A HIGH-FREQUENCY FORECASTING MODEL FOR THE MEXICAN ECONOMY

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Alfredo Coutiño has prepared a dissertation entitled

A High-Frequency Forecasting Model for the Mexican Economy

I regard this research effort to be significant because it shows how a developing country can maintain large-scale data files that enable it to track the performance of the economy frequently and regularly by producing projections that follow dynamic movements of the country. In this case, the Mexican economy can be followed, in a quantitative sense, every week and possibly more often if the need arises. That is why it is called a "High-Frequency Forecasting Model".

It is unusual for a developing country to have such a detailed and frequent statistical assessment. Although Mexico is a member of OECD, it is, in fact, a developing country, with some aspects of advanced industrialization.

Sr. Coutiño has applied advanced statistical methods for econometric analysis and has used very modern computing facilities to be able to maintain the model of the economic system on a regularly up-dated basis. In the course of his research effort he has gradually found new source material and new methods of analysis to improve his system. He has built upon earlier versions and can be expected to continue to do so in the future.

He shows great skill in using modern computer and statistical analysis, in addition to building an extremely valuable primary data file. I have followed his work carefully for more than two years, and find that his work is careful, rigorous, insightful, and thoroughly modern. It serves as an excellent example of the way to bring modern technical advances to the analysis of an expanding economy in the midst of <u>development</u>.

The exposition is clearly presented; the readings that are cited show familiarity with the field being investigated, and overall it satisfies the criterion that is used at the University of Pennsylvania – "Does the dissertation make an original contribution to knowledge?" I definitely believe that it does.

Sincerely,

Lawrence R. Klein

UNIVERSIDAD AUTONOMA DE MADRID

CERTIFICACIÓN ACADÉMICA PERSONAL

D. **FÉLIX MARINAS JIMENO**, Administrador Gerente de la Facultad de **CIENCIAS ECONÓMICAS Y EMPRESARIALES** de esta Universidad Autónoma,

CERTIFICA que D. ALFREDO COUTIÑO ZAVALA, nacido en CHIAPAS (MEXICO), , ha efectuado la **lectura de la tesis con título "UN MODELO DE PRONÓSTICOS DE ALTA FRECUENCIA PARA LA ECONOMÍA MEXICANA", con fecha 25 de noviembre de 2004, obteniendo una calificación de SOBRESALIENTE**, siendo el director de la misma D. LAWRENCE R. KLEIN.

Y para que conste a los efectos oportunos, y a petición de la persona interesada, firmo esta certificación, en Madrid a 14 de junio de 2006.

El Administrador Gerente,

P.O.

UNIVERSIDAD AUTONOMA DE MADRID
Facultad de Económicas y Empresariales
SECRETARIA

Viceadministrador

FÉLIX MARINAS JIMENO

To my parents,
brothers and sister,
with admiration and respect

ACKNOWLEDGMENTS

I present this study as the result of two and a half years of intense research work on one of the latest developments in applied econometrics. This development is starting to be expanded to some countries as one powerful instrument to monitor the short-term behavior of the economy. The methodology is called High-Frequency Forecasting Model (Current Quarter Model), and has been originally developed at the University of Pennsylvania by Dr. Lawrence R. Klein.

In applying this methodology to the Mexican case, I have had the enormous privilege of being advised by its own creator: Dr. Klein. As a Mexican student abroad, I have been rewarded with the high honor of having the direct supervision of the "Master of Masters" in econometrics as well as the particular guidance of a Nobel Prize Laureate in Economics. Thanks to him, I have been able to finish this dissertation work. His teaching, advises and patience have strongly influenced my career as an economist. To him, with my deepest gratitude, I want to dedicate this work.

I also want to dedicate this study to who have made possible my existence: my parents. For their unconditional support through my life, for their love and trust, for their decision to bring me to life, for all what they mean to me, I proudly dedicate this effort to them. And of course, to my brothers and sister for their moral support, for believing in me, and for being an example and stimulus to me. To Caroline, for her extraordinary company, comprehension and patience, for all her love.

Finally, I want to thank Dr. Abel Beltrán del Río for his help during my doctoral studies and my years as an economist at Ciemex-Wefa.

To all of them this study is dedicated.

