm{k} = 10$, cointegration testing was undertaken. The results are reported in Part A of Table 1. Using either the maximal eigenvalue (L-max) test or the trace test and a 10 percent level of significance, the null hypothesis of no cointegration $(\mathrm{r} = 0)$ is rejected, because the test statistics of 31.19 and 49.11 exceed their respective critical values.(n19) On the other hand, r = 1 cannot be rejected, which leads to the conclusion that there is a single cointegrating relation among the four variables of the model, and $(\mathrm{p} - \mathrm{r}) = 4 - 1 = 3$ stochastic trends. These data are only stationary in one direction.(n20) But because of this, the VEC model structure can be used.

Next, consider the estimated cointegrating vectors, β, in part B of Table 1. Following convention, these are reported with all terms except the residual on the left-hand side. To interpret the coefficients' signs in these equations in the context of a standard regression equation, all signs except for the diagonal elements have to be reversed. For example, the estimates in the first row of this matrix can be written as,

(3)

$$23.1^{*}\mathrm{LEMP} - 48.2^{*}\mathrm{LWAGE} + 55.6^{*}\mathrm{LUSWAGE} - 49.6^{*}\mathrm{LNLEAD} + 4.74 = \mathrm{residual}$$

where the final term is the estimated intercept not shown in the table. Normalizing by LEMP, Equation (3) may be rewritten as,

(4)

$$\mathrm{LEMP} = 2.087^{*}\mathrm{LWAGE} - 2.407^{*}\mathrm{LUSWAGE} + 2.147^{*}\mathrm{LNLEAD} - 4.74 + \mathrm{residual}$$

According to (4), the long-run elasticity of local employment with respect to the local wage rate is positive, that of the U.S. wage is negative, and the response to changes in the local leading indicator is positive. In other words, holding U.S. wage and local leading indicator constant, as the local wage increases local employment increases. But increases in the U.S. wage (holding local wage and local leading indicator constant) bring about reductions in local manufacturing employment. Similarly, as the general state of the local economy improves (as reflected in the local leading indicator), employment increases, holding both wages constant. In all cases, these signs are reasonable.(n21)

Table 1**.** Cointegration Anaysis Results

A. Cointegration Tests					
Test Statistics		Hypotheses		Critical Values	Test Statistics
L-max	Trace	H0:r	p-r	L-max 10%	Trace 10%
31.19	49.11	0	4	17.15	43.84
10.84	17.92	1	3	13.39	26.70
6.58	7.08	2	2	10.60	13.31
0.50	0.50	3	1	2.71	2.71

B. Estimated Parameters				
Beta (transposed)				
	LEMP	LWAGE	LUSWAGE	LLEAD
	23.094	-48.188	55.639	-49.629
	-0.316	33.223	-40.397	22.481
	-18.085	-30.020	24.665	3.765
	-42.903	-4.914	2.457	-15.812

C. HYPOTHESIS TESTING							
Test for Exclusion: Likelihood Ratio Test Chisq(DF)							
			Critical Value		Test Statistics		
	r	DF	CHISQ 5%	LEMP	LWAGE	LUSWAGE	LLEAD
	1	1	3.84	6.11	11.92	12.49	6.61
Test for Weak-exogeneity: Likelihood Ratio Test Chisq(DF)							
	r	DF	CHIS05%	LEMP	LWAGE	LUSWAGE	LLEAD
	1	1	3.84	5.69	13.99	3.25	3.52

An interesting aspect of these results is that the point elasticities for the two wages are not equal in absolute value.(n22) This is interesting for several reasons. First, the fact that the two wages have unequal effects indicates that the separate-wage specification is preferable to the relative wage specification. Second, it raises an interesting question about the nature of the labor migration process underlying this model. This asymmetry in wage effects may have something to do with imperfections in information dissemination, non-uniform relocation costs, or other types of frictions in the economy. This is a topic for further research, perhaps focusing more explicitly on a more formal underlying migration model.

