The University of Pennsylvania Models for High-Frequency Macroeconomic Modeling

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Preliminary version. Comments are welcomed.

1. Introduction

Forecasting of economic activity requires the use of all available information. However, data are collected at different frequencies. For example, stock prices are available instantaneously (real time), but industrial production data are available monthly, at best. This necessitates building models which utilizes data at different frequencies. This was the starting point for high-frequency macro-econometric models initiated by Klein & Sojo (1989). The approach of combining data at different frequencies is not restricted to macro-econometric models (Abeysinghe, 1998, 2000; Shen,1996). Recently, Mariano & Murasawa (2002) construct an index of coincident indicators utilizing quarterly GDP figures and monthly indicators such as personal income, industrial production, employment, and manufacturing & trade sales.

Since GDP, the most comprehensive economic indicator, is available quarterly in most of the countries, initially it may only be feasible to provide forecasts for quarterly GDP and the GDP deflator. It may be feasible to provide forecasts for components of

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GDP whenever high-frequency data are made available for likely indicators related to individual components.

Our long-standing conviction stands intact that detailed structural model building is the best kind of system for understanding the macro economy through its causal dynamic relationships, specified by received economic analysis. There are, however, some related approaches, based on indicator analysis that are complementary for use in high frequency analysis. For most economies, the necessary data base for structural model building, guided by consistent social accounting systems (national income and product accounts, input-output accounts, national balance sheets) are, at best, available only at annual frequencies. Many advanced industrial countries can provide the accounts at quarterly frequencies, but few, if any, can provide them at monthly frequencies.

A more complete understanding of cyclical and other turbulent dynamic movements might need even higher frequency observation, i.e. weekly, daily, or real time. It would not be impossible to construct a structural model from monthly data, but a great deal of interpolation and use of short cut procedures would have to be used; so we have turned to a specific kind of indicator method to construct econometric models at this high frequency. No doubt, systems of monthly accounts of national income and product will become available, in due course, for construction of complete structural models, and indicator analysis will probably then be used for even higher frequency, say, for a weekly model.

In a festschrift volume, honoring the business cycle indicator research of Geoffrey H. Moore, there is already a chapter that shows how leading indicators, that he found to be useful, already appear in some form or other in quarterly structural models.[1] This represents an ex-post treatment, in the sense that many forward-looking variables were quite naturally and understandably used in quarterly model construction and some turned out to be among the leading indicators that Geoffrey Moore developed, quite independently. A current quarter model may be used to estimate initial conditions (Klein&Sojo, 1989).

In step with new technological developments in the information sector of modern economies, attention has been paid to the use of newly available computer power, data resources, telecommunication facilities and other technical changes that made higher frequency analysis of economic statistics possible.

In a few countries, new methods of high frequency analysis (monthly or higher) have already been applied and are entirely plausible for countries such as Singapore and India, where data collection and thriving "new economy" activities have been firmly established.[2] There are excellent structural models available for India, and these have been applied on an annual basis for economic analysis (forecasting, policy implementation and quantitative historical analysis).[3] There have also been studies that use indicators. It remains to examine how these two approaches may be used in a complementary way.

The paper is in four sections. The second section deals with the methodology of the current quarter model (CQM) and performance of alternative models. The methodology used in "survey corner" is presented in the third section. Results are also

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[1] See Klein (1990).
[2] See, Klein (2000)
[3] See Mammen (1999), and Palanivel & Klein (2002).

compared with the help of various model selection criteria. Major conclusions are stated in the final section.

2. The Methodology of the Current Quarter Model (CQM)

There are at least three well-known accounting approaches to GDP measurement, and it is equally well-known (for several decades) that they rarely provide the same results.

Method 1. GDP is the sum of final purchases. This is known as demand-side estimation and happens to be the officially favored method for the USA, but not for all nations. It finds textbook expression in the accounting definition.

GDP = C(consumption)+I(investment) + G (government purchases) + X (exports) – M(imports)

In input-output accounting, it is usually displayed in the form of column sums of a rectangular matrix at the right-hand-side of the square inter-industry delivery matrix.

Method 2. GDP is the sum of income payments to the original factors of production.

It also is expressed in textbooks as

GDP = W(wages)+IN(interest)+P(profits)+R(rent/royalty)+IT(indirect tax) – S(subsidies)

In input-output accounting it is usually displayed as row sums of a rectangular matrix across the bottom of the square inter-industry matrix.

Method 3. GDP is the sum of value-added across all sectors of production. Value-added is written as

GDP = GP(gross production) – IP(intermediate production) = VA(value added)

If all statistical reports were accurate and if all economic agents were cooperative respondents or reporters, these three methods should give identical estimates. A very recent discrepancy between Method 1 and Method 2 for the USA, 2001, fourth quarter is estimated at $186 billion (seasonally adjusted annual rate). While this is a small percentage of the (unknown) total GDP of the USA, it is a very, very significant amount. It is as large as many important national policy initiatives that are meant to stabilize the economy. Revisions since 2001 change discrepancy from a large negative to a small plus, but cyclical swings are still strong. It does not go away, and it is not a random series. It has a well-established serial pattern and is closely correlated with important economic variables (Klein & Makino, 2000). The nonrandom serial correlation found in data of the discrepancy between different measures of GDP for the USA has been found in other national data, but not always between Methods 1 and 2, but sometimes between 1 and 3. Some countries do not have full statistics for Method 2.

It should be noted that there are similarities between Methods 2 and 3; they both aim for estimates of value-added, but Method 2 does this on an individual sector or industry basis, and Method 2 uses direct estimates of factor payments, while Method 3 derives factor payments (total or by sector) as a residual. It gets to value-added indirectly.

The methodology used in CQM is essentially based on Klein & Sojo (1989), and Klein & Park (1993, 1995). Real GDP and the GDP deflator are estimated using the expenditure side model (Method 1), and the income side model (Method 2).

In the expenditure side and the income side models, bridge equations are used to relate quarterly components to monthly indicators[4]. Bridge equations are statistical relationships between quarterly figures and averages of monthly indicators. For example, private fixed investment in information processing and related equipment (INV) in National Income and Products Accounts (NIPA)-which is available quarterly, is related to the quarterly average of manufacturers' shipments (SHIPMENT) of information technology-which is available monthly. These monthly indicators are the ones used by the US Department of Commerce, Bureau of Economic Analysis which is responsible for publishing the National Income and Products Accounts for the US (US Department of Commerce, 2002a, 2002b, 2002c). There are about 200 bridge equations in the US model. The detail is partly dictated by the composition of basic tables of the Commerce Department (US Department of Commerce, 2002a, 2002b, 2002c).

$$\underset{}{DLOG(INV)} = \underset{(7.43)}{0.019} + \underset{(9.38)}{0.919}\, DLOG(SHIPMENT) + \underset{(3.77)}{0.315}\, AR(1) + \underset{(3.51)}{0.294}\, AR(2) - \underset{(-2.95)}{0.244}\, AR(3)$$

[4] Augmented Dickey-Fuller (1979), Phillips-Perron (1991), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) unit root tests were implemented to study time series properties of the series used in the model. Almost all variables are non-stationary, integrated of order one, i.e. I(1). The monthly changes or percentage changes of these variables are integrated of order zero, I (0). Eviews by Quantitative Micro Software is used in all the calculations. Critical values used in testing are based on MacKinnon (1991). For modeling non-stationary processes see, Clements & Hendry (1998, 2002), and Engle & Granger (1987, 1991).

R^2=0.531, SEE=.019, F=38.14, D.W.=2.01, n=140 (1969 Q1- 2003 Q4).

