

# **Some Possibilities for Indicator Analysis in Economic Forecasting**

**Lawrence R. Klein and Suleyman Ozmucur**

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## **Abstract**

Many indicators are helpful in improving statistical performance for forecasting and policy analysis. However, no single indicator can do the necessary work by itself. The principal components methodology is used as a short-cut method to a full scale structural econometric model. Results of surveys covering consumers, producers or managers are useful in forecasting major macroeconomic variables, like personal consumption expenditures, 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.

Keywords: leading indicators, surveys, econometric models, principal components

JEL classification: C20, E20, G10

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### Biographies:

Lawrence R. Klein is the Benjamin Franklin Professor of Economics (emeritus) at the University of Pennsylvania. He has received the Nobel Prize in Economics Sciences in 1980 for his contributions to economic theory and econometric modeling.

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## *I. Structural Models and Indicator Analysis*

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.<sup>1</sup> 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.

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 India, where data collection and thriving “new economy” activities have been firmly established.<sup>2</sup> 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).<sup>3</sup> There have also been

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<sup>1</sup> See Lawrence R Klein, “Cyclical Indicators in Econometric Models”, Analyzing Modern Business Cycles, ed. Philip E. Klein, (Armonk: M.E. Sharpe, Inc.) 1990, 97-106.

<sup>2</sup> L.R. Klein, “Essay on the Accuracy of Economic Prediction”, International Journal of Applied Economics and Econometrics, 9 (Spring, 2000), 29-69.

<sup>3</sup> Thampy Mammen, India’s Economic Prospects: A Macroeconomic and Econometric Analysis (Singapore: World Scientific Publishers) 1999. T. Palanivel and L.R. Klein,

studies that use indicators (as in the present volume). It remains to examine how these two approaches may be used in a complementary way.

## *II. A Suggested Indicator Approach*

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 macroeconomic 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 cause; 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. Both timing and magnitude will matter, and the specific indicators that account for observed change need not always be the same. We 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

$$I_{it} = \text{the } i\text{-th indicator value at month } t.$$
$$i = 1, 2, \dots, 30$$

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

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“Economic Reforms and Growth Prospects in India”, Macroeconomics and Monetary Policy eds. M.S. Alhuwalia et.al. (Oxford: Oxford University Press) 2002.

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 principal components is a well-known technique often used in social and psychological measurement.<sup>4</sup> If we write for the  $i$ -th principal component

$$PC_{it} = \sum_{i=1}^{30} \gamma_i I_{it}$$

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.

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

$n_i < 30$ , 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.

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  $e_{it}$ .

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<sup>4</sup> See e.g. A.L. Nagar and Sudip Ranjan Basu, “Weighting Socio-Economic Indicators of Human Development (A Latent Variable Approach),” National Institute of Public Finance and Policy, New Delhi, 1999.

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 requires that GDP, which is close to, but not directly identified as the end result of aggregate economic activity, but is a very important summary statistics, 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 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 at least 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 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.

We choose dependent variables that are jointly associated with the indicator variables and with sample survey structures, thus we determine which principal components are significantly related, for example, to (i) real consumer expenditures, (ii) industrial production, (iii) employment, and (iv) stock market

averages. These are shown in examples, presented below, but we could equally well have used other dependent variables. The four that are selected above are clearly identified with traditional indicator analysis of the National Bureau of Economic Research and are available at monthly (or higher) frequency in the US. 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.

It should be noted that the use of principal components by Professor Nagar and his associates has been related to latent variables, that are not directly measured. In our work, we use objective estimates of variables, such as those listed above and are not forced to define what the principal components express, such as "quality of life". That type of study is, of course, equally important, but it is different.

An important early 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.<sup>5</sup>

### ***III. Some Examples***

Each of the four relationships noted in the previous section have been estimated using principal components of economy-wide indicators, and a corresponding sample survey. The first relates real consumer expenditures to selected principal components (selected on the basis of statistical significance), to the University of Michigan monthly survey of consumer sentiment and an ARIMA of the error term. The Michigan Survey has been available monthly since the 1970s. 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.