At this point, it has been established that this four-equation VEC model is a reasonable specification. The next step is to investigate the possibility of reducing the structure of this VEC model. This is done by testing for exclusion and weak exogeneity for each of the four cointegrated variables in the system. The exclusion test results shown in Part C of Table 1 indicate that, in all cases, the test statistics exceed critical values. This suggests that none of these variables can be excluded from the cointegrating space. The results are different for the weak exogeneity tests which are also shown in Part C. The test statistics for both the U.S. wage rate and the local leading indicator are less than the critical values, indicating these two are weakly exogenous to the parameters of the cointegrating space.

The exogeneity of the U.S. wage is expected because Milwaukee amounts to only a very small component of the national labor market. The exogeneity of the leading index is also not surprising. The leading indicator is supposed to signal changes in the local economy prior to their occupance, and therefore before they have an impact on manufacturing employment. The net consequence of the finding of weak exogeneity for these two variables is that the scope of the system can be reduced by moving from four equations to two, while keeping the U.S. wage and the local leading indicator in the cointegrating space.

The estimate of the resulting two-equation VEC forecasting model is shown in Table 2. To conserve space, sums of the coefficients capturing the short-run dynamics are shown in the table, along with a test statistic for the significance of each sum. The relevance of the error-correction component of the model is evaluated by considering the coefficients for the four lagged level variables. The estimated coefficient on the lagged level of the dependent variable in each equation has the expected negative sign, and each is statistically significant. Further, a test that the coefficients of the four lagged level terms in each equation are jointly different from zero establishes the statistical significance of the error-correction component of the equation. In a number of cases, the individual coefficients are statistically significant as well. All of this is consistent with the fact that, in the presence of cointegration, VEC is the proper specification, and conversely, VEC models imply cointegration. It also provides some confirmation that the reduced model is a proper specification.

TABLE 2. ESTIMATION RESULTS: TWO-EQUATION VECTOR ERROR-CORRECTION MODEL
(values in parenthesis are t- or F-statistics as appropriate)

		EQUATION	
VARIABLES	D(LEMP)		D(LWAGE)
$\Sigma_{\mathrm{D}}(\mathrm{LEMP})_{\mathrm{t-i}}$	-0.57272		0.02108
	(2.9266)$^{+}$		(0.0176)
$\Sigma_{\mathrm{D}}(\mathrm{LWAGE})_{\mathrm{t-i}}$	-0.48550		-0.30703
	(0.9472)		(1.0278)
$\Sigma_{\mathrm{D}}(\mathrm{LCPl})_{\mathrm{t-i}}$	0.35829		0.48811
	(0.4055)		(1.0901)
$\Sigma_{\mathrm{D}}(\mathrm{LUSWAGE})_{\mathrm{t-i}}$	2.47885		0.32665
	(6.9036)$^{+++}$		(0.3253)
$\Sigma_{\mathrm{D}}(\mathrm{LNLEAD})_{\mathrm{t-i}}$	0.92234		0.23335
	(12.971)$^{+++}$		(2.2527)
C*	-0.02927		0.24615
	(-0.1337)		(1.8525)$^{\#}$
$\mathrm{LEMP}(-1)$	-0.06124		0.02002
	(-1.8641)$^{\#}$		(1.0040)
$\mathrm{LWAGE}(-1)$	0.04174		-0.09343
	(1.0018)		(-3.6933)$^{\#\#\#}$
$\mathrm{LUSWAGE}(-1)$	-0.05927		0.10446
	(-1.2841)		(3.7276)$^{\#\#\#}$
$\mathrm{LNLEAD}(-1)$	0.07655		-0.07462
	(2.1240)$^{\#\#}$		(-3.4105)$^{\#\#\#}$
Adj. A-squared	0.26751		0.40763
Sum sq. resids	0.01910		0.00704
S.E. equation	0.01006		0.00610
Log likelihood	845.446		972.210
Determinant Resid. Covariance			2.05E-09
Log Likelihood			2073.598

+++ F-statistic statistic significant at .01 level
++ F-statistic statistic significant at .05 level
+ F-statistic statistic significant at .10 level

t-statistic statistic significant at .01 level
t-statistic statistic significant at .05 level
t-statistic statistic significant at .10 level
* A differential intercept, allowing for dummy variables reflecting a structural break and seasonality which are not shown for space reasons. These were statistically significant in the employment equation.