Forecasts of monthly indicators are obtained by standard Box-Jenkins (1976) ARIMA equations. For example, month-to-month change in non-farm payroll employment is expressed as auto-regressive process of orders 1, 2, and a moving average of order 2, i.e. (ARIMA (2, 1, 2)).These monthly forecasts are averaged for the quarter and then related to quarterly variables in the model. There are over a hundred monthly indicators in the most recent version of the Current Quarter Model (CQM). It is possible to include some structural variables into this equation, such as real interest rate and real credits. However, that will increase the data requirement significantly. One has to get forecasts of those variables for the coming six months. It is not difficult to imagine the added difficulty, if one has to repeat this for about 100 such equations. This is the trade-off that one has to face and make a decision.

$$\underset{(2.33)}{D(EMPLOYMENT) = 0.137} + \underset{(3.75)}{0.241\, AR(1)} + \underset{(9.36)}{0.678^*\, AR(2)} - \underset{(-3.27)}{0.346^*\, MA(2)}$$

R^2=0.589, SEE=.109, F=114.2, D.W.=2.08, n=243 (January1984 – March 2004).

Since figures based on the production method (Method 3) are released with a lag, it is not used in the US model. Instead the principal components methodology is used. The following monthly indicators are used to form the principal components which are to be used in the estimation of real GDP (Klein & Park, 1993, 1995): Real manufacturing shipments, real manufacturing orders, real manufacturing unfilled orders, real retail sales, real money supply, index of industrial production, non-farm payroll employment, average number of hours worked, housing starts, real effective exchange rate, federal funds rate, interest rate spread (prime rate – treasury bill rate), interest rate spread (10 year bond yield – 1 year bond yield). The following monthly indicators are used to form the principal components which are to be used in the estimation of the GDP deflator: consumer price index, producer price index (finished goods), producer price index (intermediate goods),import price index, farm price index, average number of hours worked, average hourly wages. Three principal components were significant in explaining growth in real GDP.

$$DLOG(GDPR)*100 = \underset{(14.46)}{0.719} + \underset{(8.81)}{0.981}\ Z1 - \underset{(-2.92)}{0.144}*\ Z2 + \underset{(2.41)}{0.045}*\ Z5$$

R^2=0.612, SEE=.351, F=29.48, D.W.=1.81, n=60 (1984 Q1- 2003 Q4).

The arithmetic average of the expenditure side model, the income side model and the principal components model is given as the final forecast presented in weekly reports. The weights of alternative methods may be adjusted based on forecast errors (Diebold, 2004; Granger & Newbold, 1973, 1986; Klein &Young, 1980).

The University of Pennsylvania Current Quarter Model has generated a great deal of interest in high-frequency models. Models for various countries have been built: Japan by Inada; Mexico by Coutino (2002); Hong Kong by Chan (2000); and France by Courbis. Recently models were built for members of the European Union (Grassman and Keereman, 2001;Baffigi, Golinelli and Parigi,2002), for USA (Payne, 2000), and Russia (Klein, Eskin and Roudoi, 2003). In Asian countries, production or value added method (Method 3) is the most common method used in calculation of the GDP[5]. The

[5] What indicators may be useful in explaining real economic activity? These indicators may depend on availability of data and the structural characteristics of the economy. As an example, Klein & Ozmucur (2003) use twenty monthly indicators in calculating principal components to get estimates of China's GDP,

expenditure method (Method 1) is the next common method used. The income method (Method 2) is not as common as in the United States.

Releases may contain some information on basic data and evaluation of weekly events and official releases. Reports by Chan (2003), Coutino (2003), Inada (2003), and Klein & Ozmucur (2004a) are examples of such releases. The principal point is, to be ready as soon as any partial data are made available during a week, to re-calculate projections.

Performances of alternative models are based on ex-ante forecasting accuracy of these models[6]. At the time of forecasting, no quarterly information was available for the quarter of interest. For example, the 2003 Q4 forecast of GDP growth is based only on monthly indicators which are forecasted econometrically. Although, forecasts are provided every week, only forecasts following the release dates are compared in this paper. For example, advance estimate of real GDP growth for 2003Q4 was given on our weekly report of February 2, 2004. Preliminary estimate was used in the March 1, 2004 report, while the final estimate was used in the weekly report of March 29, 2004. These are denoted by ADVANCE, PRELIMINARY, and FINAL. Estimates are obtained from the expenditure side model (EXPENDITURE), the income side model (INCOME), the principal components model (PRINCOM), and the average of three methods (AVERAGE). Periods prior to advance estimate is shown after the underscore. For example, AVERAGE_1 refers to forecasts of December 29, 2003 (the date of the report where the final estimate of 2003Q3 was available). Similarly, AVERAGE_2 refers to the

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although the focus of that paper was different than the present one. It interpreted history rather than estimated the future.

[6] See Klein (1991), Wallis (1995), Wallis & Whitley (1991). Diebold & Mariano (1995) propose a formal test for model comparisons. A survey on model comparison criteria are done by Mariano (2002). See, also Theil (1961) for criteria for measuring model performance.

forecast obtained two-months ahead of the advance estimate for Q4. This was dated December 1, 2003 (preliminary estimate of 2003Q3 was made available). On the other hand, AVERAGE_3 refers to the forecast obtained three-months ahead of the advance estimate for Q4. The date of that forecast was November 3, 2003 (advance estimate of 2003Q3 was made available). Since forecasts for the current quarter and the following quarter are estimated in the model, it is possible to make comparisons for up to six-month-ahead forecasts. Forecasts given in reports of September 29, 2003 (AVERAGE_4), September 1, 2003 (AVERAGE_5), and August 4, 2003 (AVERAGE_6) may be used to make comparisons with the 2003Q4 actual figure. It should be noted that in comparisons with the preliminary and the final estimate of the real GDP growth, involve additional one and two periods, respectively. For example, AVERAGE_1 is a one-month ahead forecast if compared with the advance estimate. It is a two-month ahead forecast if compared with the preliminary and a three-month ahead forecast if compared with the final estimate of real GDP growth.

There are 28 forecasts (1997:Q1-2003Q4) where actual figures are also available (Figure 1)[7]. A mechanical (naïve) model which has last quarter's growth rate is used as the benchmark model. Average absolute error for real GDP growth is 1.36 for the expenditure side model, 1.59 for the income side model, 1.30 for the principal components model, and 1.01 for the average of the three (Table 1). The average absolute error for the mechanical model (no-change model) is 1.88. Similar results are obtained in the ordering for the two-period and three-period-ahead forecasts. All in all, the average forecast gives the lowest mean absolute error, while the naïve model gives the highest

[7] Model performance results for the 1990Q2-1994Q2 period are provided in Klein & Park (1995). Periods before 1997, as well as variables such as the deflator for personal consumption expenditures, may be included in the future.

mean absolute error. These results are supported by the correlation coefficients between forecasts and actual values (Table 2), and prediction-realization diagrams (Figures 2, and 3). It is clear from these results that there is an advantage of combining forecast. Forecast errors also decrease with added information, as one gets close to the release date. It is also important to see that the expenditure side model performs relatively better when real GDP growth rate is increasing, and the principal components model performs relatively better when the growth rate is decreasing (Table 3).

When compared with the mechanical (naïve or no-change) model, Diebold & Mariano statistics are significant at the five percent level for all models except the expenditure side model. This may be due to large errors in the expenditure side model during the early years of our analysis. Diebold & Mariano (DM) statistics are 0.87 for the expenditure side model, 2.95 for the income side model, 1.92 for the principal components model, and 2.48 for the average. In summary, models perform significantly better than the mechanical model.

3. The Methodology of the Survey Corner[8]

Many indicators are helpful in improving statistical performance for forecasting and policy analysis. We do believe, however, that no single indicator (or type of indicator) can do the necessary work by itself. The principal components, which are estimated linear functions of the whole set of indicators that we choose to represent the movement of the economy as a whole, the methodology is used as a short-cut and quick method to a full scale structural econometric model.

[8] See, Klein & Ozmucur (2002b).

