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Forecasting Growth in Current Quarter Real GNP

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This paper presents a simple model for obtaining estimates of current quarter real GNP growth using data on series that are available on a monthly basis. The variables used to "forecast" GNP growth are industrial production, real retail sales, and nonfarm payroll employment. The model's forecasts compare well with the Blue Chip consensus forecast and contain information about final GNP beyond what is contained in the advance GNP estimates.

Policy actions taken today rarely have an immediate impact on the economy, and several quarters may elapse before the effects of these actions begin to show up. Consequently, policymakers must rely on forecasts of future economic activity to formulate current policy. The task of forecasting the course of the economy is complicated by the fact that the relevant data on current activity are available only with a delay. Thus, an important first step in this process is to obtain reliable *estimates* of current activity. Such information should enable policymakers to take more timely action by responding to emerging trends.

This paper presents a method of obtaining "forecasts" of current quarter real GNP growth early in the quarter, in order to improve upon forecasts of output growth obtained from econometric models that are estimated using quarterly data only. The method presented here is a statistical one; it involves forecasting current quarter output using a small number of variables. It is thus to be contrasted to techniques that require knowledge of the contemporaneous values of a large number of series constituting the various components of GNP. The hope is that an inexpensive technique that does not require keeping track of a large number of variables will provide a reasonable estimate of current quarter output.

The objective of obtaining reliable estimates of GNP early in the quarter effectively determines the nature of the exercise carried out here. First, the data series used to predict GNP must be available on a more frequent basis than the quarterly GNP data themselves. Fortunately, there are many monthly data series that, ostensibly at least, should provide some indication of emerging trends in economic activity. Second, these monthly series should be available relatively soon after the end of the month they cover. Obviously, series that are published with a lag of several months are not useful for our purposes. A number of monthly series meet this requirement as well. Finally, these series themselves should be easy to forecast (over horizons of one to three months), since we would like to predict current quarter GNP even before data on all three months of the quarter are received. Series that can be forecast reasonably accurately will lead to better estimates of current quarter output early in the quarter.

From these criteria we were able to choose a small number of series, called indicator variables, with which to construct a model for forecasting current quarter GNP. The equation that is presented here uses contemporaneous values of nonfarm payroll employment, industrial production, and retail sales, as well as lagged values of real GNP, to predict current quarter real GNP growth. We present an analysis of its forecasting performance at different points in the quarter, when varying amounts of information are available on the indicator variables. The model is not very useful in the beginning of the quarter, when we have no information about the indicator variables. The forecasting accuracy of the model improves noticeably when information on the first month of the quarter becomes available. While there is some further improvement when data on the second and third months of the quarter become available, this improvement is not large. The model's forecasts compare favorably with the Blue Chip consensus forecast. The model's forecasts also contain information about final GNP over and above that contained in the Commerce Department's advance[1] GNP release.

The paper is organized as follows. Section I discusses issues of estimation strategy and variable selection. Section II presents the estimated model, called the monthly indicators model. It provides details on the forecasting performance of the system used to predict the indicator variables and presents the equation used to predict real GNP. The next section presents the results on the model's forecasting performance over the period from 1978.3–1988.2, and a comparison of the model's forecast with the consensus Blue Chip forecast. Section IV considers the issue of combining forecasts, in order to determine whether the model forecast provides information about the final value of real GNP beyond that contained in the advance estimate of GNP released by the Commerce Department, as well as that contained in the Blue Chip forecast. This section also evaluates how the model performs relative to the Blue Chip forecast in predicting the advance GNP estimates. Section V concludes.

I. Strategy and Variable Selection

The central issue of this project is which variables to use to predict real GNP. There are several approaches to this problem. Traditional, structural macroeconomic models, for instance, focus on the product side of the National Income and Product Accounts. An alternative approach is to obtain GNP estimates from information about factor inputs—utilize Okun's Law, for example. In contrast to these two approaches, this paper uses purely statistical criteria to determine whether a given variable should be used to forecast GNP. Specifically, a variable is included in the model if it helps to reduce the "ex-ante" errors in predicting real GNP and is statistically significant in the GNP equation. (As mentioned above, only those variables for which the relevant data are available relatively early are candidates for inclusion.)

However, minimizing GNP forecast errors is not a single criterion, since we wish to make forecasts of current quarter output several times during the quarter as new information on the indicator variables becomes available. A variable that is useful in predicting GNP when all three months of information are available may not be included in the model, since we are also concerned with the variable's usefulness when we have less than three months of information on it. Thus, our ideal variable is one that minimizes GNP forecast errors whether we have one, two or three months of information for the current quarter. What this means is that the variable we choose to predict real GNP should itself be easy to forecast.

This means that the process of choosing the appropriate set of variables for forecasting real GNP can become extremely cumbersome, since each time a new variable is considered for inclusion in the GNP equation it is also necessary to respecify the equations for forecasting all the indicator variables. Selecting variables according to the criteria of minimizing forecast errors also complicates matters, since we are faced with a rather large list of potential indicator variables.