Use and Evaluation of the Model

The model in Table 2 can now be used to forecast the endogenous variables LEMP and LWAGE. Twelve 1 - through 12-step ahead rolling forecasts of these variables are performed. The first forecast period runs from 1994.01 through 1994.12. Then one new data point is added, and a forecast is made for the next twelve months. This process is repeated until the twelfth forecast period, which runs from 1994.12 through 1995.11. In this exercise, the two-equation system in Table 2 is reestimated for each forecast period, so all parameters are updated to incorporate the new information in the latest observation. For comparison purposes, a conventional two-equation VAR model that differs from our VEC model in that it excludes the error-correction terms is also estimated and used for forecasting.

Figures 1 and 2 display root mean squared errors (RMSE) derived from the one-step ahead through twelve-step ahead VEC and VAR forecasts for the employment and wage equations, respectively. In other words, the first pair of bars shows the RMSE for all one-step ahead forecasts for the VEC and VAR models, the second pair of bars shows the RMSE for all two-step ahead forecasts, and so on out to the last pair of bars that shows the RMSE for all twelve-step ahead forecasts.

Consider first the results in Figure I for manufacturing employment, LEMP. The VEO model outperforms the VAR model over all forecast periods based on its lower RMSE values. In addition, after deteriorating slightly between the one-and three-month forecast horizons, the VEC model's performance improves out through a seven-month forecast horizon, and then, except for a brief spike at nine months, stabilizes at this lower level. This improved longer-term forecasting capability is consistent with the notion of gains from incorporating the additional information contained in the cointegrating vector. Note also that the magnitude by which the VEC model outperforms the VAR initially deteriorates, but the gap widens beyond the eight-month forecast horizon. This too, is consistent with exploiting information about longer-term relations.

Very different results are shown in Figure 2 for the local wage LWAGE. In this case the VAR model outperforms the VEC model over all forecast periods. For both the VEC and VAR models, the RMSE magnitudes are relatively constant out to a five-month horizon and then begin to rise. It is only at the twelve-month horizon that the VEC model comes close to the VAR model in performance. This demonstrates that the gains in forecasting performance from exploiting cointegration information may not extend to the entire system of equations. In this case, the performance of the equation of most interest to us has improved while that of the other equation has deteriorated. This is not surprising given that there is only one cointegrating relation in this two-equation system. That relation is reflected in the employment equation, meaning that the other equation must reflect the stochastic trend. Such a trend is by its nature not readily predictable, and any attempt at prediction will certainly not benefit from long-run information contained in the cointegrating relation.(n23)

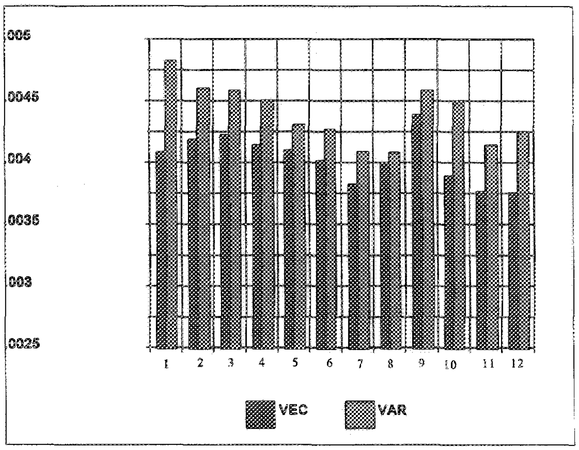

FIGURE 1. RMSE COMPARISONS: EMPLOYMENT FORECASTS.

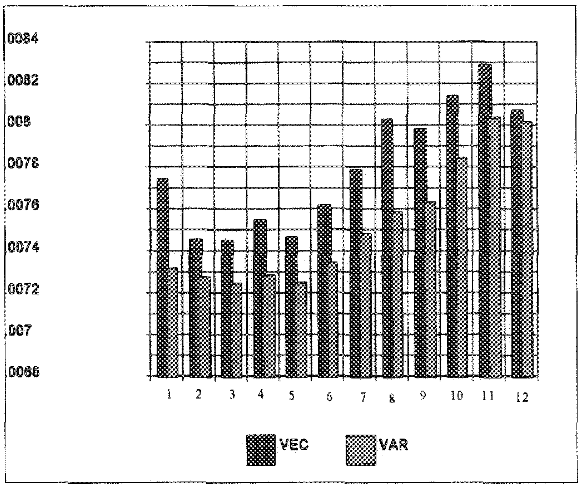

FIGURE 2. RMSE COMPARISONS: WAGE FORECASTS.