Timeliness, flexibility, and foresight are important properties of indicators, and we are especially interested in information that reflects subjective feelings of participants in the economy. Results of surveys covering consumers, producers or managers are useful in forecasting major macroeconomic variables, like personal consumption expenditures, personal income flows, industrial production, employment, and financial market averages. Our results indicate that models including survey results perform better than those that do not include survey results.

In the USA, there was extreme uncertainty following the terrorist attack of September 11, 2001. Many conflicting judgments were expressed in the financial media concerning consumption, the largest single expenditure component in GDP. Our use of the model presented here enabled sensible, objective forecasts to be made in advance of each month since then.

The surveys of investors provide fresh insight on the functioning of the US economy. Surveys are very informative, not only for the present critical situation but for analysis of the economy in a more normal environment.

The economic information system is vast and developing in many dimensions. The information is more and more frequent – decennial, annual, quarterly, monthly, weekly, daily, hourly, ... real time. The scope is both macro and microeconomic. The history dates from colonial times and grows intensively, mainly as a result of advances in the use of information technology. Our ability to process this enormous information flow is made possible by the advances in computer science, both in terms of hardware and software supply.

Vast as this information flow has become, it is focused on objective, quantitative information such as prices, transaction volumes, production, sales, costs, exports, imports, interest rates, exchange rates, and so on. These pieces of information are all readily available in quantitative form, but they often lack a qualitative dimension. They are objective but economic decision making has a large subjective component. It is this subjective and qualitative property that finds expression in responses to surveys of human populations. There are some well-known surveys of households, firms, and bureaucrats but few, if any, of investors[9]. This is the dimension in economic behavior that has been missing, but is now filled by the results of the surveys of investor optimism.

The population that is being sampled every month has well-considered thoughts about the economy, their personal economic circumstances and other relevant issues. The qualitative responses in coded quantitative index form provide both microeconomic and macroeconomic information that enables one to determine their influence on performance of markets, consumption patterns, and production patterns.

Subjective feelings are always important for the economy, but the present situation highlights their extreme significance because personal attitudes have quickly and radically been changed as a result of calculated terrorism within US boundaries. Consumers and producers are no longer being guided mainly by objective market signals, and surveys of the investor population can quickly fill the void in our analyses of the economy.

[9] See Adams (1964), Adams & Green (1965), Bram & Ludvigson (1998), Carroll, Fuhrer,& Wilcox (1994), Cashell (2003), Eppright, Arguea, & Huth (1998), Garner(2002), Howrey(2001), Klein & Ozmucur (2001), Lee, Elango & Schnaars (1997), Lovell & Tien (2000), Matsusaka & Sbordone (1995), Pain & Weale (2001) for predictive power of surveys.

The emphasis on leading, coincident, and lagging indicators for spotting or interpreting cyclical phases is very interesting, but this methodology seems to extract less from the data than is plausible, certainly less than can be sought with the new technologies. It is not purely a matter of the contributions of each individual series, examined one at a time, in trying to unfold the cyclical story, but more a matter of trying to interpret the collective message (or signal) of the group as a whole. Much of macro-econometric model building focuses attention on the final adding-up to obtain total GDP or some related aggregates from the system as a whole, at the same time that the parts are examined.

The phases of the cycle that are generated by a combination of specific shocks, together with aggregate signals, may be due to shifting forces, sometimes on the demand side, sometimes on the supply side, sometimes from pressures in market-clearing, sometimes from natural causes; sometimes from geopolitical causes, sometimes from cumulative effects of small random errors, and so on. It seems to be too narrow to base ultimate decision making on 10-15 sensitive leaders, particularly for their timing.

Short of building the ultimate high-frequency model with many potential inlets of disturbance to the economy, our approach is to measure the collective impact of several high frequency indicators at many closely spaced time intervals – weekly or even daily in this high, interconnected global environment, and let their aggregate measured impact show where the economy is going[10]. Both timing and magnitude will matter, and the specific indicators that account for observed change need not always be the same. We

[10] See Liu & Hwa (1974) for a monthly econometric model for the US. Liu & Hall (2001) estimate monthly GDP for the US using Kalman filter methodology. See, Hamilton (1994a, 1994b), Harvey (1987, 1989), Kalman (1960, 1961), Kalman & Bucy (1961), Kim &Nelson (1999), Stock &Watson (1991, 2002) for the application of Kalman filters.

are looking for a generalization of the traditional indicator approach. To be specific, we collect and combine the joint effects of 20 to 30 (or even more) high frequency indicators. Each is separately measured, but the signal evolves from an aggregative measure.

We propose to form principal components of the monthly indicators whose periodic values appear at either different or similar time points of each month. An indicator will be denoted as

I_{it} = the i-th indicator value at month t.

i = 1,2,…, 30

The actual number of indicators will depend on the status of the data files of the economy being studied, and 30 need not be the limit of what can be used.

Another kind of variable will be an anticipatory or expectational variable, giving some subjective impression in advance, based on sampling human populations. Surveys of ordinary households, investing households, business executives, or possibly public officials may be used. These will be written as

S_{it} = sample survey response of the i-th economic agent at month t. The agents are asked to respond to future intentions or judgments, to contemporary or recent feelings or intentions.

The outcome of the economic decision will be X_{it} = i-th economic measurement or outcome such as consumer spending by households, business production or capital formation by firms, or financial market price averages by investors.

Having formed principal components of relevant indicators, we plan to regress important substantive variables jointly on sample survey indexes, allowing lagged (carry-over) effects from earlier sample results, generally of the most recent past months, as well as the current month, and also upon those principal components that show significant relationships to the chosen substantive variables (consumer spending, industrial production, capital formation, or financial market averages).

It is noteworthy that these substantive variables constitute some of the important coincident indicators of the US economy, while consumer surveys are one of the leading indicators of the US economy, as are the financial market (i.e. stock market) averages.

The method of principal component analysis is a well-known technique often used in social and psychological measurement (Anderson, 1984)[11] . In econometrics, it has been used for reduction of large data collections into more manageable form, especially to deal with problems of multicollinearity and shortage of degrees of freedom.

If we write for the i-th principal component

$$PC_{it} = \sum_{i=1}^{24} \gamma_i I_{it}$$

our procedure can be stated as one that estimates regression relationships between the specific economic variables that we want to project and the principal components, which, in turn, are based on the primary indicators.

$$X_{it} = \sum_{j=1}^{n_i} \alpha_{ij} PC_{jt} + \beta_{iq} S_{t-q} + e_{it}$$

$n_i < 24$, is the subset of principal components that are found to be significantly related to X_{it}, a magnitude that we are trying to project.

S_{t-q} = coefficient of a relevant Survey index referring to the q-th period (lag). In many cases we distribute the lag in S_t over a few recent months.

e_{it} = random error.

[11] See Nagar & Basu (1999), and Nagar & Rahman (2002).

Simultaneously, in estimating the coefficients in the above relationship we also represent e_{it} as an ARIMA process

$$e_{it} = \sum_{j=1}^{3} \rho_{ij} e_{it-j} + \sum_{j=1}^{3} \mu_{ij} u_{it-j}$$

where both e_{it} and u_{it} are independent random variables. The "noise" in this process comes from e_{it}.