In all, more than a dozen monthly series satisfied the criterion of being available early in the quarter and were considered for inclusion in the monthly indicators model. These are listed in the Appendix. Variables that did relatively well when no information on the current quarter was available but did relatively badly otherwise were dropped from consideration early in the specification search.[2] In addition, early work also revealed that variables that did reasonably well in predicting real GNP when all three months of data were available also tended to do well when only one or two months of data were available. (The reasons for this are discussed below.)

As a consequence, the latter part of the specification search was carried out in two separate stages. In the first stage, the focus was on the usefulness of the indicator variables in predicting real GNP when information on all three months of the quarter was available. This allowed elimination of more than half the variables in the original list. The second stage involved specifying equations for forecasting the indicator variables themselves, and then using these forecasts to obtain forecasts of real GNP.

Bayesian Vector Autoregressions (BVARs) were estimated to obtain forecasts of the monthly values of the indicator variables. This is an inexpensive forecasting technique pioneered by Robert Litterman that has been shown to produce macroeconomic forecasts comparable to those obtained from large, commercial forecasting services. (See Litterman [1986] and McNees [1986] for a comparison.) The technique uses the forecaster's prior beliefs about the behavior of the variables in question to modify the coefficients that would be obtained from unrestricted estimation of a vector autoregression.[3] The use of priors reduces the probability of picking up spurious correlations in the data. Unrestricted vector autoregressions tend to pick up such correlations and consequently explain in-sample observations relatively well but tend to forecast rather badly.

The general form of the prior employed here has come to be known as the "Minnesota prior," which postulates that most economic time series behave like random walks with drift.[4] Consequently, the estimated coefficients are pushed towards this specification. Specifically, for each variable, the coefficient on its own first lag is pushed towards one, while the coefficients on all other right-hand-side variables are pushed towards zero. How much the coefficients are pushed towards this prior is determined by examining the forecasting performance of alternative specifications and choosing the one that does the best. Considerations of space preclude a complete description of this prior and the technique here. The interested reader is referred to Todd (1984) for a clear, nontechnical discussion. Roberds (1988) provides a more technical and complete description of how to set up such a model.

Different BVARs were estimated for each combination of variables included in the equation used to forecast GNP. The indicator variable forecasts obtained from each of these BVARs were then used to obtain forecasts of real GNP at different points in the quarter. The final model was selected on the basis of these GNP forecast errors.

II. The Monthly Indicators Model

This section presents the model that was obtained through this process. Choosing variables on the basis of forecasting criteria leads to an eclectic set of indicator variables. The model's GNP equation contains a measure of production, industrial production (denoted IP); a measure of factor inputs, nonfarm payroll employment (denoted EMP); and a measure of consumption, real retail sales (denoted RRS). An important advantage of the set of variables used in the model is that all data for a particular month are available by the middle of the following month.[5]

The producer price index for finished commodities (PPI) has been used to deflate retail sales. At first glance, it might seem more appropriate to use a consumption deflator. However, the deflator for personal consumption expenditures becomes available more than a month after the PPI. Another alternative is the consumer price index (CPI). It turns out that the forecasting performance of the GNP equation is not very sensitive to whether the PPI or the CPI is used to deflate retail sales. A benefit of using the PPI is that it is released about two weeks before the CPI.

Intuition also suggests that a measure of labor hours may be preferable to a measure of aggregate employment, because average worker hours can be changed (within limits) to vary production without changing employment. However, using aggregate hours instead of employment leads to no appreciable difference in the GNP forecasts when all three months of data are available. In addition, forecasting labor hours turns out to be somewhat harder than forecasting employment. As a result, GNP forecasts based on one or two months of information are somewhat worse when hours are used to predict GNP than when employment is used. Experiments with specifications including various measures of average weekly labor hours in addition to employment were similarly unsuccessful.

Another potential problem has to do with the retail sales variable. In the last few years, sales incentives offered by automobile dealers have led to wide swings in quarter-to-quarter automobile sales, distorting quarterly retail sales data. To correct for these distortions one could omit automobile sales from consideration altogether and use retail sales net of autos in the GNP equation. This alternative specification led to poorer forecasting performance than did the specification that included auto sales. Another approach would be to include automobile sales as a separate variable in the GNP equation. Although this approach does lead to a statistically significant impact of changes in the growth rate of auto sales on real GNP growth, the estimated coefficient is quite small. Furthermore, there is no appreciable difference between the forecasting accuracy of the version of the model that contains automobile sales separately and that which lumps them together with non-auto retail sales. Consequently, automobile sales were not included separately in the final version of the model.

Obviously, the small set of indicators used here omits everybody's favorite variable. Two variables that might seem particularly important are the merchandise trade balance and inventories. The merchandise trade balance was not included primarily because of the lack of a continuous series over a period long enough to allow reliable estimation. In addition, including this variable in the model is not likely to add much information to "real-time" forecasts, since data on the merchandise trade balance for a particular month do not become available until approximately two months later.

Similarly, it seems that incorporating inventory data should help, since inventory swings are a significant component of quarterly variation in real GNP growth. However, trials with several alternative measures of nominal inventories failed to turn up a measure that either was significant in the real GNP equation or did not worsen its forecasting performance. Series on real inventories were significant in the real GNP equation, but these were not included in the final specification because they become available with more than a one quarter lag. Attempts to deflate the nominal inventory data with various price level measures and so create a useful measure of real inventories were also unsuccessful.

