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Abstract

This paper uses Bayesian vector autoregressive models to examine the usefulness of leading indicators in predicting US home sales. The benchmark Bayesian model includes home sales, the price of homes, the mortgage rate, real personal disposable income, and the unemployment rate. We evaluate the forecasting performance of six alternative leading indicators by adding each, in turn, to the benchmark model. Out-of-sample forecast performance over three periods shows that the model that includes building permits authorized consistently produces the most accurate forecasts. Thus, the intention to build in the future provides good information with which to predict home sales. Another finding suggests that leading indicators with longer leads outperform the short-leading indicators.

1. Introduction

The housing sector affects the macroeconomy in a variety of ways. Building permits issued and housing starts, for instance, lead the economy into and out of recessions. Housing activity that includes the volume of home sales, new construction, and renovations of existing property affects the demand for goods of various industries ranging from construction materials such as cement and wood to consumer durable goods such as furniture and household appliances. Predictions of housing activity, thus, provide useful insights into the future state of the economy.

This paper focuses on forecasting US home sales, significantly extending the housing sector model described in Dua and Smyth (1995) by adding six different leading indicators of economic activity. We examine the predictive ability of each of these leading indicators by evaluating the accuracy of out-of-sample forecasts of home sales over three time periods. We estimate the forecasting models for home sales in a Bayesian vector autoregressive framework using monthly data from January 1979 to August 1995.[1]

Section 2 discusses different aspects of a Bayesian vector autoregressive model. Section 3 describes the alternative forecasting models. Section 4 evaluates the accuracy of alternative forecasting models. The last section gives the conclusions.

2. Unrestricted VAR and Bayesian VAR Models

Forecasting models frequently use simultaneous equations structural models. Two drawbacks, however, exist with structural models. First, for proper identification of individual equations, we must exclude the correct number of variables from each equation in the model. As argued by Cooley and LeRoy (1985), such exclusions often have little theoretical justification. Second, structural models generally perform poorly as forecasting tools since such models require projected future values of the exogenous variables.

A VAR model offers a particularly useful alternative approach for forecasting purposes. Although "atheoretical," a VAR model can approximate the reduced form of a structural system of simultaneous equations. Zellner (1979), and Zellner and Palm (1974)

[1] Dua and Smyth (1995) use quarterly data to estimate their model.

show that any linear structural model reduces to a VAR moving average (VARMA) model, the coefficients of which are combinations of the structural coefficients. Under certain conditions, a VARMA model reduces to a VAR model or a VMA model. Thus, a VAR model shares many common characteristics with a large-scale simultaneous structural model; the differences basically reflect their best use. VAR models perform best as forecasting tools; structural models, for policy analysis.

The VAR technique uses historical data to forecast future values of the variables in the model. Economic theory selects these economic variables for inclusion in the model. An unrestricted VAR model as suggested by Sims (1980) appears as follows:

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

where y = an (nx1) vector of variables;

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

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

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

e = an (nx1) vector of white noise error terms.

A model with n variables incorporates n separate equations, the coefficients of which are estimated by ordinary least squares. Using the same lag length for all variables produces an equation in the model that contains (nxp)+1 coefficients, where p is the lag length. Such models can suffer from overparameterization causing multicollinearity and loss of degrees of freedom. This can generate large out-of-sample forecasting errors. To limit the number of estimated parameters, we can exclude statistically insignificant variables and lags. This, however, amounts to imposing zero restrictions on the insignificant coefficients.

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 assuming that they more likely approach zero than the coefficients on shorter lags and/or more important variables. If, however, strong effects exist from longer lags and/or less important variables, the data can override this assumption.

Simply stated, the Bayesian technique allows the modeler to use prior statistical and economic knowledge in a scientific way to guess the values of all coefficients. The modeler also specifies confidence in the values of these coefficients. The extent to which the data revise the modeler's estimate of a particular coefficient depends on the modeler's confidence in the guess. With high confidence, the patterns in the data receive low weight. The prior variance or standard deviation of the coefficients measures the modeler's confidence. A small prior variance indicates that the modeler is confident that the coefficient closely matches the best guess. A large variance implies that the coefficient may vary significantly from the modeler's best guess.