" Economists are not musicians
to tune up econometric models
as if they were musical instruments "

- Lawrence R. Klein
Nobel Prize in Economics 1980

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CHAPTER I

INTRODUCTION

A method for anticipating quarterly estimates of Gross Domestic Product (GDP) and its main components in advance of the official publication is presented in this study, using high-frequency information, time series equations and regression analysis. This methodology is based on the technique of the Current Quarter Model for the U.S. economy, developed by Dr. Lawrence R. Klein at the University of Pennsylvania in 1990, and expanded to a few other countries, including Mexico. Dr. Klein has named this new development as "a purely econometric system with no personal data adjustment".

From the basic macroeconomic point of view, the measure of an economy's performance in producing goods and services is given by the calculation of GDP, using the National Accounting Framework. The National Accounting methodology provides the conceptual framework for computing the economy's total output by at least three different ways from different sources of statistics: Production, Income and Expenditure. On the Production side, the total GDP is defined as the value added or the value of final goods and services produced, and is obtained as the difference between the value of gross production and intermediate inputs. Regarding the Income side, the GDP is computed as the payments to the production factors involved (labor, capital, land) or the income that the owners of the production factors receive. In the case of the Expenditure side, the GDP represents the economy's total absorption or the purchases by domestic and foreign residents of the total output produced. Each of these three methods uses some independent sources of information for computing the total GDP. Consequently, statistical discrepancies arise if each method is separately used.

The National Accounting framework for Mexico estimates the quarterly GDP by two sides: Production and Expenditure (there are no estimates for the quarterly GDP by the Income side). On the Production side, the computation is made by collecting information on the output produced by each sector in the economy. In the case of the Expenditure side, the GDP is computed by the aggregate demand components. For most of the Production and Demand components there exist monthly series closely related to each of them, which allow us to track the very short-term behavior of the whole economy.

The availability of high-periodicity information on economic activity and financial markets, on a daily, weekly or monthly basis, permits one to monitor the economy more frequently, and in ever-increasing detail. This continuous flow of high-frequency economic indicators has dramatically increased in the last decade, thanks to the development of information systems and telecommunications.

The use of high-frequency economic information is essential not only for very short-term forecasting purposes but also for improving the general predictive accuracy of structural econometric models. This is done through the joint use of a high-frequency forecasting model, together with a system of econometric relationships among economic and financial indicators. This latter model is specified to forecast the quarterly GDP and its main components beyond the immediate short run and for simulation analysis. High-frequency indicators can be used to establish initial conditions for the structural model without any subjective personal judgement.

Using monthly economic indicators, the High-Frequency Forecasting Model aims to predict the quarterly GDP from three different approaches: the Production side, the Expenditure side, and from Principal Components of major economic indicators.

The first two approaches follow National Accounting methodology, and are based on monthly indicators that are similar to those the statisticians in charge of the National Accounts use to estimate the observed components of GDP. Thus, with these major monthly indicators we can establish the corresponding entries in the NIPA (National Income and Product Accounts). Future values of monthly indicators for forecasting purposes are estimated from ARIMA (time-series) equations.

The Production side model uses monthly information on the different productive sectors of the economy, which is averaged in a General Economic Index (GEI). The monthly GEI covers 85% of the performance of the economy-wide production activity. This model estimates the quarterly GDP using the general index of economic activity as the explanatory variable. The model also provides estimates for the three main production sectors: Primary, Secondary and Tertiary.

The Expenditure side model estimates the GDP by summing the aggregate demand components (private consumption, government consumption, fixed investment, and net exports). We use monthly indicators that are similar to those the statisticians use to compute each of the demand aggregates. We establish the correlation between the 3-month average of each monthly indicator and its corresponding demand component in the NIPA. The summation of all of the demand components will give us an estimate of the total GDP.

The third approach is based on the statistical methodology of the Principal Components, and uses a set of strategic monthly indicators, which are closely related to real GDP. The Principal Components are estimates of the main independent sources of variation of the set of monthly indicators, transformed into mutually uncorrelated variables that explain all or most of the variation of the monthly variables. Once we have extracted the principal components, we regress the quarterly GDP on its associated quarterly principal components. In the end, we estimate the GDP as a function of the main sources of variation based on the original set of variables. Future values for the monthly indicators are obtained from ARIMA equations.