Predicting the Indicator Variables

The BVAR used to predict the monthly values of the three indicator variables contains five variables: the indicator variables themselves plus average weekly hours of production workers on private, non-agricultural payrolls, and the six-month commercial paper rate. The last two

Table 1
Forecasts of Indicator Variables: July 1978 to June 1988
(Annualized Growth Rates)

(A) Nonfarm payroll employment

	Univariate AR Forecast				BVAR Forecast			
Months ahead	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic
1	0.06	1.60	2.46	0.81	0.01	1.51	2.23	0.73
2	0.07	1.69	2.46	0.82	0.05	1.59	2.23	0.73
3	0.12	1.82	2.66	0.87	0.09	1.67	2.33	0.77

(B) Industrial production

	Univariate AR Forecast				BVAR Forecast			
Months ahead	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic
1	1.04	7.21	9.62	0.90	0.06	6.50	8.78	0.82
2	1.61	7.95	10.40	0.86	0.13	6.74	9.17	0.76
3	1.98	7.92	10.68	0.84	0.24	6.75	9.26	0.73

(C) Real Retail Sales

	Univariate AR Forecast				BVAR Forecast			
Months ahead	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic
1	0.84	16.16	24.16	0.75	3.50	13.43	18.93	0.59
2	0.98	16.30	23.82.	0.86	3.29	13.90	19.88	0.72
3	1.06	16.15	23.39	0.91	2.97	13.82	19.80	0.77

variables increase the precision of the forecasts of the indicator variables, but are not useful in predicting GNP. Each equation contains 12 lags of each of the variables. Given the nature of the exercise, presenting the estimated coefficients does not appear to be particularly useful.[6] (The computer program used to estimate the BVAR is available from the author on request.) Instead, Table 1 presents forecast error statistics for the one-month ahead to the three-month ahead horizons over a 10-year period extending from July 1978 to June 1988 (a total of 120 forecasts). Each forecast was obtained by estimating the BVAR up to the period prior to the first month being forecast.[7] For comparison purposes, the Table also includes error statistics on forecasts obtained from univariate autoregressions.

Although both the BVAR and the univariate autoregressions predict the log levels of the indicator variables, the forecasts have been converted to annualized growth rates in order to facilitate interpretation of the various error statistics shown in the table. Four different measures of forecast accuracy are presented there: the Mean Error, the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and Theil's U-statistic. A MAE close to the Mean Error implies that the errors are generally of the same sign, meaning that the forecasts are generally either too low or too high. A comparison between the RMSE and the MAE provides information about the relative size of the errors: if the errors are roughly of the same size, the two measures will be close. A mixture of large and small errors will lead to a RMSE above the MAE. Theil's U-statistic is unit free and provides a comparison of the model's forecast with the naive forecast of no change in growth rates. Values larger than one imply that the model's forecast is worse than the naive forecast.

As shown in Table 1, there is a substantial difference in the size of the errors made in predicting the three indicator variables. For instance, the MAEs and the RMSEs of the real retail sales forecasts are about eight times larger than the MAEs and the RMSEs of the employment forecasts. This is largely because the industrial production and real retail sales series are much more volatile than the employment series. Over the forecast period, the standard error of the growth rate of real retail sales is nearly seven times larger than the standard error of the growth rate of employment, while that for industrial production is more than three times as large as that for employment.[8]

A comparison of the MAEs and the RMSEs of the BVAR and the univariate autoregressions shows that the BVAR forecasts are better for all three variables. A similar conclusion holds for the U-statistics shown there. The Mean Errors from the BVAR are smaller than those for the univariate autoregressions for both employment and industrial production but are larger in the case of real retail sales. While it is possible to respecify the BVAR's prior to get smaller mean errors for retail sales, doing so raises the RMSEs of all three variables.

Predicting Contemporaneous GNP Growth

The equation used to predict current quarter GNP is

$$\begin{aligned} RGNP_t = {} & \underset{(2.16)}{0.81} + \underset{(2.81)}{0.17}\, IP_t + \underset{(3.77)}{0.14}\, RRS_t + \underset{(4.95)}{1.13}\, EMP_t \\ & - \underset{(-3.01)}{0.21}\, RGNP_{t-1} - \underset{(-1.41)}{0.09}\, RGNP_{t-2} - \underset{(-3.95)}{.26}\, RGNP_{t-3} \end{aligned}$$

Adjusted $R^2 = 0.74$, S.E.E. = 2.17
Estimation Period: 1968.2 to 1988.2.
t statistics are shown in parentheses

All variables are in (annualized) growth rates. The starting date was determined by the availability of the retail sales data. The number of lags was determined by using the FPE criterion.[9] The Lagrange Multiplier test for first order serial correlation produced a Chi-Square(1) statistic of 0.2, with a marginal significance level of 0.6. Hence, first order serial correlation is not a problem here. (The conventional Durbin-Watson statistic cannot be used because of the presence of lagged values of real GNP on the right hand side. See Pagan [1984] for a discussion of the Lagrange Multiplier test.) Omitting lagged values of real GNP leads to serially-correlated residuals and worsens the forecasting performance of the equation. Experimentation with different priors to restrict the coefficients on the lagged values of GNP did not lead to an improvement in forecasting performance.