There is much data processing and analysis in these various steps, but the structure of the system pays much attention to the underlying structure of the social accounts. It is not a purely empirical approach. In particular, it depends very much on the structure of a social accounting system, involving national income and product accounts (NIPA), the input-output accounts (IO), and the flow-of-funds accounts (F/F). It should be noticed that appropriate accounting balance among these three accounts seems to track the GDP, which is close to, but not directly identified as the end result of aggregate economic activity, but is a very important summary statistic, which is the objective of much economic analysis. It is well known that GDP can be expressed as the sum of all final expenditures, as shown in the NIPA system. This represents the demand side of the economy. But, as we indicated above, GDP can also be expressed as the sum of all payments to the primary factors of production that are responsible for aggregate output. The primary factors are labor, capital, land, and public services. This represents the supply side of the economy. The sum of all primary factor payments can also be evaluated for each sector of the economy as the sum, sector-by-sector, of gross sector output less intermediate sector output, to obtain sectoral value-added. These totals can be computed from a full IO table. By double entry accounting principles, the independent computation of these three estimates of GDP should be identical, but errors and emissions of observation infiltrate each method in practice, so the three sums do not necessarily agree. They may differ from each other by <u>at least</u> as much as one or two percent, and this can be important, especially since it does not turn out to be a random variable; therefore in choosing indicator variables, there must be strong representation from the demand side of the accounts, from the supply side, and from sectoral production flows. Also there should be consistency with the F/F accounts, dealing with saving and investment balances, from which specific indicators can be extracted.

The accounting balances arise from double-entry bookkeeping and even from quadruple-entry bookkeeping in the F/F accounts, which are important for financial market clearing. Hence, the indicator list should contain interest rates, inflation rates, exchange rates, and prices of factor inputs. In the applications, described below, the diversification of indicators follows those principles very carefully.

Also, since the objectives are forecasting, there should be indicators for the future, in the form of forward and futures market variables in addition to the anticipatory components of sample surveys. In this sense, a great deal of economic analysis goes into the selection of indicators.

We form principal components of indicators by extracting the characteristic root of correlation matrices among indicator values. The normalized variables in correlation analysis avoid sensitivity to units of measurement. Since the terrorist attacks of September 11, 2001 in the US, it has been widely noted that these variables have all had key roles in supporting the US economy in an entirely new environmental situation, and we have been following their patterns, month-by-month, in regularly updated studies of their movement on the basis of equations that affect the general economy, people's attitudes, and stochastic dynamic (ARIMA) error terms.

An important early economic use of principal components, though not expressly for indicator analysis, was introduced by Richard Stone, more than 50 years ago. He regressed objective measured variables on components, for his purposes of analysis.[12] Each of the four variables (consumer spending, industrial production, employment, and financial market averages) noted in the previous section have been estimated using principal components of economy-wide indicators, and a corresponding sample survey. Following the regression of the designated series to be explained, we present diagnostic test statistics for serial correlation and normality of distribution of residuals. These are followed by extrapolation of the dependent variable from equations that are re-estimated every month, up to the last month prior to extrapolation. Each re-estimated equation is extrapolated one-month ahead. The regression that is presented is only the last case in the sequence of re-estimates. The specification remains unchanged in this sequence.

Twenty-four indicators are used to calculate principal components to be used in the prediction of monthly employment. These indicators are: new orders (%chg) , housing starts (%chg), number of building permits (%chg), average hourly earnings (%chg), average hours worked (%chg), consumer price index (%chg), producer price index (%chg), real retail sales (%chg), trade-weighted real exchange rate (%chg), real money supply (%chg), real consumer credit (%chg), inventory/sales ratio (chg), ratio of budget revenues to budget expenditures (chg), federal funds rate (chg), prime rate (chg),

[12] See Richard Stone, "On the Interdependence of Blocks of Transactions", Supplement to the Journal of the Royal Statistical Society IX(1, 1947), 1-45.

corporate bond rate (chg), 3-month treasury bill rate (chg), 1-year bond yield (chg), 10-year bond yield (chg), S & P 500 index (%chg), Dow-Jones index (%chg), real personal income (%chg), manufacturing & trade sales (%chg), new claims for unemployment insurance (chg).

The final equation estimated using 243 observations (January 1984 – March 2004) includes two principal components, the employment index of the Institute for Supply Management (ISM)[13], and autoregressive and moving average processes of residuals. The determination coefficient (R^2) for the equation is 0.638, and all parameters associated with principal components and the Index are significant at the five percent level, most of them at the one percent level. There is no serial correlation in residuals based on Durbin-Watson, Breusch-Godfrey Lagrange Multiplier test and Lyung-Box-Pierce Q test, but the Jarque-Bera test indicates that they are not normally distributed, and Engle's test indicates that there is no autoregressive-conditional heteroscedasticity. Ramsey's RESET test indicates that there is no misspecification, and Chow breakpoint test indicates stability in the relationship.

D(EMPLOYMENT) = -615.804 + 11.361*PC2 - 10.293*PC4 + 6.368*ISM_EMP
(-4.96) (2.46) (-2.11) (7.73)

+ 4.776*ISM_EMP(-1) + 3.184*ISM_EMP(-2) + 1.592*ISM_EMP(-3)+[AR(1)=0.97,MA(1)=-0.77]
(7.73) (7.73) (7.73) (63.0 (-12.7)

R^2=0.638, SEE=102.37, F=83.50, D.W.=2.10, Jarque-Bera=8.1, Lyung-Box Q(2)=1.54, Q(12)=11.18, Breusch-Godfrey LM (2)=1.64, LM(12)=12.72, Engle ARCH(1)=1.83, Ramsey RESET(2)=1.13, Chow breakpoint (1994:01)=4.49 , n=243, (January 1984-March 2004).

[13] See Bretz (1990), Dasgupta & Lahiri (1992), Klein & Moore (1991), Pelaez (2003), Torda (1985) for the use of ISM (formerly NAPM) surveys. Palaez (2003) proposes the use of different weights to improve the predictive power of the composite index. See, Garcia-Ferrer & Bujosa-Brun (2000) for the use of business surveys in OECD countries.

The real consumer expenditures (CONS) is related to selected principal components (selected on the basis of statistical significance), to polynomial distributed lag (Almon lag) of the UBS index of investor optimism and an ARIMA of the error term.

$$\underset{}{DLOG(CONS)*100} = \underset{(16.54)}{0.244} + \underset{(2.58)}{0.0187}*PC1 + \underset{(7.35)}{0.1018}*PC2 + \underset{(2.72)}{0.0467}*PC10 + \underset{(3.18)}{0.0945}*PC14 +$$

$$\underset{(6.32)}{0.000386}*UBS + \underset{(6.32)}{0.000289}*UBS(-1) + \underset{(6.32)}{0.000193}*UBS(-2) + \underset{(6.32)}{0.0000965}*UBS(-3) +$$

$$[AR(1)=\underset{(3.49)}{0.341}, MA(1)=\underset{(-130.18)}{-0.981}]$$

R^2=0.636, SEE=0.256, F=19.21, D.W.=2.01, n=85, (February 1997-February 2004).

The Maximum likelihood estimation of the GARCH(1,1) model (Engle, 1982; Bollershov, 1986) for the S&P 500 with price/earnings ratio (PE) and two principal components (PC1, and PC4) yields the following results[14]:

$$DLOG(S\&P500) = \underset{(5.40)}{0.0078} + \underset{(4.64)}{0.1479}*DLOG(PE(-1)) - \underset{(-5.84)}{0.00497}*PC1 - \underset{(-4.13)}{0.00509}*PC4$$

$$s^2=\underset{(1.826)}{0.000083}+\underset{(3.82)}{0.1664}\, u(t-1)^2 +\underset{(11.54)}{0.7732}\, s(t-1)^2$$

R^2=0.104, SEE=0.034, F=7.05, D.W.=1.71, n=372, (February 1973-January 2004).

Principal component analysis is based on our general point of view that a country's (<u>any</u> country's) economic growth is highly multivariate. No single measured economic activity can account for anything as complex as a modern economy. We

[14] See Chauvet & Potter (2000), and Niemera (1991) for leading indicators of the stock market index. Boughton & Branson (1991), Dasgupta &Lahiri (1991), Gibson & Lazaretou (2001), Roth (1991) propose leading indicators for inflation.

examine many time series, select those that seemed to have a priori importance. In order to conserve degrees of freedom we narrowed the list of right hand side variables in the regression as much as possible. This has been an important motivation in adopting the principal component methodology. What is more, these components account for a high degree of variation of the total set. Also, by construction, the components are mutually uncorrelated; therefore we can handle the multicollinearity problem from a statistical point of view. Each component depends, in some way or another, on the whole set of indicators, yet their inter-correlation, which is naturally high, does not confound the interpretation of the regression estimates, and we have plausible associations between GDP growth and individual indicator growth.