From an econometric standpoint, we impose restrictions on the coefficients by specifying normal prior distributions with means zero and small standard deviations for all coefficients and with decreasing standard deviations on increasing lags. The coefficient on the first own lag of a variable provides the exception and has a mean of unity. This "Minnesota prior" owes its name to its development 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:

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

$$f(i,j) = 1 \text{ if } i=j \text{ and } k \text{ otherwise } (0 \le k \le 1);$$

$$g(m) = m^{-d},\ d>0,$$

where s_i is the standard error of a univariate autoregression for variable i. The ratio s_i/s_j scales the variables to account for differences in units of measurement and thus enables specification of the prior without consideration of the magnitudes of the variables. The term w describes the overall tightness and also measures the standard deviation on the first own lag. A tighter prior evolves as the value of w decreases. The parameter g(m) gives the tightness on lag m relative to lag 1. This is assumed to have a harmonic shape with decay factor d. This prior tightens on increasing lags by using a larger value of d. The parameter f(i,j) captures the tightness of variable j in equation i relative to variable i. Reducing the value of k, (i.e., decreasing the interaction) tightens the prior.

To illustrate, if 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. The standard deviation of all other lags equals 0.2s_i/s_j\{g(m).f(i,j)\}. For m=1 through 4 and d=1, g(m)=1, 0.5, 0.33, 0.25, respectively, showing the decreasing influence of longer lags. The value of the parameter 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%. A tighter prior emerges by decreasing w, and/or increasing d, and/or decreasing f(i,j).

We estimate the BVAR model using Theil's (1971) mixed estimation technique that involves supplementing data with prior information on the distributions of the coefficients. For each restriction on the parameter estimates, the number of observations and degrees of freedom increase by one in an artificial way. The loss of degrees of freedom due to overparameterization in a VAR model disappears in the BVAR model.

Some concerns exist regarding the Minnesota prior when the variables in the VAR are cointegrated.[2] Lutkepohl (1993, p.375), for example, claims that the Minnesota prior is not a good choice if the variables are cointegrated. His argument interprets the prior as stating that the variables are roughly unrelated random walks. Engle and Yoo (1987) argue that the Minnesota prior implies a model that approaches the classical VAR model with differenced data and that this model is misspecified for cointegrated data because it excludes an error correction term.

These arguments, however, misrepresent the Minnesota prior which sets the mean of the first lag of each variable equal to one in its own equation and sets all other coefficients to zero. This prior does imply that each variable is a random walk if the prior means are the true parameter values. The prior probability that the coefficients are actually at the prior mean is, however, zero. Indeed, the Minnesota prior places high probability on the class of models that are stationary.

In other words, Engle and Yoo (1987) argue that if a model specified in levels is equivalent to one in differences, then the sum of the coefficients on the own lags equals one

[2] Christopher A. Sims provided invaluable help in writing up the current and the following two paragraphs.

while the sum of the coefficients on the lags of other variables exactly equals zero. Though this is true for the mean of the Minnesota prior, the prior actually gives zero probability to the class of parameter vectors that satisfy this restriction. Of course, if a very tight prior is used, the estimated model will be close to a model showing no cointegration. But the Minnesota priors used in practice are not so tight to produce these results.

3. Bayesian VAR Forecasting Models for Home Sales

Economic theory suggests that several factors may explain movements in unit home sales, including home prices, the mortgage interest rate, and current and expected future economic conditions.[3] We estimate twelve alternative BVAR models based on these variables to forecast home sales using monthly data from January 1979 through August 1995. We evaluate the accuracy of the forecasts relative to those from the benchmark BVAR model - Model 1.

The benchmark BVAR model includes home sales, the price of homes, the mortgage rate, real personal disposable income, and the unemployment rate. Two measures of current economic activity therefore enter this model -- the unemployment rate and real personal disposable income. This resembles the BVAR model for home sales reported in Dua and Smyth (1995) but does not include any measure of expected future economic conditions. Home sales are measured by the volume of existing single-family home sales and come from the National Association of Realtors. Home prices are measured by the median sales price of existing single-family homes and come from the National Association of Realtors. The mortgage rate is measured by the contract interest rate on single-family existing home purchases and is provided by the Federal Housing Finance Board. Real personal disposable income is measured in billions of 1987 dollars. The unemployment rate is the civilian rate, 16 years and over. The last two series come from the Federal Reserve Bank of St. Louis' database.

[3] For a discussion of the variables to include in models of the housing market, see, for example, Arnott (1987), Schwartz (1988), Smith et al. (1988), and Megbolugbe et al. (1991).