III. Forecasting Performance

Table 2 presents the error statistics for the GNP forecasts. For each forecast, the equation was estimated up to the previous quarter and the resulting coefficients used, together with the current quarter values of the indicator variables, to predict real GNP growth in that quarter. I present results for two sample periods. The first one extends from 1983.3 to 1988.2, a total of 20 forecasts. The intent is to focus upon the most recent period. However, it is likely that a sample of 20 forecasts is not large enough to provide a reliable test of the model's performance. Accordingly, Table 2 also presents summary statistics on the model's forecasting performance over the period from 1978.3 to 1988.2, a total of 40 forecasts.

Four different exercises were performed for each sample period to duplicate the varying amounts of information available over the course of the quarter. The first one tests the forecasting capabilities of the model during the first month of each quarter, when no information is available on the indicator variables. In this case, the BVAR forecasts the values of the indicator variables for all three months of the quarter and these values are used in the GNP equation to forecast GNP growth. The second assumes that we are in the second month of the quarter, when data for one month are available on the indicator variables, and the BVAR is used to forecast the values of the indicator variables for the remaining two months of the quarter. Similarly, the third set of GNP forecasts is based on two months of data for the indicator variables, and the BVAR is used to forecast the values of the indicator variables in the third month of the quarter. Finally, the fourth set is based on all three months of actual data for the indicator variables, so that no BVAR forecast is required to forecast GNP growth.

Table 2
Comparison of Real GNP Forecast Errors
(Annualized Growth Rates)

(A) Forecasts over 83.3–88.2 (20 forecasts)

	Monthly Indicators Model Forecasts				Blue Chip Forecasts			
Month of forecast*	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic
1	0.13	2.41	3.29	1.14	0.72	2.18	2.62	0.91
2	0.29	1.62	1.96	0.68	0.96	2.19	2.62	0.91
3	0.38	1.58	1.95	0.67	0.92	1.91	2.31	0.80
4	0.40	1.39	1.86	0.64	0.80	1.80	2.14	0.74

(B) Forecasts over 78.3–88.2 (40 forecasts)

	Monthly Indicators Model Forecasts				Blue Chip Forecasts			
Month of forecast*	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic	Mean Error	Mean Abs. Error	Root Mean Sq. Error	Theil's U-Statistic
1	0.17	2.45	3.34	0.70	0.61	3.00	3.77	0.82**
2	0.20	1.45	1.81	0.38	0.71	2.69	3.30	0.69
3	0.22	1.41	1.73	0.36	0.74	2.16	2.64	0.55
4	0.22	1.30	1.69	0.35	0.64	1.80	2.16	0.45

*These dates refer to the month of the quarter in which the forecast becomes available. The 4th month is the month after the quarter ends. This dating convention implies that the model forecast may be based on as much as 1 month of additional information compared to the Blue Chip forecast. See text for details.

**Based on 39 forecasts only. (The first published Blue Chip survey is dated August 1978.)

An important issue in evaluating the forecasting performance of the model has to do with the use of real-time versus final data. Ideally one would like to duplicate the data sets that were actually in use at each point of the sample period to compare the model's forecasts with those available from other sources. Unfortunately, while it is possible (with considerable effort) to obtain preliminary data, it appears virtually impossible to find out the dates at which subsequent revisions were made for each of the series in the model. Consequently, it is not possible to duplicate the data sets that were used for the real-time forecasts made over this period. Therefore, all the statistics presented below have been computed on the basis of currently available (August 1988) data.[10]

Table 2 reveals that the real GNP forecasts obtained when the BVAR forecasts the indicator variables for all three months of the current quarter (that is, forecasts made in the first month of the quarter) are not very good, with a RMSE above 3.25 percent (at an annual rate) in both sample periods. In fact, for the short sample period Theil's U-statistic is greater than one, implying that a naive forecast of no change in growth rates would have been better than the monthly indicators model's forecast over this period. This is not a major shortcoming, however, since the purpose of the model is to forecast real GNP using contemporaneous information on the indicator variables.

The performance of the model improves noticeably when information on the first month of the quarter becomes available (that is, for forecasts made in the second month of the quarter), with the RMSE falling below two percent. Over the shorter sample period, forecasts made in the third month of the quarter (shown in the third row) are no more accurate than those made in the second month, although they are slightly more accurate for the full sample period. Similarly, forecasts made one month after the quarter has ended (that is, forecasts that use actual data on all three months of the quarter) are not much better than forecasts made in the third month of the quarter. In fact, the RMSE of the forecast made in the month after the end of the quarter being forecast is only around 0.1 percentage points smaller than the RMSE of the forecast made two months earlier.

The relatively small impact of the second and third months' data on the model's forecast accuracy reflects the fact that quarterly growth rates are a weighted average of monthly growth rates. For example, in computing the growth rate for the second quarter from monthly data, the growth rates for February and June get a weight of 1/9 each, those for March and May get a weight of 2/9 each and that for April gets a weight of 3/9. Thus, the arrival of information on the first month of the quarter doubles the amount of information we have on the quarterly growth rate (from one-third to two-thirds). By contrast, information on the third month of the quarter gives us only one-ninth of the information required for the quarterly growth rate. That is why the model's forecasts will not change significantly when data on the second and third months of the quarter become available.