The performance of these two models can also be evaluated by reviewing both in-sample and out-of-sample dynamic simulations. Representative plots are shown in Figures 3 and 4.(n24) Figure 3 demonstrates that both VEC and VAR models accurately capture the movements in employment over the 20+ years of the sample. In general, the VEC model tends to stay closer to the actual series while the VAR model tends to temporarily drift away by larger magnitudes and for longer time periods.

The superior employment forecasting performance of the VEC model is more evident for the out-of-sample simulation shown in Figure 4. The VAR model forecast drifts away from actual employment very early on, and shows, at best, only limited evidence of moving back in line. In contrast, the VEC model forecast tends to track closely with employment through early 1995, and the brief episode of drifting apart in mid 1994 is quickly corrected. The fairly large deviation that occurs in mid 1995 can be attributed to an unusually large and extended decline in the local leading indicator that so far has not been followed by an employment downturn. But even this relatively large deviation (which is driven by the questionable signal in the leading indicator) shows signs of being overridden. This can be seen by the corrective movement that takes place at the end of the sample period as the forecast starts moving toward the actual employment time path. This is consistent with the previous work reviewed in the third section, and confirms that when cointegration can be established a VEC model should outperform a VAR model, at least for the equation reflecting the cointegrating relation.

Conclusion

Taken in isolation, the forecasting performance of the VEC model estimated in this paper is quite respectable. A model for a modest sized local economy was produced. It contained a longer-run cointegrative relation among national and local variables and it produced improved manufacturing employment forecasts that should provide more reliable information about this critical sector to local policy makers.

Throughout this paper, however, the focus has been on a broader perspective that emphasizes model development and testing. From this perspective, the outcome of this exercise in local forecasting model development is even more encouraging. A fairly large multi-variate time-series model was initially formulated by drawing upon an underlying theoretical model which was expanded modestly by drawing upon economic intuition. Based on a series of statistical tests it was established that a (single) long-term relation existed among the primary variables. Establishing this provided information about the link between the local and national labor markets (through the wage linkage), and set the stage for incorporating this added information into the forecasting process by inclusion of an error-correction component.

The information about the structure of the local economy was both interesting in its own right (e.g., the nonsymmetry of wage effects) and was useful for model refinement (e.g., the exogeneity of several variables). The end result was a local model that, in some respects, was a hybrid of those found in the recent literature. The model was not limited to purely local series. It was not comprised of purely local variables with national causal drivers. Nor was it an all- encompassing model that contained separate equations for all local and national endogenous variables. Rather, it was a model that incorporated an underlying long-run relation among a combination of four local and national variables, yet was reduced in scope because it contained only two endogenous local variables. This local forecasting model had a more elaborate structure than some of the previous models because of the presence of national variables and the allowance for cointegration. At the same time, it was simpler than others because of its reduced structure, which has the added bonus of allowing forecasting of the local series of interest conditional on externally generated forecasts of relevant exogenous variables.

The end result is a model that is fairly simple and easy to maintain, gives improved employment forecasts, and can be used for relatively simple policy simulations. It is also a model that offers potential for refinement by identifying additional cointegrating relations with either national or local data series. Establishing the former would more fully determine Milwaukee's connection to the national economy. Establishing the latter would produce a more complete picture of the local economy. Indeed, developing comparable models of other local sectors, and then linking them with this model is an obvious next step for subsequent research.