Models 2 through 12 include, in turn, various leading indicators as measures of expected future economic activity. Leading indicators predict future economic activity. They signal the onset and end of recessions and thus provide valuable information about the future path of the economy. A composite leading indicator combines information from several leading indicators that collectively forecast future movements of the economy. Each component of a leading index provides some information about future economic activity but it is unlikely that the individual components will show identical turning points. The combined information in leading indices generally produces better predictions about the future path of the economy. We examine the performance of two leading indicators and four composite leading indicators (leading indices) in alternative models for home sales.

Model 2 extends Model 1 by including a housing sector leading indicator -- building permits authorized. This variable is an index of private housing units authorized by local building permits and comes from various issues of the Survey of Current Business. A building permit represents the intention to spend and build and usually increases before a recession ends and decreases before an expansion ends or a recession begins. It is the only housing series included in the composite index of eleven leading indicators.

Model 3 adds an alternative housing sector leading indicator to Model 1 -- housing starts. Housing starts are new private housing units started and come from various issues of the Survey of Current Business. This series differs from new building permits issued since it represents actual home-building activity, not just the intention to build. As such, housing starts may provide a shorter lead time than building permits authorized. The two series are similar, however, in that both lead economic recoveries and recessions.

Model 4 includes the variables in Model 1 and the US Department of Commerce's composite index of eleven leading indicators.[4] The index of new private housing units authorized by local building permits, as noted above, is the only housing series in the composite index. Other components of the index appear in the appendix. The composite index, thus, combines information in building permits with ten other predictors of future

[4] Starting January 1996, the composite index of leading indicators is maintained by the Conference Board.

economic activity. Data for the composite leading index come from various issues of the Survey of Current Business.

Models 5 and 6 extend Model 1 by including two leading indices developed and produced by the Center for International Business Cycle Research (CIBCR) at Columbia University -- the short- and long-leading indices.[5] The components of the long-leading index typically have a longer lead than those of the short-leading index at both business cycle troughs and peaks. The index of new private housing units authorized by local building permits appears in the CIBCR's long-leading index. Thus, while the US Department of Commerce's leading index includes components with both short and long leads, the CIBCR constructs two leading indices based on the average leads of the components. Five of the eleven components of the CIBCR's short-leading index enter as components of the Commerce Department's composite index of eleven leading indicators. Two of the six components of CIBCR's long-leading index are included in the Commerce Department's composite leading index. One of these is the index of new private housing units authorized by local building permits. The components of the Commerce Department's leading index and CIBCR's long- and short-leading indices appear in the appendix and their construction is described in Cullity and Moore (1991).

Model 7 extends Model 1 by including yet another leading index constructed by CIBCR that focuses solely on employment related variables. Since housing activity closely relates to employment conditions, this model considers whether the leading employment index contains useful information for forecasting home sales. Dua and Miller (1996) find that the leading employment index for the Connecticut economy improves the accuracy of forecasts of Connecticut home sales. We consider whether this result holds at the national level as well. The components of the national leading employment index appear in the appendix and its construction is described in Moore (1981, 1985).

Models 8 through 12 add building permits to Models 3 through 7. These models test whether including information on housing permits to Models 3 through 7 improves the

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[5] Geoffrey H. Moore was the Director of the CIBCR when we completed this paper. He kindly provided these indexes for our use. Since then, Dr. Moore has left the CIBCR to start a new venture, the Economic Cycle Research Institute, Inc.

accuracy of forecasts of home sales. Note that Model 4 and Model 6 already include building permits as a weighted component of the Commerce Department's leading index and CIBCR's long-leading index respectively.

We estimate the BVAR models using monthly data from 1979:1 through 1989:12 and examine the out-of-sample accuracy of the forecasts from 1990:1 to 1995:8. Since this period encompasses fluctuations in economic activity, in particular, the downturn in economic activity during the July 1990 to March 1991 recession, we also examine the performance of the models for two sub-periods. The first sub-periods runs from 1990:1 to 1991:12 and incorporates the recession years. We expect the forecasting models to perform the worst in this period since a turning point in economic activity is hard to predict. The second sub-period covers the same number of months as the first period and runs from 1992:1 to 1993:12.