Notice that the RMSEs of the real GNP forecasts made on the basis of three months of information are smaller than the standard error of the estimated GNP equation. This implies that the variables that are used to forecast real GNP are doing more than picking up random movements. Finally, while the error statistics for the shorter sample period tend to be somewhat larger than those for the full sample, the difference is not large enough to suggest that the forecasting ability of the model has changed over time.

Comparison with the Blue Chip Consensus

Table 2 also includes forecast error statistics for the consensus real GNP forecast from the Blue Chip survey. This survey is based on a panel of 51 forecasts and is contained in a newsletter titled, *Blue Chip Economic Indicators*, published by Capitol Publications. The consensus forecast is the average of the 51 individual forecasts. For the Blue Chip forecasts I have chosen a dating convention based on when the forecasts are released. The official release date of the survey is the 10th of the month, but the survey itself is conducted over the first week of the month. I have dated the forecast released on the 10th of the month as the forecast for that month. For example, the first quarter Blue Chip forecast released on the 10th of April is the forecast that is compared to the model forecast available on the 15th of April. From a policymaker's perspective, this comparison is the relevant one, since the two forecasts are lined up according to the dates when they actually become available.

However, if we want to assess the relative accuracy of the two forecasts, it would be better to compare the model forecast errors in one row with the Blue Chip forecast in the following row, since the Blue Chip average in any row will be based on less information about the economy than the model forecast in the same row. For example, the error statistics on the model's forecasts available in the second month of the quarter should be compared to the error statistics on the Blue Chip forecasts available in the third month of the quarter. Note, however, that this comparison will overcompensate in those months where employment data for a given month are released in the first few days of the following month, because the Blue Chip survey respondents are likely to have incorporated this information into their forecasts by the time of the survey.[11]

Table 2 reveals that over both the 83.3–88.2 sample period and the 78:3–88:2 sample period, the Mean Error, MAE and the RMSE of the model forecasts available in the second month of the quarter are all smaller than the corresponding error statistics for the Blue Chip consensus forecast available in each of the following two months. The model forecast does worse than the Blue Chip forecast only for forecasts made when no information on the current quarter is available. Thus, once information about the first month of the current quarter becomes available, the monthly indicators model performs better than the Blue Chip forecast.

Needless to say, this comparison exaggerates the relative advantage of the monthly indicators model, since it was estimated with the benefit of hindsight and it uses more accurate data than was available to individuals making real time forecasts over this period. Nevertheless, it does provide some reassuring evidence on the forecasting capabilities of the model. In addition, early versions of the model have been used to make real-time forecasts of output growth since the third quarter of 1987. These forecasts are presented in Table 3, along with the Blue Chip consensus forecast. Over this period (87.3–88.2), the mean error of the model's real time forecasts made using three months of data on the indicator variables is 0.7 percent, the MAE is 1.1 percent and the RMSE is 1.5 percent. Over the same period the mean error of the comparable Blue Chip forecast is 2.0 percent, the MAE also is 2.0 percent and the RMSE is 2.4 percent. For the model forecasts based on one month of information, the mean error is 0.9 percent, the MAE is 1 percent and the RMSE is 1.4 percent. While this sample of four observations is much too small for the results to be considered proof of the model's real-time forecasting capabilities, these results are at least consistent with the statistics presented in Table 2.

Finally, Chart 1 compares real GNP growth and the forecasts from the model for the period from 1983.3 to 1988.2. Two different forecasts are shown: first, forecasts made on the basis of one month of data on the current quarter and second, forecasts made on the basis of three months of data on the current quarter. The two forecasts are similar, as the RMSEs reported in Table 2 would suggest.

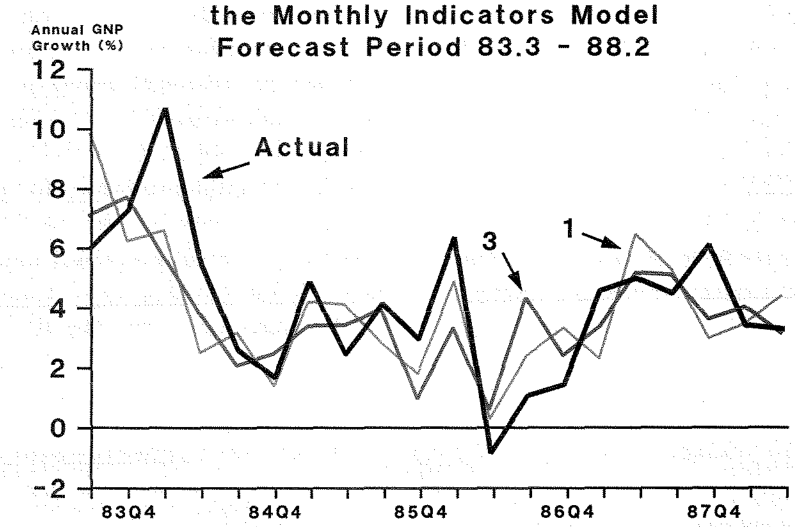
To summarize the results of this section, the forecast errors reveal that the monthly indicators model is not very useful when no information is available on the current quarter. The forecasting ability of the model increases noticeably once the first month of information becomes available, although the improvement is likely to be smaller when the model makes real-time forecasts because only preliminary data will be available at first. The model's forecasts should be much more reliable once data on the second month are available, especially because data for the first month of the quarter are often revised at this time and hence are likely to be more accurate.