It should be noted that results of consumer sentiment or business expectation surveys are useful in improving forecasts. In general, such survey results improve forecast accuracy. Klein & Ozmucur (2001, 2002b) show that the index of investor optimism and the index of consumer confidence improve forecasts of real personal consumption expenditures, while the index of purchasing managers improves forecasts of industrial production and employment. Klein, Mariano & Ozmucur (2001) show that results of business expectation surveys in Singapore improves employment forecasts. Results of surveys covering subjective evaluations of managers or households should be used whenever available.

Forecasts are useful not only for studying the short term developments of the economy, but also for adjusting lower frequency macro-econometric models so that they are solved from up-to-date initial conditions (Klein & Sojo, 1989, Klein &Park, 1995). Comparisons are based on ex-ante forecasting accuracy of these models. These forecasts are based on no available information for the month of interest, except survey results. For example, the April 2004 forecast of employment is based on indicator variables which are forecasted econometrically. Since “Survey Corner” forecasts have been available since March 2003, forecasts are compared for the period beginning in March 2003. There are 13 forecasts (March 2003-March 2004) for employment and 12 forecasts for industrial production (March 2003 – February 2004) where actual figures are also available. A mechanical (naïve) model which has last month’s change or percentage change is used as the benchmark model. Results are presented in Tables 4 and 5. Since general interest is in the month-to-month change in non-farm payroll employment and month-to-month growth in industrial production index, forecasts and error statistics are presented as changes or percent changes. Survey corner performs better than the current quarter model (monthly ARIMA equation) and the naive model. Average absolute error for month-to-month changes in employment are 74 thousand for the “survey corner”, 80 thousand for the “current quarter model”, and 92 thousand for the “naïve model”. Correlation coefficients between actual and forecasted month-to-month changes in employment are 0.64 for the survey corner, 0.46 for the current quarter model and 0.47 for the naïve model (Figure 4). Average absolute error for month-to-month percent changes in industrial production index are 0.23% for the “survey corner”, 0.35% for the “current quarter model”, and 0.40% for the “naïve model”. Correlation coefficients between actual and forecasted month-to-month percent changes in industrial production index are 0.82 for the survey corner, 0.42 for the current quarter model, and 0.35 for the naïve model (Figure 5).

4. Conclusion

Forecasts are useful not only for studying the short term developments of the economy, but also for adjusting lower frequency macro-econometric models so that they are solved from up-to-date initial conditions. The advantage of combining forecast is clear from results provided by the Current Quarter Model. It is also clear that forecast errors decrease with added information, as one gets close to the release date. It is also important to see that the expenditure side model performs relatively better when real GDP growth rate is increasing, and the principal components model performs relatively better when the growth rate is decreasing. This indicates a possibility of improving forecasts by using different weights at different stages of the economy.

Results of consumer sentiment or business expectation surveys are useful in improving forecasts. Surveys are very informative, not only for the present critical situation but for analysis of the economy in a more normal environment.

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Table 1. Absolute values of forecasts of alternative models

	Absolute Errors (1997:1 - 2003:4)				
	EXPEND._1	INCOME_1	PRINCOM_1	AVERAGE_1	NAIVE_1
Mean	1.36	1.59	1.30	1.01	1.88
Median	1.34	1.49	0.93	0.77	1.37
Maximum	3.94	5.69	3.82	3.07	5.62
Minimum	0.00	0.16	0.07	0.01	0.06
Std. Dev.	1.19	1.28	1.11	0.92	1.44
Skewness	0.82	1.51	0.95	1.09	1.05
Kurtosis	2.77	5.76	2.79	3.07	3.40
	EXPEND._2	INCOME_2	PRINCOM_2	AVERAGE_2	NAIVE_2
Mean	1.71	1.58	1.54	1.39	2.13
Median	1.49	1.43	1.32	1.01	1.87
Maximum	4.52	7.29	4.85	3.92	6.19
Minimum	0.00	0.02	0.03	0.03	0.31
Std. Dev.	1.44	1.47	1.21	1.02	1.57
Skewness	0.63	2.27	1.21	0.80	0.88
Kurtosis	2.18	9.42	4.08	2.70	3.17
	EXPEND._3	INCOME_3	PRINCOM_3	AVERAGE_3	NAIVE_3
Mean	1.86	1.97	1.80	1.67	2.15
Median	1.56	1.78	1.63	1.33	1.74
Maximum	4.78	6.36	5.29	4.39	6.40
Minimum	0.19	0.14	0.03	0.20	0.07
Std. Dev.	1.33	1.67	1.43	1.25	1.55
Skewness	0.67	1.12	0.65	0.63	1.08
Kurtosis	2.30	3.95	2.58	2.36	3.60

Table 2. Correlation Coefficients Between real GDP growth rates and Model Estimates (numbers following the model name refer to number of months before the advanced estimate)

	Correlation Coefficients		
	ADVANCE	PRELIMINARY	FINAL
EXPENDITURE_1	0.67	0.62	0.63
INCOME_1	0.54	0.48	0.47
PRINCOM_1	0.58	0.58	0.57
AVERAGE_1	0.76	0.71	0.70
EXPENDITURE_2	0.48	0.45	0.47
INCOME_2	0.44	0.38	0.37
PRINCOM_2	0.43	0.40	0.40
AVERAGE_2	0.65	0.59	0.60
EXPENDITURE_3	0.40	0.30	0.29
INCOME_3	0.27	0.21	0.19
PRINCOM_3	0.26	0.18	0.15
AVERAGE_3	0.41	0.31	0.28
ADVANCED	1.00	0.96	0.96
PRELIMINARY	0.96	1.00	0.99
FINAL	0.96	0.99	1.00

Note: Comparisons with the preliminary and the final estimate of the real GDP growth, involve additional one and two periods, respectively. For example, AVERAGE_1 is a one-month ahead forecast if compared with the advance estimate. It is a two-month ahead forecast if compared with the preliminary and a three-month ahead forecast if compared with the final estimate of real GDP growth.

Table 3. Absolute values of errors of alternative models

Sample: 1997:1 2003:4 IF ADVANCE<ADVANCE(-1)

	EXPEND._1	INCOME_1	PRINCOM_1	AVERAGE_1
Mean	1.256	1.402	0.947	0.787
Median	1.225	1.555	0.585	0.705
Maximum	3.680	2.500	2.740	2.780
Minimum	0.000	0.160	0.070	0.070
Std. Dev.	1.123	0.738	0.881	0.707
Skewness	0.761	-0.673	0.912	1.586
Kurtosis	2.709	2.371	2.555	5.545
Observations	14	14	14	14

Sample: 1997:1 2003:4 IF ADVANCE>ADVANCE(-1)

	EXPEND._1	INCOME_1	PRINCOM_1	AVERAGE_1
Mean	1.456	1.780	1.655	1.234
Median	1.520	1.360	1.150	0.915
Maximum	3.940	5.690	3.820	3.070
Minimum	0.050	0.190	0.410	0.010
Std. Dev.	1.293	1.666	1.228	1.072
Skewness	0.803	1.218	0.702	0.638
Kurtosis	2.623	3.520	2.058	1.973
Observations	14	14	14	14