We estimate Model 1 with twelve lags of each variable implying 61 parameters (including the constant) in each equation. Models 2 through 7 include 73 parameters and Models 8 through 12 have 85 parameters in each equation. We measure all the variables in logs (except the unemployment rate and the interest rate that are percentages). We specify the variables in levels because as Sims et al. (1990, p. 136) note "...the Bayesian approach is entirely based on the likelihood function, which has the same Gaussian shape regardless of the presence of nonstationarity, [hence] Bayesian inference need take no special account of nonstationarity."[6]

The specification of the Bayesian prior involves selecting the overall tightness and harmonic lag decay parameters and the interaction function f(i,j). The selection of the parameters of the prior is based on minimization of the Theil U-statistic for the out-of-sample forecasts, i.e,. the parameters that generally yield the most accurate out-of-sample forecasts are chosen. Doan (1990) recommends 0.1 or 0.2 for the overall tightness prior and 1 or 2 for the harmonic lag decay parameter. The overall tightness, w, and the harmonic lag decay, d, are set at 0.2 and 1 respectively since these values generally yield the most accurate out-of-sample forecasts of home sales. Dua and Smyth (1995) also use these values. A symmetric interaction function f(i,j) is assumed with k=0.7. Doan recommends k=0.5, the value used by

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

Dua and Smyth (1995). We, however, find that k=0.7 generally improves the accuracy of the out-of-sample forecasts. Overall, therefore, we find that a loose prior (high w, low d, and high k) generates more accurate out-of-sample forecasts.[7]

4. Evaluation of Forecast Accuracy

We evaluate the out-of-sample forecast accuracy for the period 1990:1 to 1995:8 and the sub-periods 1990:1 to 1991:12 and 1992:1 to 1993:12 using the Theil U-statistic. If A_{t+n} denotes the actual values 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 statistic is defined as:

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

The U-statistic measures the ratio of the root mean square error (RMSE) of model forecasts to the RMSE of naive, no-change forecasts. A comparison with the naive model is therefore implicit in the U-statistic. A U-statistic of 1 indicates that the model forecasts match the performance of naive, no-change forecasts. A U-statistic >1 shows that the naive forecasts outperform the model forecasts. If U is <1, the forecasts from the model outperform the naive forecasts. The U-statistic is therefore a relative measure of accuracy and is unit-free

We generate the Theil U-statistics using the Kalman filter algorithm in RATS. The models are estimated for the initial period 1979:1-1989:12. Forecasts for up to 6-months ahead are computed. One more observation is added to the sample and forecasts up to 6-months ahead are again generated and so on. Based on the out-of-sample forecasts, the Theil U-statistics are computed for 1- to 6-months-ahead forecasts and the average of the six U-statistics is calculated.

Table 1 reports the average U-statistics for 1- through 6-months-ahead forecasts for seven alternative BVAR models. For the sake of comparison, we also report the average U-statistic for the unrestricted VAR version of Model 1. Model 1 includes home sales, the price of homes, the mortgage rate, real personal disposable income, and the unemployment rate and serves as the benchmark model to evaluate the contribution of various leading indicators in

[7]Dua and Ray (1995) also find that BVAR models with a loose prior generally outperform alternative models.

forecasting home sales. We evaluate the accuracy of the models over three periods -- 1990:1-1995:8, 1990:1-1991:12, and 1992:1-1993:12 where we expect the worst accuracy in the 1990:1-1991:12 period, as noted in the previous section. A model that produces the most accurate forecasts during the recession years identifies itself as a strong candidate for the "best" forecasting model.

The Bayesian version of Model 1 consistently outperforms the unrestricted VAR counterpart, although the most marked improvement occurs in the sub-period that encompasses the 1990-91 national recession. The VAR model generates extremely inaccurate forecasts (U-statistic>1) in two of the three periods. Dua and Ray (1995) and Dua and Miller (1996) also find that Bayesian VAR models generally outperform unrestricted VAR models. We now focus on alternative BVAR models.

Compared to the Bayesian version of Model 1, Model 2 produces more accurate forecasts for all three periods. Model 2, in fact, outperforms all alternative models. Table 1, therefore, reports the percentage change in the average U-statistic of the alternative models compared to Model 2. A positive sign indicates an increase in U relative to Model 2 or a deterioration in accuracy. Using this measure, the deterioration in average accuracy moving from Model 2 to Model 1 varies from 13 percent to 20 percent. The maximum deterioration occurs in the period of the recession, as expected. The large deterioration in accuracy of up to 20 percent justifies the inclusion of building permits in the model for home sales. This finding implies that the performance of the model used by Dua and Smyth (1995) improves significantly by including building permits.

Model 3 replaces building permits with housing starts. The negligible deterioration in average accuracy relative to Model 2 - between 2 and 4 percent - suggests that housing starts reasonably substitute for building permits.