Table 3
Real time forecasts of Real GNP Growth

Quarter being forecast	Monthly Indicators Model Forecast available in the 2nd month	3rd month	4th month	Blue Chip Consensus forecast available in the 2nd month	3rd month	4th month	Final GNP estimate*
87.3	3.5	3.9	3.8	2.4	2.7	2.9	4.5
87.4	3.6	3.0	3.2	1.5	1.9	2.1	6.1
88.1	3.0	4.0	4.1	0.4	0.7	1.4	3.4
88.2	3.2	2.9	3.0	2.0	2.3	2.5	3.0
Mean Error:	0.9	0.8	0.7	2.7	2.3	2.0	
Mean Absolute Error:	1.0	1.1	1.1	2.7	2.3	2.0	
Root Mean Square Error:	1.4	1.6	1.5	3.0	2.7	2.4	

*Real GNP data as of September 30, 1988.

Chart 1
Real GNP Forecasts from the Monthly Indicators Model
Forecast Period 83.3 - 88.2



Numbers refer to months of current-quarter data used in making forecast.

IV. Combining Forecasts

The results presented above reveal that the model's forecasts are reasonably accurate. However, we have not yet examined the issue of optimality. In other words, are the model's forecasts the best available, or can they be improved by combining them with information from some other source? Although it is not possible to determine what is *the* best forecast overall, this section considers the possibility of combining the model's forecast with the advance GNP estimate and the Blue Chip consensus forecast to determine whether the model's forecasts can be improved.

The Model Forecast and the Advance GNP Estimate

We begin by looking at what happens when the advance GNP estimate (which is released by the Commerce Department about three to four weeks after the end of the quarter) is combined with the model forecast to predict final GNP. The first part of Table 4 presents regressions of final GNP on the advance GNP estimate and on the model forecast obtained by using all three months of current quarter data. Once again, results are presented for two different sample periods. The first two columns of the Table show that over 1983.2–1988.2 both estimates are unbiased (that is, the hypotheses that the constant term is zero and that the coefficient on the forecast is one cannot be rejected at conventional significance levels in either equation). Also, both equations explain about the same share of the total variation in final GNP.

The third column presents a regression including both variables. When forecasts are pooled using regression analysis it is common practice to exclude the constant term and constrain the coefficients on the two forecasts to sum to one. This procedure has the advantage that if the two individual forecasts are unbiased, the combination forecast will be unbiased as well. However, Granger (1984) points out that the forecast error obtained from such a procedure is not necessarily uncorrelated with the individual forecasts. Thus, it is possible that the forecast error itself can be forecast from one of the individual forecasts, implying that the combination procedure is not optimal. To avoid this, Granger recommends that the estimated equations include a constant and not place any restrictions on the coefficients. Accordingly, column (3) of Table 4 presents results from unrestricted regressions.

The unrestricted regressions produce coefficients on the model forecast and on the advance GNP estimate that are about the same size. The standard error of this equation is about 10 percent smaller than the equation containing the advance GNP estimate alone, suggesting that the monthly indicators model does contain information over and above that contained in the advance GNP data. Unfortunately, the coefficients in equation 3 are not estimated very precisely. Thus, the 70% confidence interval for the coefficient on the model forecast extends from .31 to .83, while the 70% confidence interval for the coefficient on advance GNP extends from .29 to .88.

Columns (4)–(6) present the same regressions over the entire sample period. A comparison of these results with those in columns (1)–(3) reveals that there is not much difference between the coefficients of either variable across the two sample periods. However, the adjusted R^2 for the full sample period is noticeably higher.

The bottom half of the Table presents the error statistics obtained when the advance GNP estimate and the model's forecast are combined to predict the final GNP number. The sample period extends from 83.3 to 88.2. (The entire sample period cannot be used since the model's forecasts over the 78.3–83.2 period are used to estimate the prediction equation.) The procedure is the same as in Table 2, that is, the forecast for each quarter is obtained by estimating the underlying equation up to the previous quarter.

Combining the two forecasts leads to a MAE of 1.26 percent and a RMSE of 1.65 percent over this period. A comparison with the results in Table 2 reveals that the MAE obtained from the combination forecast is about 10 percent less than the MAE of the model's forecast. A similar reduction is obtained for the RMSE. This combination forecast is also an improvement on the results obtained when advance GNP is itself treated as a forecast of real GNP. If the advance GNP estimate is used by itself to forecast real GNP over the 83.3–88.2 period, the mean error is 0.54 percent, the MAE is 1.52 percent and the

Table 4
Combining the Advance GNP Estimate and the Model Forecast

(A) Real GNP Regressions

Dependent Variable: Final Estimate of Real GNP Growth

	83.3–88.2			78.3–88.2		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Coefficients*:						
Constant	0.96	0.47	−0.13	0.38	0.21	0.13
	(1.1)	(0.5)	(−0.1)	(1.1)	(0.6)	(0.5)
Advance GNP	0.88	—	0.59	0.97	—	0.47
	(4.4)		(2.0)	(12.4)		(3.5)
Model Forecast	—	0.99	0.57	—	1.01	0.58
		(4.0)	(2.2)		(13.2)	(4.2)
(B) Adjusted-R^2	.49	.44	.58	.80	.82	.86
(C) S.E.E.	1.82	1.91	1.66	1.81	1.71	1.50
(D) Durbin-Watson Statistic	2.15	1.76	2.01	2.24	2.31	2.31

(B) Error statistics for Combination Forecasts

Forecast period: 1983.3–1988.2

Mean Error	Mean Abs. Error	Root Mean Sq. Error
0.21	1.26	1.65

*t-statistics are shown in parentheses.