Table 4. Forecasts Based on Alternative Models at the beginning of the month (Changes in Non-farm Payroll Employment)

	actual	forecast	forecast	forecast
		survey		
	actual	corner	CQM	Naive
2003.01	143		-6	-101
2003.02	-308		4	143
2003.03	-108	-41	-4	-308
2003.04	-48	-83	-72	-108
2003.05	-17	-94	-86	-48
2003.06	-30	-51	0	-17
2003.07	-44	-22	-4	-30
2003.08	-93	-8	-19	-44
2003.09	57	-2	-24	-93
2003.10	126	-25	20	57
2003.11	57	20	113	126
2003.12	1	120	112	57
2004.01	112	151	65	1
2004.02	21	144	79	112
2004.03	308	187	72	21
2004.04		201	167	308
average absolute error		74	80	92

Table 5. Forecasts Based on Alternative Models at the beginning of the month (Percentage Changes in Industrial Production)

	actual	forecast survey	forecast	forecast
	actual	corner	CQM	Naive
2003.01	0.73		-0.01	
2003.02	0.09		0.20	
2003.03	-0.54	-0.37	0.15	0.09
2003.04	-0.45	-0.67	-0.06	-0.54
2003.05	0.18	0.09	-0.14	-0.45
2003.06	0.09	0.18	-0.02	0.18
2003.07	0.46	0.16	0.04	0.09
2003.08	0.09	0.09	0.16	0.46
2003.09	0.36	0.09	0.16	0.09
2003.10	0.27	0.45	0.21	0.36
2003.11	0.89	0.45	0.21	0.27
2003.12	0.08	0.44	0.41	0.89
2004.01	0.79	0.44	0.28	0.08
2004.02	0.73	0.44	0.36	0.79
2004.03		0.44	0.56	
2004.04		0.43	0.53	
average absolute error		0.23	0.35	0.40