Table 1 also reports models with four different composite leading indicators. Model 4 that includes the Commerce Department's leading index fares worst with a deterioration in accuracy of up to 38 percent. Moreover, the performance is generally worse than Model 1 that does not include any leading indicators. In fact, the composite index detracts from the forecasting performance of Model 1. This is a little surprising since the Commerce

Department's leading index includes building permits. A possible explanation of this is that building permits are combined with ten other leading indicators to produce the composite index and the composite index may not necessarily duplicate movements in any one of the components.

The deterioration in average accuracy of Model 5, which includes the CIBCR's short-leading index, is large. It varies from 17 to 25 percent suggesting that Model 2 is clearly a better choice. Nonetheless, the short-leading index performs better than the Commerce Department's leading index in two of the three forecast periods.

Model 6, which includes CIBCR's long-leading index, performs rather well in the full out-of-sample period and in the period after the recession with a deterioration in average accuracy relative to Model 2 of 9 and 6 percent, respectively.

Of the three models that include CIBCR indices, the model that includes the leading employment index (Model 7) produces the smallest range of deterioration -- from 11 to 13 percent. Relative to Model 2, therefore, on average, forecast accuracy falls by the same percentage in all three periods. These results do not conform with those reported by Dua and Miller (1996) who find that a model for Connecticut home sales that includes the Connecticut leading employment index outperforms the model that includes building permits as the leading indicator. A possible explanation is that housing markets are local so that current and future regional employment activity have a large effect on the regional housing market. At the national level, however, a leading indicator specific to the housing sector provides more information than the overall state of future employment conditions.

In sum, of the models reported in Table 1, Model 2 produces the most accurate forecasts in all three periods. Model 2 thus emerges as the "best" forecasting model. Model 3 produces almost equally accurate forecasts. Models 6 and 7 rank next in forecast performance. Model 2 clearly dominates Models 4 and 5. These results have, at least, two important implications for modeling the housing sector. First, housing starts can replace building permits in the model with a negligible loss in accuracy. Second, compared to short leaders, long leaders prove to be better predictors of home sales. This can be verified by comparing the accuracy of Models 5 and 6. One possible explanation is that home sales themselves generally lead business cycle peaks and troughs (i.e., they reach a peak before the economy enters a recession and hit the trough before the end of a recession). Figure 1 illustrates this point by plotting home sales from 1979:1 through 1995:8. The dates of the U.S. business cycle recessions are also marked. To be useful for forecasting home sales, a leading indicator must therefore have a longer lead. Building permits and other components of CIBCR's long-leading index meet this requirement. It also appears that combining indicators with short and long leads does not improve the forecast performance. Model 4 provides support for this conclusion.

To examine if the forecasting performance of Models 3 through 7 improve by including building permits, we estimate Models 8 through 12. Table 2 reports the results. The U-statistics for Model 2 also appear in Table 2 for ease of comparison. All the models now perform almost as well as Model 2. There is a negligible improvement in the performance of Model 8 compared to Model 3 reinforcing the result that housing starts are a reasonable substitute for building permits. Models 9 and 11 that now include housing permits in two ways, as an additional variable and as a component of the respective composite leading indices, still do not outperform Model 2. This suggests that including building permits solely as an additional variable produces more accurate forecasts. Model 12 outperforms Model 2 by a very small margin in two of the three sub-periods. The small margin, however, cannot justify including both building permits and the leading employment index in the forecasting model for home sales.

Overall, the results suggest that Model 2 produces the most accurate forecasts. This robust finding holds across different time periods.

5. Conclusions

This paper examines the forecasting performance of six alternative leading indicators in alternative models for home sales. The benchmark model resembles the Dua and Smyth (1995) model and includes home sales, the price of homes, the mortgage rate, the unemployment rate, and real disposable income. The model that includes building permits as a leading indicator produces the most accurate forecasts of home sales. Replacing building permits with housing starts generates equally accurate forecasts of home sales. Four composite leading indicators of overall economic activity do not outperform building permits. After adding building permits to the models that already contain the composite leading indices, the extended models nearly match the performance of the model that includes building permits as the only leading indicator. Compared to the performance of the benchmark model, these results indicate that some gains occur from extending this model to include a leading indicator, and that the maximum gain occurs by adding building permits to the Dua and Smyth (1995) model.

We also find that leading indicators with a longer lead perform better than those with a shorter lead. This result may occur because home sales themselves lead economic activity. Thus, indicators with longer leads predict home sales better. In addition, the three leading indices compiled by the CIBCR, including the CIBCR's short-leading index, generally provide superior forecast performance to the Commerce Department's leading index. As a rule, the Commerce Department's leading index detracts from the forecasting performance of a model without information on leading variables.