RMSE is 1.82 percent. These errors are roughly the same size as the errors of the monthly indicators model forecast based on three months of information (see Table 2). Thus, pooling the model's forecast and the advance GNP estimate leads to forecasts that are an improvement on either one considered by itself.

The Model Forecast and the Blue Chip Forecast

Table 5 presents the results of combining the model forecast and the Blue Chip consensus forecast. The regressions shown in the first part of the table are based on forecasts that become available in the first month after the end of the quarter. Column (1) shows that the Blue Chip forecast is an unbiased estimator of final GNP, a result that is not too surprising because the forecast itself is an average. A comparison of this equation with equation (2) of Table 4 reveals that the model forecast explains a somewhat greater share of the in-sample variation of real GNP than does the Blue Chip forecast. Regressing real GNP on both the Blue Chip and the model forecast (column 2 of Table 5) improves the explanatory power of the equation, although this equation does not do quite as

Table 5
Combining the Blue Chip and Model Forecasts

(A) Real GNP Regressions

Dependent Variable: Final Estimate of Real GNP Growth

	83.3–88.2		78.3–88.2	
	(1)	(2)	(3)	(4)
(A) Coefficients*:				
Constant	0.90	−0.60	0.43	0.12
	(0.8)	(−0.6)	(1.1)	(0.4)
Blue Chip Forecast	0.97	0.59	1.11	0.41
	(3.2)	(2.1)	(10.3)	(2.6)
Model Forecast	—	0.74	—	0.71
		(2.9)		(5.2)
(B) Adjusted-R^2	.33	.53	.73	.84
(C) S.E.E.	2.09	1.76	2.09	1.60
(D) Durbin-Watson Statistic	1.61	1.75	2.18	2.33

(B) Error statistics for Combination Forecasts

Forecast period: 1983.3–1988.2

Month of Forecast	Mean Error	Mean Abs. Error	Root Mean Sq. Error
1	0.44	2.21	3.00
2	0.25	1.71	2.04
3	0.10	1.55	1.90
4	0.06	1.33	1.76

*t-statistics are shown in parentheses.

well as the one that contains the model forecast and the advance GNP estimate. The coefficients are not estimated very precisely here either. A 70% confidence interval for the coefficient on the Blue Chip forecast extends from .30 to .87, while that for the coefficient on the model forecast extends from .48 to .99. Roughly the same sort of results are obtained for the full sample period. These are shown in columns (3) and (4) of the table.

The second part of the table presents the error statistics obtained when the two forecasts are combined to predict final GNP. The forecasts are generated in the same way as they were in Table 4. However, four sets of forecasts are presented here, to allow for the possibility that the relative weights on the two forecasts may not be the same at different points in the quarter. Unfortunately, these results do not suggest that the two forecasts can be combined very profitably in the early parts of the quarter. The Blue Chip forecast made in the first month of the quarter is generally better than the forecast obtained by combining the model and the Blue Chip forecast. By contrast, the model forecast made in the second month of the quarter is better than the combination forecast. And while the combination forecast made in the third month of the quarter is an improvement over the model forecast, the difference between the two is not striking (for instance, the RMSE falls from 1.95 to 1.90). There is a somewhat larger gain for combination forecasts made in the first month following the end of the quarter (the RMSE falls from 1.86 to 1.76); however, these forecasts are worse than those obtained by combining the model forecast and the advance GNP estimate.

Finally, it is worth asking if the error in predicting final GNP can be reduced by combining all three measures: the model forecast, the Blue Chip forecast, and the advance GNP estimate. Unfortunately, this does not lead to any improvement in the GNP forecast. The equation that contains all three variables turns out to be no better than the one that contains only the model forecast and the advance GNP estimate over either sample period. Further, an equation that contains the advance GNP estimate and the Blue Chip forecast does no better than an equation that contains only advance GNP. (For the 83.3–88.2 period, the coefficient on the Blue Chip forecast is 0.01 while that on advance GNP is 0.87.)

Table 6
Predicting Advance GNP

Dependent Variable: Advance Estimate of Real GNP Growth

	83.3–88.2			78.3–88.2		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Coefficients*:						
Constant	1.01	−0.07	−0.69	0.15	0.11	−0.02
	(1.1)	(−0.1)	(−1.0)	(0.4)	(0.4)	(−0.1)
Blue Chip Forecast	—	1.10	0.94	—	1.11	0.81
		(6.4)	(5.2)		(15.7)	(6.5)
Model Forecast	0.70	—	0.31	0.90	—	0.31
	(3.1)		(1.9)	(11.1)		(2.9)
(B) Adjusted-R^2	.31	.68	.72	.76	.86	.88
(C) S.E.E.	1.73	1.18	1.10	1.82	1.37	1.25
(D) Durbin-Watson Statistic	1.74	1.53	1.84	2.16	1.80	1.94

*t-statistics are shown in parentheses.