Figure 1. Real GDP Growth Forecasts by Alternative Models

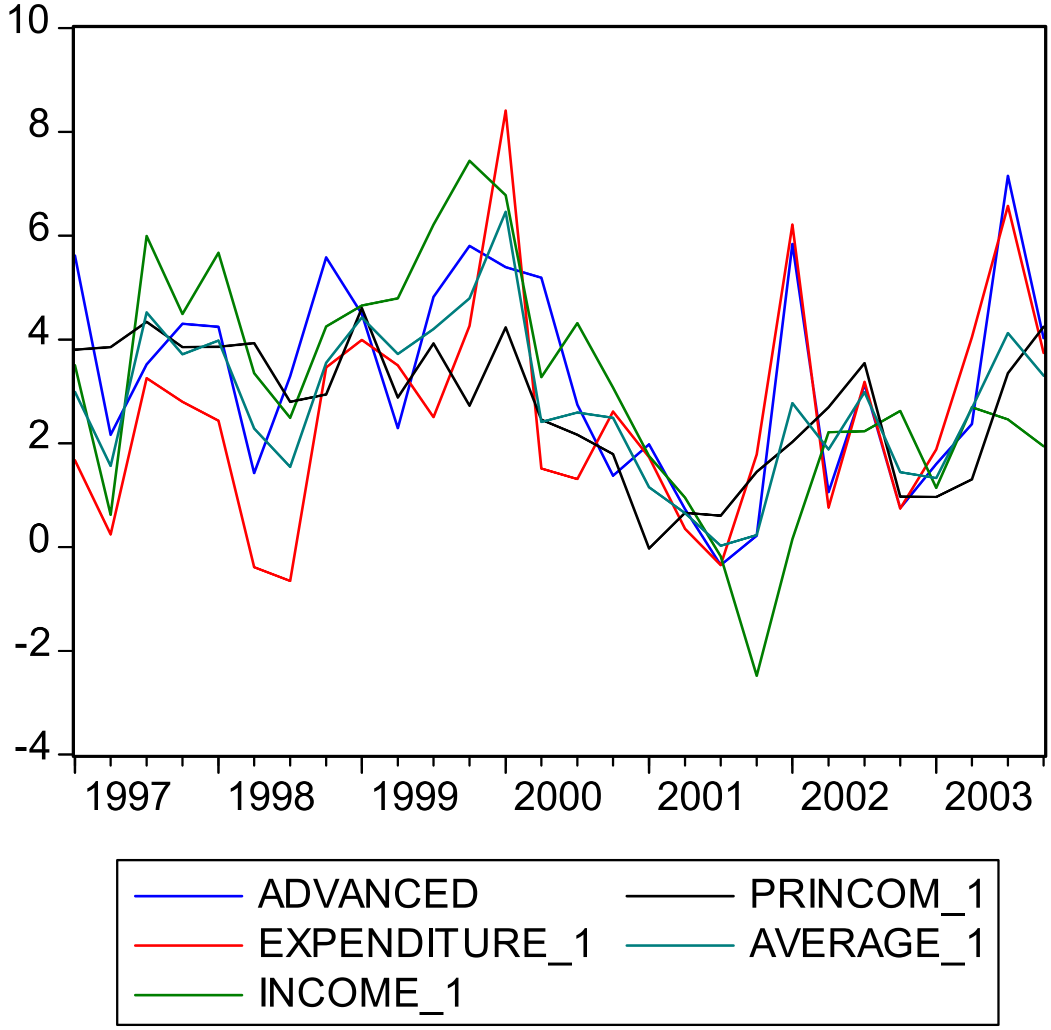


Figure 2a. Real GDP Growth Forecasts by Alternative Models

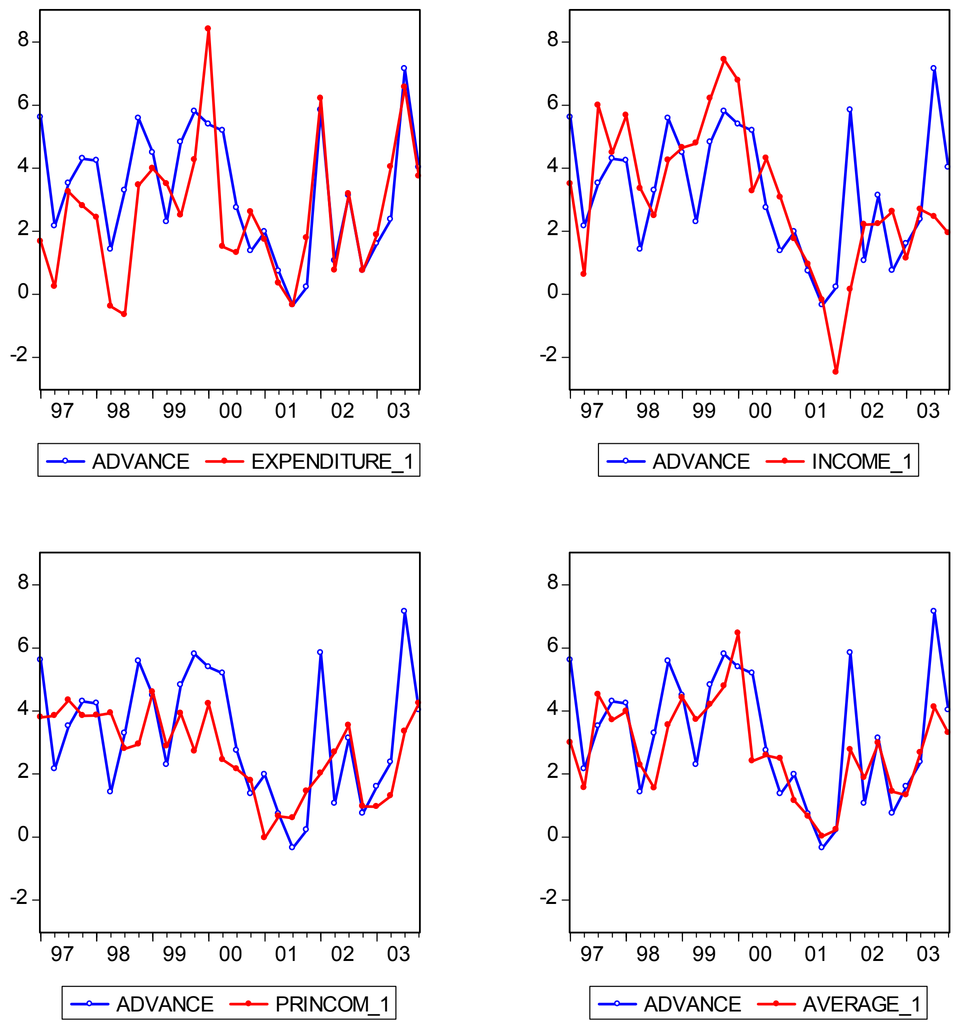


Figure 2b. Prediction-Realization Diagrams for one-month-ahead forecasts

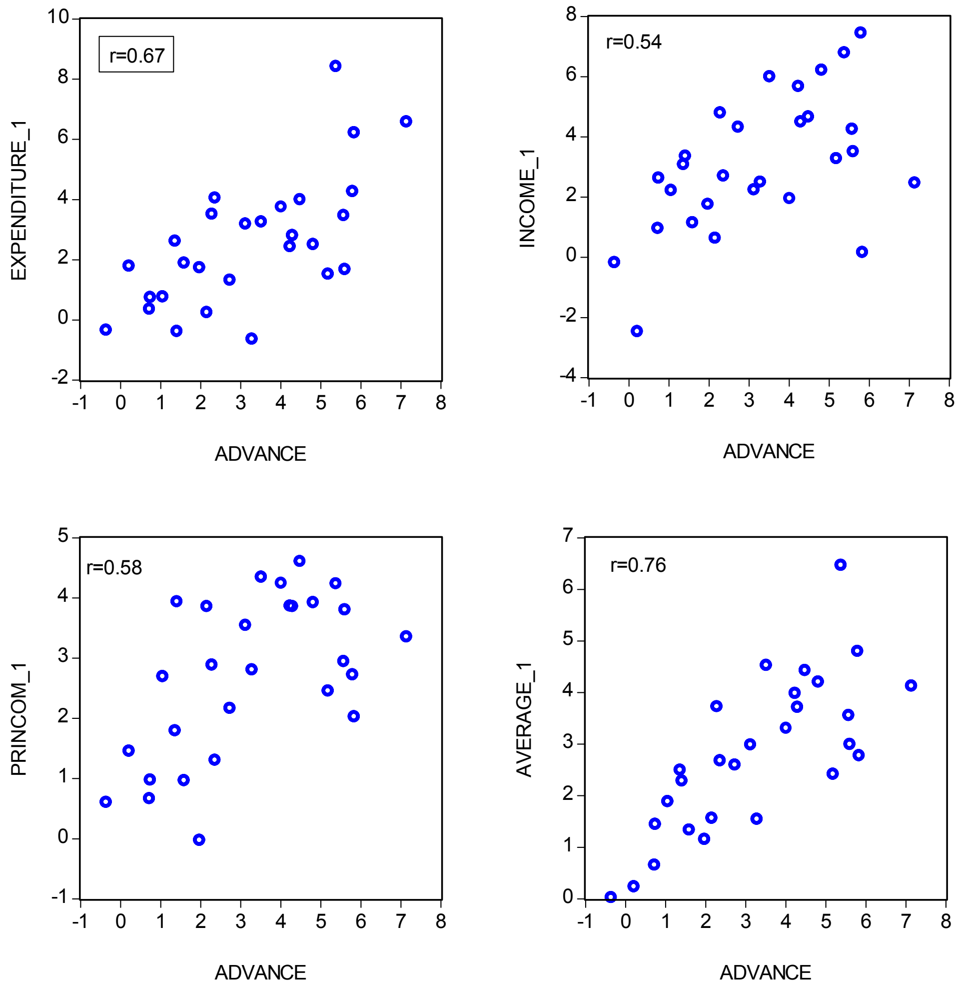


Figure 2c. Prediction-Realization Diagrams for one-month-ahead forecasts

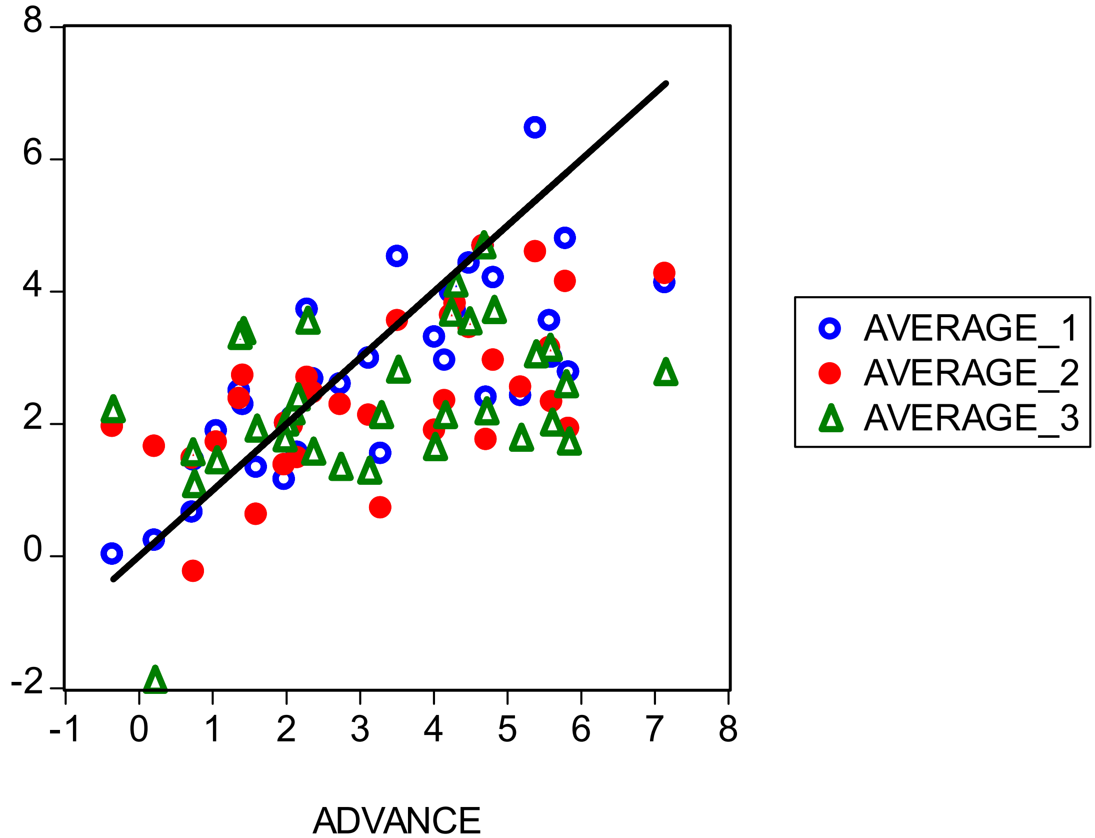
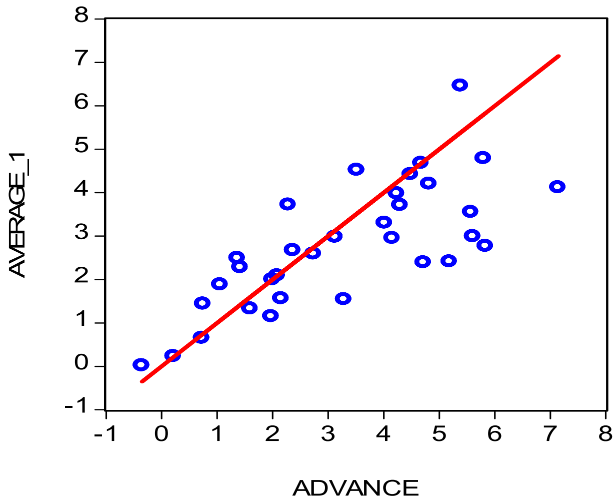
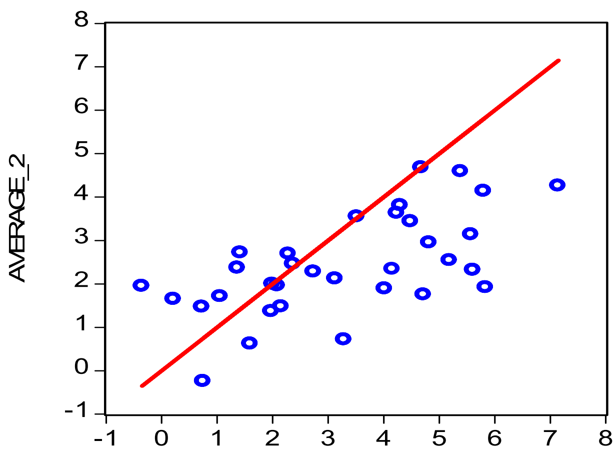