The consumption equation estimated most recently is given in the Appendix. We are reporting results on consumption only for sake of brevity. The equation is estimated with 295 monthly observations from May 1978 to November 2002 (Equation A1). The equation includes thirteen principal components, which account for over 75% of the variation in 27 indicators, a polynomial distributed

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<sup>5</sup> See Richard Stone, "On the Interdependence of Blocks of Transactions", Supplement to the Journal of the Royal Statistical Society IX(1, 1947), 1-45.

lag of the Michigan Index of Consumer Sentiment, and moving average process of residuals.

Indicators used for personal consumption expenditures are: new orders (%chg) , housing starts (%chg), real value of construction put in place (%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), unemployment rate (chg), federal funds rate (chg), prime rate (chg), 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), index of industrial production (%chg), non-agricultural employment (%chg), manufacturing & trade sales (%chg).

The determination coefficient ( $R^2$ ) for the equation is 0.71, and all parameters associated with principal components are significant at the five percent level, most of them at the one percent level. The Michigan index of Consumer sentiment is significant at the six percent level. The actual, fitted and residual diagram indicates the degree of closeness of fit. In addition to Durbin-Watson statistics (1.97), Ljung-Box-Pierce Q statistics (6.04 for 12 lags) and Breusch-Godfrey Lagrange multiplier tests for 12 lags ( $\chi^2=6.68$ ) indicate that there is no serial correlation in residuals. Engle's ARCH test indicates that there is no autoregressive conditional heteroscedasticity ( $\chi^2=0.4$ ). Residuals are not only random, but they also are normally distributed, as indicated by the low Jarque-Bera statistic ( $\chi^2=4.48$ ).

These tests are based on the final equation estimated (the longest sample). In order to test the forecasting power of the model, the equation is first estimated using data from May 1978 to July 2001, and the real consumption expenditure is extrapolated for August 2001. The equation is then estimated using data from May 1978 to August 2001, and the real consumption expenditure is extrapolated for September 2001. The process has been continued up to the latest data point available (November 2002). This is as close as one can get to the test of the, one-period ahead, ex-ante forecasting power of the model. There is a close relationship between actual and extrapolated real consumption expenditures (Table A1). Correlation between the actual and extrapolated values exceeds 0.9 (Figure A1). One-period ahead forecast errors are well below one percent, with the exception of April 2002. Mean absolute percent error (MAPE) is 0.41.

Twenty-six indicators are used to calculate principal components to be used in the prediction of monthly index of industrial production. These indicators are: new orders (%chg) , housing starts (%chg), real value of construction put in place (%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), unemployment rate (chg), federal funds rate (chg), prime rate (chg), 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), non-agricultural employment (%chg), manufacturing & trade sales (%chg).

The final equation estimated using 349 observations (November 1973 – November 2002) includes ten principal components, which account for over 90% of the variation in twenty-six monthly indicators, the composite index of the Institute for Supply Management (ISM), and autoregressive processes of residuals. The determination coefficient ( $R^2$ ) for the equation is 0.69, 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 (Equation A2). Residuals are normally distributed, with no serial correlation. One-period ahead forecast errors are well below one percent, with the exception of July 2002. Mean absolute percent error (MAPE) is 0.42.

Twenty-six 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), real value of construction put in place (%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), corporate bond rate (chg), 3-month treasury bill rate (chg), 1-year bond yield (chg), 10-year bond yield (chg), 20-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 357 observations (March 1973 – November 2002) includes seven principal components, which account for over 55% of the variation in twenty-six monthly indicators, the employment index of the Institute for Supply Management (ISM), and autoregressive and moving average processes of residuals (Equation A3). The determination coefficient ( $R^2$ ) for the equation is 0.64, 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, but Jarque-Bera test indicates that they are not normally distributed, and Engle's test indicates that there is autoregressive-conditional heteroscedasticity. One-period ahead forecast errors are quite low. Mean absolute percent error (MAPE) is 0.075. This error corresponds to an employment of 100 thousand.