We thus have three different estimates of the quarterly GDP obtained by the three different approaches (Production, Expenditure and Principal Components). The final result for the quarterly GDP is obtained as the simple average of the three estimates, which are computed independently of each other. Given that each of the estimation methods uses different sources of information, each one generates independent errors. This procedure permits us to reduce error variances in forecasting the real GDP, as the average of the three independent approaches.

Finally, we can also try to anticipate the short-term movements of the GDP Price Deflator, using the flow of high-frequency information through the application of the Principal Components methodology. The Principal Components model for the GDP Price Deflator uses a set of strategic monthly prices and also incorporates futures prices, forward rates and market expectations. We extract the principal components from this set of strategic variables, and regress the GDP Price Deflator on a linear function of the main sources of price variation (principal components). The relevance of including futures, forwards and expectations derives from the fact that changes in News, Rumors, and Political and Social events, immediately affect the expected values of key prices, and this, in turn, is transmitted to leading economic variables. This is particularly important for a developing country in which agent and market expectations are more sensitive, given the memory of dramatic crisis episodes in the past. The inclusion of futures, forwards and expectations in our model certainly improves the quality of the estimates. But it also allows us to use the model as a simulation tool of the future impact of recent developments in the economy. The change in market expectations as a result of present shocks allows us to perform simulations without subjective assumptions about future values of relevant variables.

At the very end, this methodology will allow us to provide an anticipation of the quarterly real GDP, its price deflator, and the nominal GDP, prior to the government data release.

CHAPTER II

METHODOLOGICAL APPROACH

II.1.- INTRODUCTION

This chapter focuses on the description and development of the methodology to construct a High-Frequency Forecasting Model. We explain the methodological approach used by the econometric technique of the high-periodicity models, also called "current quarter models".

The extensive use and development of the econometric technique for high-frequency models began at the end of the 80's and beginning of the 90's at the University of Pennsylvania, and under the leadership of Lawrence R. Klein, Nobel Laureate in Economics 1980. This methodology appeared as a technical advance in the field of applied econometrics, and as a response to the market demand for very short-term econometric tools.

A high-frequency forecasting model is defined as a purely econometric system with no subjective intervention of the economist in the determination of arbitrary assumptions or initial conditions. The methodology combines high-frequency information, times series equations, and regression analysis. The model was originally designed to anticipate the quarterly GDP for the U.S. economy, in advance of the official release date.

The methodology estimates the GDP by three independent approaches: production, expenditure, and by principal components. It is based on the same approach used in the preparation of the National Accounts, to estimate the final production of goods and services in an open economy.

In order to explain the high-frequency methodology to construct the model for the current quarter GDP, this chapter presents a brief review of Lawrence Klein's pioneer works on this topic, and some other related studies. Furthermore, we explain the general methodology and our proposal for the specific case of the Mexican economy. At the end, we present some concluding remarks.

II.2.- BIBLIOGRAPHIC REVIEW

Until the end of the 50's, the information for national and social accounts was available only on an annual frequency in all the countries. This database, in turn, determined the annual periodicity of the econometric models. It was not until the beginning of the 60's when a few industrialized countries began to generate quarterly databases, which would enable econometricians to construct higher-periodicity models, in this case quarterly models.

Nowadays, the flow of economic and financial information is basically continuous or in real time, allowing the construction of models with higher periodicity. In this regard, we can classify the annual econometric models as "low-frequency models", and those of higher periodicity as "high-frequency models".

One of the pioneer works in the field of construction of higher periodicity models was the quarterly model of Wharton Econometrics, headed by Lawrence Klein and constructed at the beginning of the 70's. At that time, the quarterly model was used to generate the initial conditions for the annual model. In other words, the quarterly model generated forecasts for the first two years, and the annual model was given to take those estimates for the short run, and from there the annual model generated its own forecasts for the medium term.

A different approach was presented by Liu and Hwa in 1974[1/]. They used monthly series to interpolate quarterly data from national accounts; and then, they elaborated a system of monthly accounts. Based on this monthly system, they constructed a monthly macro model for the U.S. economy.

Further developments continued by the end of the 70's and into the 80's on the use of high-frequency information for forecasting purposes. Among these studies we can find the following: a).- the monthly econometric model of the Federal Reserve, used to estimate and to forecast the monthly national product; b).- the development of the VAR and VARMA models, which gives origin to the high-frequency model of the University of Michigan; c).- of course, the model of the University of Pennsylvania, which combines time series equations with regression analysis, and began to work at higher frequency by the end of the 80's.