Predicting the Advance GNP Estimate

The results presented above suggest that the Blue Chip consensus forecast is closely related to the advance GNP estimate. Table 6 provides direct evidence on this issue, in the form of regressions of the advance estimates of real GNP on both the model forecast and the Blue Chip forecast. A comparison of columns (1) and (2) reveals that while both estimates are unbiased predictors of the advance GNP estimate, the Blue Chip forecast is much more closely related to advance GNP than is the model forecast over the 83.2–88.2 period. Column (3) shows that if both variables are used to forecast advance GNP, the coefficient on the Blue Chip forecast is three times that on the model forecast. A comparison of the adjusted R^2s and the standard errors of equations (2) and (3) shows relatively little difference between the two. Thus, the model forecast provides very little information about advance GNP once the information available in the Blue Chip forecast has been taken into account. The results over the entire sample period are similar, though the model forecast does noticeably better by itself.

The fact that the Blue Chip consensus is so much better at predicting advance real GNP than the model probably reflects the way that the underlying forecasts have been constructed. Private sector forecasters follow methods that are very similar to those used in constructing the advance GNP release. Since markets react to the advance release, it seems plausible that market participants will focus their efforts on obtaining forecasts of this number. In contrast, estimation of the monthly indicators model has used final GNP data and no attempt has been made to predict the advance numbers, since policymakers presumably are concerned about the actual level of economic activity, and not its first estimate.

V. Conclusions

This paper has presented a simple model to obtain estimates of current quarter real GNP growth based on a small number of variables. Information on the set of variables that is used to forecast GNP becomes available relatively early. In addition, these variables are relatively easy to predict, so that by the middle of the second month of the quarter being forecast we have a forecast of final GNP growth with a Root Mean Square Error that is less than 2 percent at an annual rate. Nor is it very difficult to generate the GNP forecasts. Obtaining these forecasts requires keeping track of a small number of monthly series, and the forecast itself can be generated very quickly on a personal computer.

The results presented here reveal that the model's forecasts based on one month of data for the current quarter are about as good as those based on all three months of data. Further, these forecasts compare well to the consensus Blue Chip forecast. Finally, the monthly indicators' forecast provides useful information on final GNP even after the advance GNP estimate is released.

APPENDIX

The set of variables over which I searched to find the best specification for the monthly indicators model contained:

- Nominal Manufacturing Shipments
- Nominal Manufacturing Inventories
- Book Value of Manufacturing and Trade Inventories
- Housing Starts
- Six Month Commercial Paper Rate
- Ten Year Bond Rate
- Producer Price Index—Finished Goods
- Consumer Price Index
- Aggregate Labor Hours Index
- Average Nonfarm Hours
- Average Manufacturing Hours
- Automobile Sales
- Retail Sales Net of Autos
- Industrial Production
- Nonfarm Payroll Employment
- Retail Sales

ENDNOTES

1. This release was known as the preliminary GNP estimate prior to 1988.3.

2. In general, these are variables that are relatively easy to forecast but are not as closely correlated to contemporaneous GNP as the variables that were finally included in the model. It is worth pointing out that this strategy is part of the reason that the monthly indicators model does relatively badly when no information on the indicator variables is available (see Table 2).

3. In a vector autoregression each variable is regressed on past values of itself and the other variables included in the vector.

4. A series y_t is said to be a random walk with drift if its behavior over time can be described as

$$y_t = a + y_{t-1} + e_t,$$

where e_t is a serially uncorrelated error term. In this case, our best guess of the value of y tomorrow is its value today plus the constant term a (the drift).

5. Employment data for a given month are generally released on the first Friday of the following month. Data on industrial production, retail sales, and the producer price index become available around the 15th.

6. Since there is no straightforward conceptual relationship between the variables included in the BVAR, it is not clear what interpretation can be placed upon the estimated coefficients. Even if this were possible, it would be difficult to analyze the 60-odd coefficients contained in each of the equations.

7. This is to avoid using coefficient estimates based on information obtained after the forecast was made. This exercise still exaggerates the degree of precision we would obtain in real time because we use revised data. This issue is discussed in the next section.

8. A secondary reason for the large difference in the forecast errors of the different variables is that I tended to favor priors that improved the forecast accuracy of the employment number at the expense of the others. This is because the employment number has a much greater weight in the equation for predicting real GNP than the other variables.

9. See Judge, et. al [1984] for a description of this criterion.

10. Braun (1987) provides an estimate of the effect of data revisions in a study that uses labor market data to predict contemporaneous output. He reports that using preliminary instead of currently available data raises the Root Mean Square Error (RMSE) of the real GNP forecasts by between 0.2 to 0.4 percentage points.

11. It is also worth pointing out that a Blue Chip forecast made in the second month following the end of the quarter being forecast is not available because no forecasts are compiled once the advance estimate of real GNP is released.

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