Thirty indicators are used to calculate principal components to be used in the prediction of monthly average of the stock market index (the S & P Index). These indicators are: new orders (%chg), unfilled orders (%chg), housing starts (%chg), real value of construction put in place (%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), export/import ratio (chg), real money supply (%chg), real consumer credit (%chg), inventory/sales ratio (chg), ratio of budget revenues to budget expenditures (chg), unemployment rate (chg), federal funds rate (chg), prime rate (chg), corporate bond rate (chg), 3-month treasury bill rate (chg), 1-year bond yield (chg), 10-year bond yield (chg), 20-year bond yield (chg), mortgage rate (chg), real personal income (%chg), index of industrial production (%chg), non-agricultural employment (%chg), manufacturing & trade sales (%chg), expected inflation (%chg) (measured as the difference between the yields of indexed and non-indexed treasury notes).

The final equation estimated using 65 observations (July 1997 – November 2002) includes seven principal components, which account for over 50% of the variation in thirty monthly indicators, the UBS Index of Investor Optimism, and autoregressive and moving average processes of residuals (Equation A4). The determination coefficient ( $R^2$ ) for the equation is 0.77, and all parameters associated with principal components and the Index are significant at the one percent level, with the exception of P10 which is significant only at the 13 percent level. Residuals are normally distributed, but there is serial correlation according to the LM statistic. One-period ahead forecast errors are below five percent, with two exceptions: September 2001 (15.89%), and January 2002 (8.73%). Mean absolute percent error (MAPE) is 4.1.

#### ***IV. Conclusion***

Many indicators are helpful in improving statistical performance for forecasting and policy analysis. We do believe, however, 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, methodology is used as a short-cut and quick method to a full scale structural econometric model.

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, 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 judgements 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.

## Appendix

Equation A1.

$$\text{DLOG}(\text{CONSUMPTION}) * 100 = 0.255 + 0.136 I_2 - 0.062 I_3 + 0.029 I_4 + 0.060 I_6$$

(26.06) (15.10) (-5.71) (2.12) (2.98)

$$+ 0.038 I_8 - 0.067 I_9 + 0.087 I_{12} + 0.238 I_{13} + 0.062 I_{14} + 0.148 I_{15} - 0.088 I_{17}$$

(2.34) (-3.64) (4.54) (9.52) (3.25) (5.10) (-3.14)

$$+ 0.094 I_{18} - 0.134 I_{19} + 0.00631 D(\text{MICHIGAN}) + 0.00473 D(\text{MICHIGAN}(-1))$$

(2.91) (-3.95) (1.89) (1.89)

$$+ 0.00315 D(\text{MICHIGAN}(-2)) + 0.00158 D(\text{MICHIGAN}(-3)) - 0.437 \text{MA}(1)$$

(1.89) (1.89) (-7.72)