A more recent procedure was used by Payne[2/] from the U.S. Department of Commerce. Payne's model tries to predict the GDP growth in anticipation of the official release from the Bureau of Economic Analysis. This study is also based on the use of high-periodicity information linked to the quarterly aggregate demand components. This model estimates GDP from the demand side only, although similar procedures could be developed for the income or production sides.

[1/] Liu and Hwa (1974), also mentioned in Klein and Park (1993).
[2/] Payne (2000).

The original idea of the model of the University of Pennsylvania[3/] referred to the combination of high and low frequency information in macroeconometric models. This approach was based on the use of monthly information to estimate quarterly components of the national accounts. In other words, it tried to establish links between short and long-term models. The methodology included two types of variables that were used in two types of equations. The two variables were: monthly indicators and quarterly components from the national accounts. The equations were: ARIMA's associated with the extrapolation of the monthly indicators, and "bridge equations" to link monthly indicators with quarterly components. In this way, this methodology could be used to estimate GDP from both, expenditure and income side, as in the national accounts approach.

This original idea developed by L. Klein at the end of the 80's, constitutes an essential part of the high-frequency forecasting model for the U.S. economy, also known as "current quarter model" from the University of Pennsylvania. This model has been working since the beginning of the 90's and generates weekly updates for the current quarter GDP estimates of the U.S. economy.

Klein's model at present, Current Quarter Model (CQM)[4/], estimates the quarterly GDP through three different approaches: incomes, expenditures, and principal components of monthly indicators. The first two approaches follow the national accounts methodology, using monthly indicators to estimate the quarterly sub aggregates of GDP. The third approach is based on the statistical technique of the principal components extracted from a set of monthly variables highly correlated with GDP. The model combines high-frequency information, time series equations and regression analysis. These three approaches generate three different estimates for the quarterly GDP, which are averaged to obtain a final estimate.

The details of each approach are explained in the following methodological section. Although for the case of Mexico we will use the production approach (value added) instead of the income side (due to the absence of information for quarterly income components), the general methodology remains the same.

II.3.- METHODOLOGICAL APPROACH

A.- The Macroeconomic Frame

The total production of final goods and services in an economy is called Gross Domestic Product (GDP). This measurement of total production is expressed by the fundamental macroeconomic identity[5/] :

[3/] Klein and Sojo (1989).

[4/] Klein and Park (1993), Klein and Park (1995).

[5/] Dornbusch and Fisher (1990), Rivera-Batiz (1994), Krugman and Obstfeld (1994).

$$GDP = Cp + Cg + I + \Delta S + X - M$$

where Cp stands for private consumption, Cg represents government consumption, I stands for gross fixed investment, ΔS is the change in inventory, and $X - M$ represents net exports.

The macroeconomic identity indicates that the total production in the economy is equal to the total absorption. But also, the identity can be expressed in terms of the payments received by production factors. In other words, the total production in an economy is exhausted by the payments to production factors, the latter constituting the income side.

In macroeconomic terms, we can say that the fundamental identity gives origin to three different approaches to compute the total production of the economy: production or value added, income, and expenditure. This macroeconomic methodology generates the National Income and Product Accounts (NIPA).

a).- Production or Value Added approach

This methodology computes the GDP through the value added in each productive sector or in each production process. It says, the supply of sectoral production of final goods and services.

In computing the value added, the national accounts use the value of gross production and subtract intermediate inputs, in order to avoid double counting in the final product.

$$\underset{\text{(Value Added)}}{\text{GDP}} = \underset{\text{Production}}{\text{Gross}} - \underset{\text{Inputs}}{\text{Intermediate}}$$

b).- Income approach

This method estimates the value of the total production of goods and services as the sum of all payments to production factors. It says, the value of total production is distributed as the income paid to all the factors that intervene in the production process.

Roughly speaking, we can say that the original factors intervening in the production process are: labor, capital, and land. In this way, the national accounts compute the GDP through the payment to workers (W), income paid to capital owners (P), rent paid to landowners (R), and interest payments (In), plus indirect taxes net of subsidies (Tx).

$$GDP = W + P + R + In + Tx$$

c).- Expenditure approach

This approach estimates the total output through the sum of all final expenses in the economy. In other words, it is equal to the sum of all the purchases of the national production by national residents and foreigners. The sum of all these expenses is also known as the total absorption of the economy.