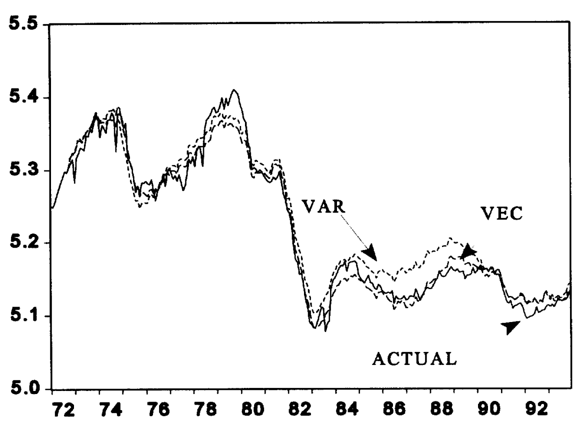

FIGURE 3. DYNAMIC IN-SAMPLE SIMULATIONS EMPLOYMENT EQUATION

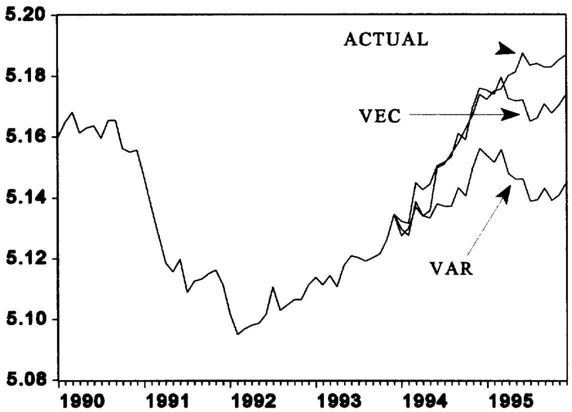

FIGURE **4. DYNAMIC** OUT-OF-SAMPLE FORECASTS EMPLOYMENT EQUATION

NOTES

(n1.) Such series are said to be difference stationary as opposed to trend stationary. A more complicated, but less frequently encountered situation involves series that are $\mathrm{I}(2)$. We do not consider this situation, and refer the interested reader to Johansen (1995).

(n2.) This is because, for these models, the standard errors of the parameter estimates are unreliable, and the forecast error variances are large (and even unbounded). See Engle and Granger (1987) for more details.

(n3.) More formally, cointegrated series are two or more series that are each I(1), but one or more linear combinations of them are 1(0). These linear combinations are the cointegrating relations which summarize the long-run relationships among the series.

(n4.) One can also write the final term PiXt-k in Equation (2) using lag t-1. This produces somewhat different estimation results, but the subsequently described test results are unaffected. An alternative approach is to specify Equation (2) as follows,

$$\Delta_{xt} = \mu + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \ldots + \Gamma_{k-1} \Delta X_{t-k+1} + \alpha e_{t-1} + \varepsilon_t$$
$$\text{where } e_{t-1} = X_{i,t-1} - X_{j,t-1}\,\beta, \text{for all } i \neq j.$$

(n5.) These tests are conducted very much like conventional hypothesis tests. However, Johansen and Juselius (1990) have shown that the trace and maximal eigenvalue test statistics do not follow the standard χ^2 distribution. Using simulation, they developed tables containing the proper critical values for the test statistics appropriate for a limited number of model specifications. Others have extended these critical values tables to a wider range of models, and they are now routinely incorporated into econometrics packages such as CATS in RATS and EVIEWS.

(n6.) Weak exogencity can be described more formally as follows: Consider X_i and X_j, two different series in our vector X_t. If X_j is weakly exogenous with respect to X_i, then the conditional distribution of X_i is completely determined by the joint distribution of X_i and X_j. This means that the marginal distribution of X_j provides no useful additional information beyond what we already have through the conditional distribution of X_i. On the other hand, if X_j is not weakly exogenous, then the data generating process for X_j does contain additional information that would have to be incorporated explicitly into the process of estimating the conditional mean of X_i.

(n7.) For a complete treatment of weak and strong exogeneity, along with related concepts, see Engle, Hendry, and Richard (1983), or, for a less technical summary, Davidson and MacKinnon (1993, pp. 624-31). Various applications and extensions of these concepts within the Johansen framework appear in Johansen (1992).

(n8.) Here we mean causality and noncausality in the Granger sense. X_i is said to "cause" X_j if adding lagged values of X_i significantly improves the forecasting ability of an equation that predicts X_j using its own lagged values. If X_i and X_j are $I(1)$, it is the changes in the series that are used for this test. If the series are I(0), the levels of the two series are used.