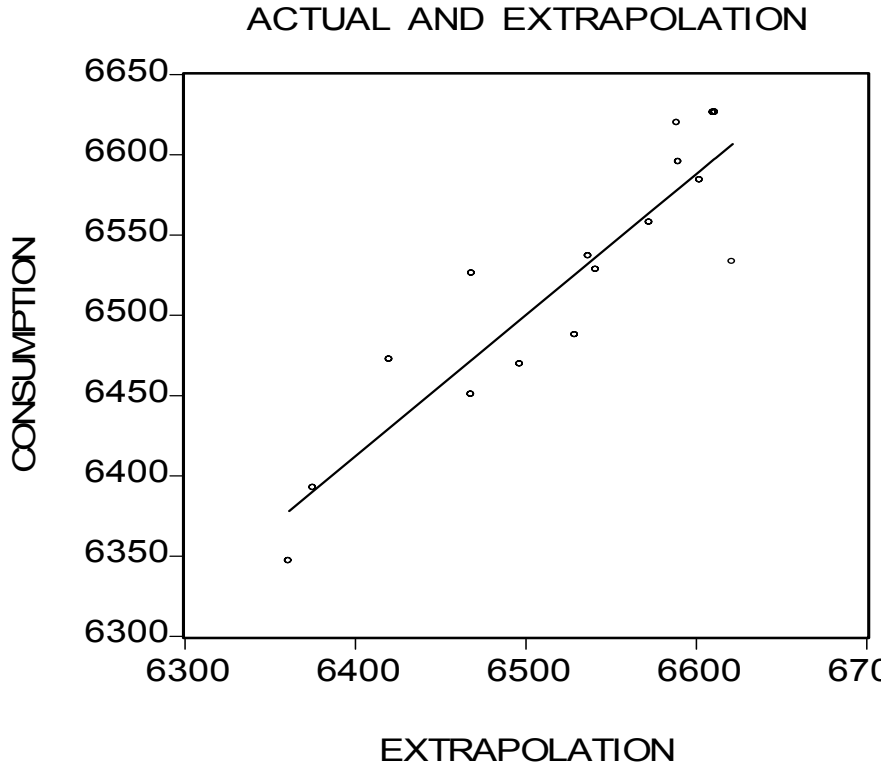
$R^2=0.709$ ,  $\text{SEE}=0.303$ ,  $F=45.22$ ,  $D.W.=1.973$ ,  $\text{Jarque-Bera}=4.48$ ,  $\text{Jyung-Box}$   
 $Q(2)=0.05$ ,  $Q(12)=6.04$ ,  $\text{Breusch-Godfrey LM}(2)=1.51$ ,  $\text{LM}(12)=6.68$ ,  
 $\text{ARCH}(1)=0.40$ ,  $n=295$  (May 1978-November 2002)

Notes:  $I_2, I_3, \dots, I_{19}$  - Selected principal components,  $\text{MA}(1)$ - moving average error term

Table A1. One-period Ahead Extrapolation

Obs	Extrapolation	Consumption	%error	Extrapolation (%chg)	Consumption (%chg)
2001:08	6375.6	6392.3	-0.26		
2001:09	6361.1	6346.9	0.22	-0.49	-0.71
2001:10	6420.3	6472.3	-0.80	1.16	1.98
2001:11	6468.2	6450.3	0.28	-0.06	-0.34
2001:12	6496.9	6469.3	0.43	0.72	0.29
2002:01	6529.3	6487.4	0.64	0.93	0.28
2002:02	6468.6	6526.0	-0.88	-0.29	0.59
2002:03	6541.4	6528.1	0.20	0.24	0.03
2002:04	6621.2	6533.2	1.35	1.43	0.08
2002:05	6537.1	6536.6	0.01	0.06	0.05
2002:06	6572.8	6557.5	0.23	0.55	0.32
2002:07	6589.1	6619.7	-0.46	0.48	0.95
2002:08	6610.3	6625.9	-0.24	-0.14	0.09
2002:09	6602.3	6584.0	0.28	-0.36	-0.63
2002:10	6589.9	6595.3	-0.08	0.09	0.17
2002:11	6611.5	6626.1	-0.22	0.25	0.47

Figure A1. Real Personal Consumption Expenditures – Actual and Extrapolation



Equation A2.

$$\text{DLOG(INDPRODUCTION)} * 100 = 0.20 + 0.129A1 + 0.145A2 - 0.111A3 - 0.128A4$$

(3.74) (14.91) (9.84) (-5.78) (-7.98)

$$-0.134A5 + 0.049A6 - 0.072A7 + 0.069A9 + 0.118A15 - 0.101A18 + 0.0336D(\text{ISM})$$

(-6.82) (3.13) (-2.72) (2.54) (3.31) (-2.51) (4.72)

$$+0.0252 D(\text{ISM}(-1)) + 0.0168 D(\text{ISM}(-2)) + 0.0084 D(\text{ISM}(-3)) - 0.181 \text{AR}(1)$$