The economy's total expenditure or absorption is equal to the sum of the private expenses of final goods and services (Cp), the expenses of the public sector (Cg), the gross investment of government and private sector (I), the change in inventory (ΔS), the value of exports of goods and services (X), less the value of imports of goods and services (M).

$$GDP = Cp + Cg + I + \Delta S + X - M$$

B.- The Model's Frame

The methodology used by the high-frequency forecasting model, to estimate the quarterly GDP, is based on three different approaches as well. The first two approaches come from the national accounts frame: production and expenditure side[6/]. The third approach comes from the statistical method of the principal components. With these three approaches, we obtain three different estimates of GDP, which are averaged to get the final estimate.

Both approaches, production and expenditure, follow the same methodology of the national accounts to compute the GDP. We do try to use the same monthly indicators that the statisticians of the national accounts use to estimate each component of the quarterly GDP. In this way, the high-frequency forecasting model tries to replicate the national accounts methodology (in two of its three approaches), to anticipate the quarterly GDP using high-periodicity information (monthly indicators).

The production and expenditure methods use two sets of variables that are used in two different types of equations. The first set of variables is the monthly indicators (I_{it}), which are the same or similar indicators to the ones used by the national accounts to estimate the quarterly components of GDP. The second set of variables is the quarterly components of GDP (N_{it}).

The monthly indicators I_{it}, give rise to the first set of equations, the ARIMA's that are used to obtain the future values of those monthly variables.

[6/] Because of the absence of quarterly information for the Income side of GDP, in the case of Mexico we use the production side instead of the income approach, which is a difference with the U.S. model.

$$I_{i,t} = \alpha_{i1}\ I_{i,t-1} + \alpha_{i2}\ I_{i,t-2} + \ldots + \alpha_{ik}\ I_{i,t-k} + \beta_{i1}\ e_{i,t-1} + \ldots + \beta_{ik}\ e_{i,t-k}$$

In order to link the monthly estimates to the quarterly components of GDP, we form the 3-month average of the monthly indicators.

The second set of variables, which are the quarterly components, generates the second type of equations: "bridge equations". The bridge equations are used to establish the links between the monthly indicators and the corresponding quarterly aggregates of the national accounts.

$$N_{i,T} = \alpha_i + \beta_i\ I_{i,T} + \varepsilon_{i,T}$$

where I_{iT} represents the 3-month average of the monthly indicator, which is used in the equation of the quarterly component of GDP ($N_{i,T}$).

In this way, we establish the corresponding links between the monthly indicators and the quarterly aggregates of GDP, as the statisticians of the national accounts do.

If we use the bridge equation in percentage change, and if the monthly indicator is exactly the same as the one used by the statisticians of the national accounts, then we can expect that $\alpha_i = 0$ and $\beta_i = 1$. It says, the percentage change in I_{iT} should explain the percentage change in $N_{i,T}$.

Certainly, in the application of these two macroeconomic approaches (production and expenditure), we need to choose the same indicators used by the national accounts, or similar indicators at least. From here, we obtain two different estimates of GDP given by these two methods.

The third approach uses the statistical method of the principal components. This method is based on the idea of having a set of strategic variables, highly correlated with GDP, we can extract the main independent sources of variation, which are called the principal components. In other words, given a set of original indicators, we can construct a set of mutually non-correlated linear combination of variables that explains the total variation of the original set. We then use this set of principal components as the explanatory variables in the regression of GDP.

Now, in the application of the principal components method, we use two types of equations. The first is a set of equations given by the vector of principal components extracted from the original set of strategic indicators. The second is the regression of GDP as a function of the principal components.

Regarding the first set of equations, the principal components, suppose that we have an original set of explanatory variables (X_1, X_2, …., X_k) highly correlated with GDP, and from which we want to find its main independent sources of variation or principal components. The methodology of the principal components defines a vector of linear functions (Z_i) from the original variables (X_k) that captures the most of its variation[7/].

$$Z_i = a_{i1} X_1 + a_{i2} X_2 + \ldots + a_{ik} X_k$$

Where the a's are chosen such that the variance of the Z's are maximized. Putting it in another way, the principal components method finds the vector of Z's, which are linear combinations, mutually non-correlated or independent, and with the maximum variance. Thus, Z_1 is the first principal component with the highest variance, Z_2 is the second principal component with the second highest variance (but not correlated with Z_1), and so on.