Finally, as a general rule, the Bayesian VAR models outperform the benchmark unrestricted VAR model, especially during the recession years. Since out-of-sample forecasts of recessionary periods provide an acid test of any forecasting model, our findings strongly endorse the advantages of the Bayesian forecasting approach.

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Table 1
Accuracy of Alternative Models

Alternative Models	***Out-of-Sample: 1990:1-1995:8***		***Out-of-Sample: 1990:1-1991:12***		***Out-of-Sample: 1992:1-1993:12***	
	Average U	***% Change in Average U vs. Model 2***	***Average U***	***% Change in Average U vs. Model 2***	***Average U***	***% Change in Average U vs. Model 2***
Model 1 - VAR	1.129	--	1.687	--	0.841	--
Model 1	0.826	+13%	0.959	+20%	0.830	+16%
Model 2: Model 1 + Building Permits	0.732	--	0.799	--	0.718	--
Model 3: Model 1 + Housing Starts	0.751	+3%	0.830	+4%	0.733	+2%
Model 4: Model 1 + Com. Dept. Leading Index	0.876	+20%	1.103	+38%	0.828	+15%
Model 5: Model 1 + CIBCR Short-Leading Index	0.858	+17%	0.997	+25%	0.859	+20%
Model 6: Model 1 + CIBCR Long-Leading Index	0.798	+9%	0.932	+17%	0.762	+6%
Model 7: Model 1 + CIBCR Employment Leading Index	0.815	+11%	0.904	+13%	0.796	+11%

Notes: "Average U" is the average Theil U-statistic for 1 through 6-month-ahead forecasts

Table 2
Accuracy of Alternative Models with Housing Permits

Alternative Models	***Out-of-Sample: 1990:1-1995:8***		***Out-of-Sample: 1990:1-1991:12***		***Out-of-Sample: 1992:1-1993:12***	
	Average U	***% Change in Average U vs. Model 2***	***Average U***	***% Change in Average U vs. Model 2***	***Average U***	***% Change in Average U vs. Model 2***
Model 2: Model 1 + Building Permits	0.732	--	0.799	--	0.718	--
Model 8: Model 3 + Building Permits	0.734	+0.3%	0.805	+1%	0.716	-0.3%
Model 9: Model 4 + Building Permits	0.774	+6%	0.849	+6%	0.786	+10%
Model 10: Model 5 + Building Permits	0.759	+4%	0.805	+1%	0.739	+3%
Model 11: Model 6 + Building Permits	0.749	+2%	0.827	+4%	0.721	+0.4%
Model 12: Model 7 + Building Permits	0.732	+0%	0.788	-1%	0.708	-1%

Notes: See notes to Table 1.

Appendix: Components of Leading Indices

US Department of Commerce Leading Index

1. Average weekly hours, manufacturing
2. Average weekly initial claims for unemployment insurance
3. Manufacturers' new orders, consumer goods and materials
4. Vendor performance, slower deliveries diffusion index
5. Contracts and orders for plant and equipment, billions
6. Index of new private housing units authorized by local building permits
7. Change in manufacturers' unfilled orders, durable goods, smoothed
8. Change in sensitive materials prices, percent, smoothed
9. Index of stock prices, S&P 500
10. Real money supply M2
11. Index of consumer expectations, University of Michigan

CIBCR Short-Leading Index

1. Average weekly hours, manufacturing
2. Average weekly initial claims for unemployment insurance
3. Manufacturers' new orders, consumer goods and materials
4. NAPM vendor performance, slower deliveries diffusion index
5. Contracts and orders for plant and equipment
6. NAPM inventory change, diffusion index
7. Change in index of materials prices, smoothed, Journal of Commerce index
8. Index of stock prices, S&P 500
9. Layoff rate under five weeks
10. Change in index of business population
11. Change in deflated domestic nonfinancial debt, smoothed

CIBCR Long-Leading Index

1. Index of new private housing units authorized by local building permits
2. Real money supply M2
3. Dow-Jones bond price index, 20 bonds
4. Ratio of price to unit labor cost in manufacturing
5. Change in CPI services, smoothed
6. Change in output per hour in manufacturing, smoothed

CIBCR Leading Employment Index

1. Average weekly hours, manufacturing
2. Average weekly initial claims for unemployment insurance
3. Average weekly overtime hours, manufacturing
4. Short duration (under 15 weeks) unemployment rate
5. Ratio of voluntary to involuntary part-time employment
6. Layoff rate under five weeks