Figure 2d. Prediction-Realization Diagrams for one-month-ahead forecasts





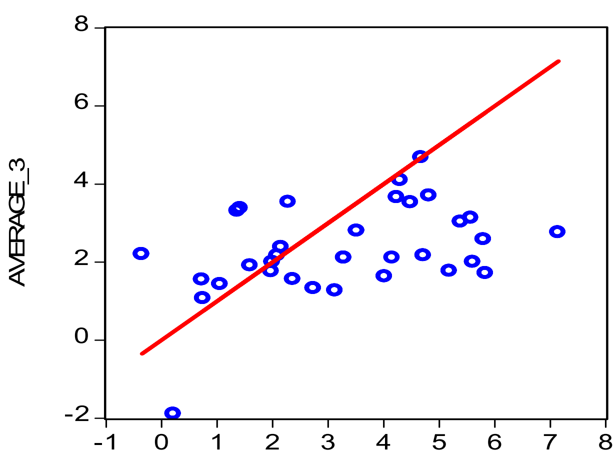


Figure 3. Prediction-Realization Diagrams for one, two and three-month-ahead forecasts

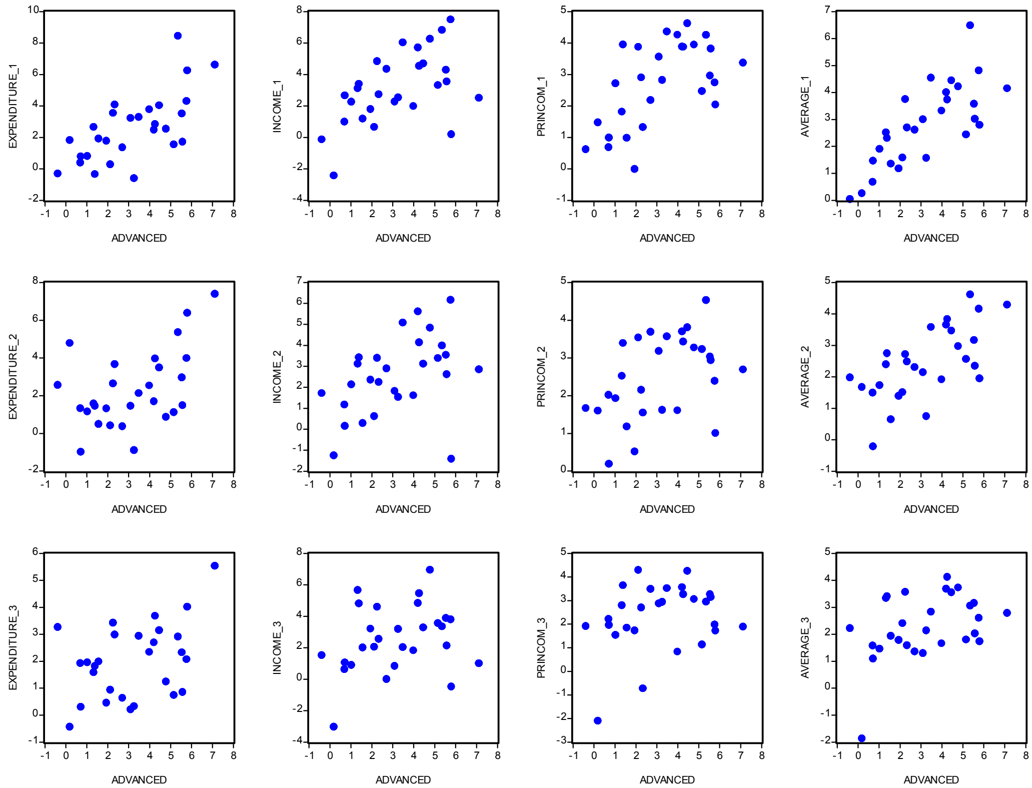
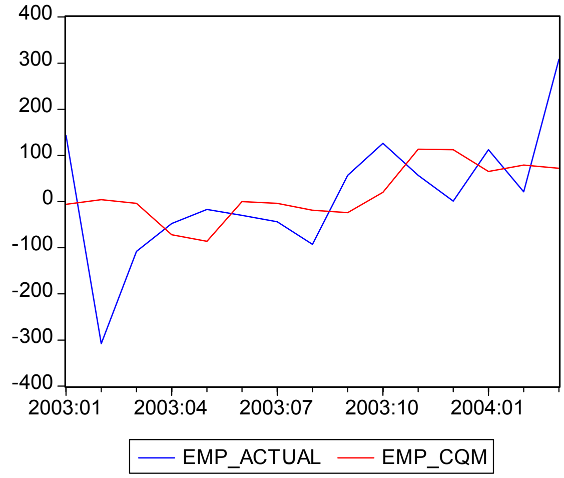
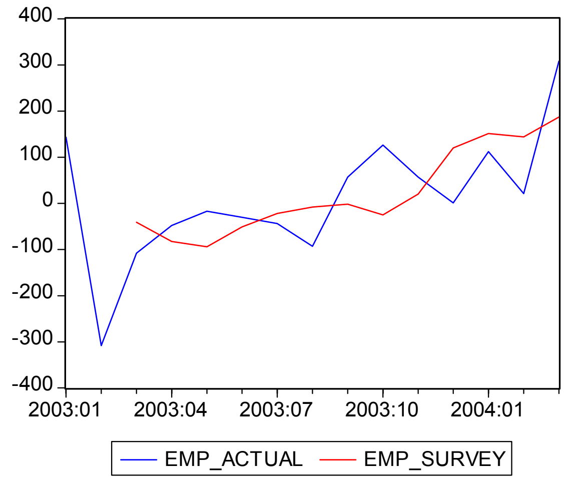


Figure 4.Actual and Extrapolation of Monthly Changes in Non-Farm Payroll Employment





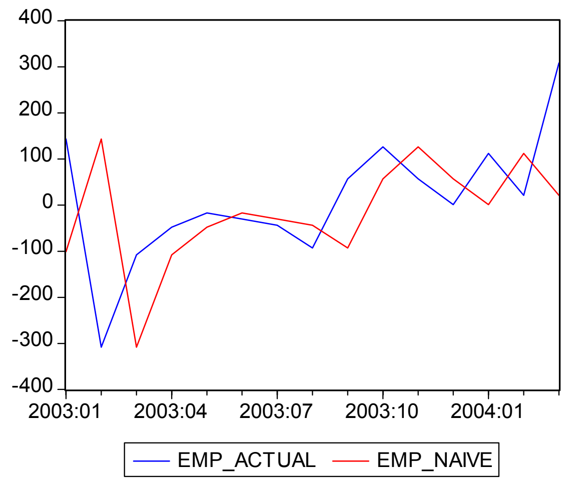


Figure 5. Actual and Extrapolation of Monthly Percentage Changes in Industrial Production