The second type of equation in the model of principal components, establishes the relationship between the quarterly GDP and the quarterly principal components extracted from the original variables (PC_i).

$$GDP_t = f(PC_i)$$

It is important to notice that the original set of variables is monthly, which determines that the principal components are also monthly. Therefore, we need to get the 3-month average of the principal components in order to be linked to the quarterly GDP equation.

With this third equation for GDP, we obtain the third quarterly estimate. This new estimate is averaged with the other two estimates, obtained from the production and expenditure side, in order to get the final estimate of the quarterly GDP.

Note that in here we use monthly data, estimate monthly principal components, and average the components, for use in quarterly regression. We could, alternatively, average the indicators into quarterly values and then find the principal components, and from this point proceed as in the other case.

II.4.- GENERAL REMARKS

The methodology of the high-frequency forecasting model allows us to estimate the quarterly GDP through three different approaches: production, expenditure, and principal components. The three different approaches generate three independent estimates, which are averaged to obtain the final estimate of the quarterly GDP.

The high-frequency forecasting technique combines the use of high-periodicity information, time series equations, and regression analysis. This methodology allows us to

[7/] Maddala (1992), Dhrymes (1970), Greene (1997).

anticipate the quarterly GDP in advance of the official release, and with certain degree of accuracy.

Given that the methodology generates a mechanical system of econometric relationships, the high-frequency forecasting model avoids the subjective intervention of the economist in the determination of arbitrary assumptions or initial conditions.

This methodology is based on the macroeconomic frame of the national accounts, which makes it feasible to be adapted to any other country with at least a system of quarterly national accounts and monthly information on economic and financial activity.

Finally, whenever new data become available (every month), the database can be immediately enlarged with all data revisions for prior periods and then generate new projections, with a Current Quarter Model , we can inch-along quarter-by-quarter.

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CHAPTER III

THE PRINCIPAL COMPONENTS MODEL FOR REAL GDP

III.1.- INTRODUCTION

During the last decade the development of information systems and telecommunications has made possible the immediate availability of economic information. This flow of economic indicators, on a daily, weekly or monthly basis, permits one to monitor the economy more frequently, and in ever-increasing detail.

The Principal Components Model constitutes one of the three approaches of our High-Frequency Forecasting Model to estimate the quarterly real GDP. This model uses a set of strategic monthly economic and financial indicators closely related to real GDP.

The general idea of the principal components approach refers to the fact that, having a set of major important indicators, we can extract the main independent sources of variation from this set of variables. In other words, the principal components are the variables that explain all or most of the variation of the total set of main indicators selected. Statistically, the principal components theory deals with the problem of defining a number of mutually uncorrelated (independent) variables exhibiting maximal variance[8/]. Note that all variables are standardized so that there is no choice in the units of measurement.

For the case of the real GDP equation, we have selected a set of monthly indicators from industrial production, expenditure, money stock, interest rates, wages, employment, and trade, which are strategic indicators. In order to eliminate serial correlation, we filter the series by seasonally adjusting and detrending. Then we extract the principal components from this set of variables (can be done automatically by computer software), which represent the variables that practically account for the total variation of the entire set. Having the monthly principal components, we compute their 3-month averages in order to get quarterly series, then we regress the quarterly GDP on its associated quarterly components. This will generate an equation to estimate the quarterly GDP as a function of quarterly indicators.

Given that the principal components represent mutually uncorrelated sources of variation of the major indicators, then the GDP estimate will be an additive function of the variation of all these main economic indicators.

[8/] An early use of principal components in econometrics was done by Stone (1947). He used the NIPA frame to compute principal components from interdependent blocks, but not for forecasting purposes.

III.2.- STRATEGIC INDICATORS FOR PRINCIPAL COMPONENTS

A.- Selecting the Strategic Indicators

The principal components theory is based on the idea of extracting the main independent sources of variation from a set of major indicators. We can use these principal components as independent variables in the regression of a particular dependent variable. For example, in the case of GDP, we can have a set of monthly indicators closely related to the behavior of real GDP, then we can extract the principal components from this set of variables and regress the GDP on them.