(4.72) (4.72) (4.72) (-3.34)

$$+0.162 \text{AR}(3) + 0.181 \text{AR}(4) + 0.142 \text{AR}(5) + 0.168 \text{AR}(6) + 0.115 \text{AR}(9)$$

(2.95) (3.02) (2.56) (3.47) (2.26)

$R^2=0.691$ ,  $\text{SEE}=0.407$ ,  $F=43.48$ ,  $D.W.=1.987$ ,  $\text{Jarque-Bera}=2.97$ ,  $\text{Jyung-Box}$   
 $Q(2)=1.83$ ,  $Q(12)=5.85$ ,  $\text{Breusch-Godfrey LM}(2)=4.34$ ,  $\text{LM}(12)=16.82$ ,  
 $\text{ARCH}(1)=1.55$ ,  $n=349$  (November 1973-November 2002)

Notes: A1, .. A18-principal components, AR(1)..AR(9) autoregressive errors

Equation A3.

$$D(\text{EMPLOYMENT}) = -641.3 + 30.015 Z2 + 11.892 Z5 - 19.754 Z6 + 14.218 Z11$$

(-6.96) (8.27) (2.08) (-3.66) (2.00)

$$-20.512 Z13 - 31.66 Z14 + 22.737 Z19 + 6.752 \text{ISM\_EMP} + 5.064 \text{ISM\_EMP}(-1)$$

(-2.04) (-3.17) (1.89) (9.13) (9.13)

$$+ 3.3763 \text{ISM\_EMP}(-2) + 1.6881 \text{ISM\_EMP}(-3) + 0.945 \text{AR}(1) - 0.843 \text{MA}(1)$$

(1.89) (1.89) (30.67) (-12.52)

$R^2=0.643$ ,  $\text{SEE}=123.12$ ,  $F=62.40$ ,  $D.W.=2.14$ ,  $\text{Jarque-Bera}=444.4$ ,  $\text{Jyung-Box } Q(2)=4.84$ ,  $Q(12)=7.80$ ,  $\text{Breusch-Godfrey LM}(2)=4.53$ ,  $\text{LM}(12)=7.79$ ,  $\text{ARCH}(1)=59.0$ ,  $n=357$  (March 1973-November 2002).

Notes: Z2, Z5, .. Z19-principal components, AR(1).. MA(1)- autoregressive-moving average error terms

Equation A4.

$$D\text{LOG}(\text{SANDP500}) * 100 = 0.716 + 0.141 P1 + 0.496 P5 - 0.983 P8 + 0.371 P10$$

(21.39) (3.86) (6.00) (-4.16) (1.54)

$$+ 1.852 P17 + 2.647 P18 + 3.103 P21$$

(3.36) (9.38) (6.82)

$$+ 0.157 D(\text{UBS}) + 0.118 D(\text{UBS}(-1)) + 0.078 D(\text{UBS}(-2)) + 0.039 D(\text{UBS}(-3))$$

(18.44) (18.44) (18.44) (18.44)

$$- 0.84 \text{AR}(2) - 0.54 \text{AR}(4) - 0.71 \text{MA}(1) - 0.272 \text{MA}(3) - 0.518 \text{MA}(5) + 0.516 \text{MA}(8)$$

(-7.75) (-4.30) (-4.81) (-2.85) (-9.76) (3.46)

$R^2=0.774$ ,  $\text{SEE}=2.233$ ,  $F=12.25$ ,  $D.W.=2.346$ ,  $\text{Jarque-Bera}=0.67$ ,  $\text{Jyung-Box } Q(2)=2.79$ ,  $Q(12)=10.92$ ,  $\text{Breusch-Godfrey LM}(2)=7.26$ ,  $\text{LM}(12)=22.41$ ,  $\text{ARCH}(1)=0.87$ ,  $n=65$  (July 1997-November 2002)

Notes: P1, P5, .. P21 - principal components, AR(2).. MA(3)- autoregressive-moving average error terms