(n9.) Note that even if a test of joint significance of lagged differences of X_i in the equation for X_j produces no evidence of causality between the two series, it does not mean that there is no causal relationship between them. The fact that there is a cointegrating relation between them implies causality. As Miller and Russek (1990) point out, one should also test the statistical significance of the coefficients of the error-correction terms in the VEC model. Note also that, even if no cointegration exists, there can still be a causal relationship among the variables of interest since cointegration is only a sufficient condition for causality.

(n10.) In situations where both weak exogeneity and Granger noncausality occur, we have the more stringent condition of strong exogeneity.

(n11.) The Dickey-Fuller (1979) unit root test is a univariate test of integration based on an OLS regression of the first-difference of a series on its own lagged level and lagged differences.

(n12.) See Engle and Granger (1987, p. 261). Also see Stock and Watson (1988).

(n13.) In principle, this should probably be the wage in the rest of the U.S. excluding Milwaukee. However, given the tiny share of overall U.S. manufacturing that is in Milwaukee, ignoring this refinement is unlikely to have material consequences.

(n14.) It should be recognized that there are some potential problems with using a traditional leading indicator in this capacity. For example, the construction process for the index explicitly introduces an employment trend, which might create, by construction, a spurious cointegrating relation. Second, the leading index might really be a purely exogenous variable, since, by construction, movements in the index are supposed to be correlated with movements in future values of employment, not current values, whereas any cointegrating regression must be contemporaneous. More fundamentally, there is a question regarding the appropriateness of including a variable that reflects purely short-run influences in a long-run relation.

(n15.) The centered seasonal dummy variables are calculated as 11/12 for the month in question and -1/12 otherwise. Conventional seasonal dummy variables would be calculated as 1 for the month in question and 0 otherwise. Centered seasonal dummies are typically used in this setting because they sum to zero in a given time period, and thus, unlike conventional seasonal dummy variables., they do not alter the distributional properties of test statistics.

(n16.) Manufacturing employment recorded a cyclical decline of 12.0% during the 1980 recession that was very much in line with the 10.4% cyclical decline that occurred during the previous recession in 1973-74. While employment recovered during the rest of the 1970s to reach new heights, during 1981 there was only a brief advance after which manufacturing employment plummeted an additional 19.4%. Once this bottomed out, employment resumed its cyclical pattern, but never recovered much more than half of this secondary decline over the subsequent years in the sample. The dummy variable controls for this second, atypical decline in employment.

(n17.) This presumes that prices do not belong in the cointegrating space and are weakly exogenous. We choose this specification because the CPI is a national figure which is unlikely to be significantly affected by Milwaukee price movements.

(n18.) These tests are incorporated into the CATS module of the RATS regression package used for much of the empirical work reported in this paper.

(n19.) A 10 percent level of significance is typically used due to the low power of cointegration tests.

(n20.) Finding only a single cointegrating relation indicates that the long-run relationship among these variables is not very stable; they are only tied together in one direction. The more cointegrating relations, the more stable is the relationship among a set of variables because they are tied together in more directions. See Dickey et al. (1991, p. 65).

(n21.) Care must be exercised in interpreting the signs of what is essentially a reduced-form equation that mixes both supply and demand influences. For example, the positive relation between local employment and local wage over time is the net effect of both local labor supply and demand effects. Similarly, in a disequilibrium labor market migration context, the negative relation between local employment and national wage could be the net effect of a negative local labor supply effect (as more workers migrate out of the state) and a positive local labor demand effect (as local manufacturers attempt to exploit a cost advantage).

(n22.) We tested whether the elasticities were equal in value with opposite signs, and the hypothesis was rejected: Chi Square with one degree of freedom of 14.75 which has a rounded p-value of 0.001.

(n23.) This outcome is independent of the normalization rule. Whether we normalize either equation (or both equations) on employment or wages, the improved forecasting result will be associated with the equation reflecting the cointegrating relation. We thank a referee for helping us clarify this issue.

(n24.) To conserve space, only one simulation of each type is presented, and the out-of-sample simulation is extended through the end of the available data. A review of the graphs of rolling month-by-month simulations indicates the patterns shown in Figures 3 and 4 are representative. Graphs of the month-by-month simulations are available upon request.

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