Given that the principal components methodology is based on statistical correlations among variables, it could be said that this model is an exercise in "measurement without theory"[9/]. This model, however, is just one part of three different ways to compute the GDP. The remaining two approaches of GDP measurement (Production and Expenditure) will use one branch of economic analysis, namely social accounting.

Based on a purely empirical approach, however, we can say that real GDP is closely correlated with the most important principal components derived from the total set of production indicators. In this way, we can choose a set of variables closely related to GDP from different sectors such as industrial production, employment, wages, sales, money, and trade. These major economic indicators represent the monthly signals that help us to monitor the short-run behavior of GDP.

For the case of the Mexican economy, we selected a preliminary set of fifteen variables as the most representative monthly indicators for computation of the principal components for real GDP. In a sense, each indicator tells a different economic story. They are not entirely different, however, and that is why we compute the uncorrelated principal components.

1) Manufacturing Production Index (IMI)
2) Construction Industry Index (ICI)
3) Industrial Production Index (IPI)
4) Gross Fixed Investment Index (GFII)
5) Real Wholesale Sales Index (WSI)
6) Real Retail Sales Index (RSI)
7) Index of Man-Hours Worked in Manufacturing (HOUR)
8) Index of Real Average Wages in Manufacturing (WAR)
9) Employment Rate (EMR%)
10) Maquiladora Real Exports (MAQR)
11) Volume of Crude Oil Exports (EXOV)
12) Real Money Supply: M1 (MSR)

[9/] Klein (1993)

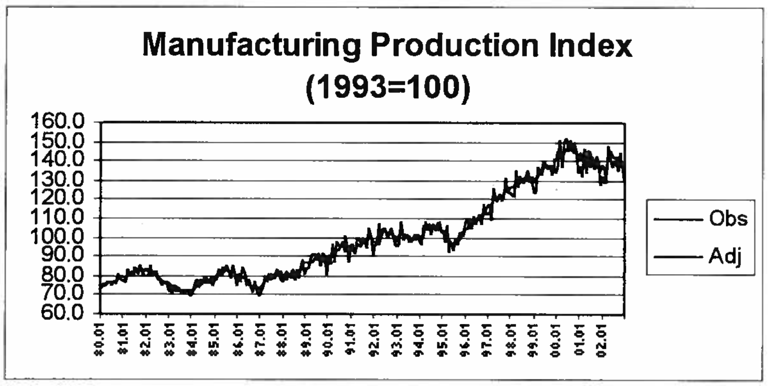
13) Real Interest Rate (IRR)
14) Real Exchange Rate (ERR)
15) Real Tourism Balance (TOUR)

These series are released monthly by the National Institute of Statistics (INEGI) and by the Central Bank of Mexico (BANXICO) in the form of unadjusted data, that is, not seasonally adjusted. A few of them, however, are officially adjusted for seasonal variation.

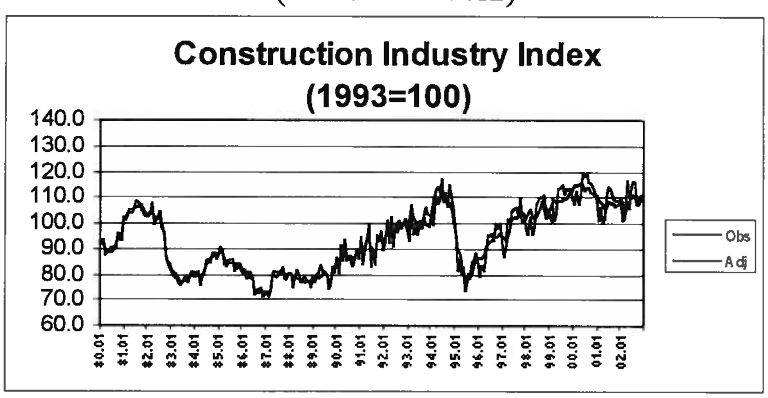
It is helpful to see the graphical behavior of each of these main indicators in order to determine whether there exists a seasonal component or a trend. The graphs show that, in most of the monthly indicators, there exist both components: seasonality and trend, in particular during the last eight years. Given that we are working with highly serially correlated indicators, seasonality could be a problem at the high-frequency level of information. In order to deal with the seasonal problem, we work with adjusted series.

The following graphs show each series against time in both formats, observed data (obs) and seasonally adjusted data (adj).

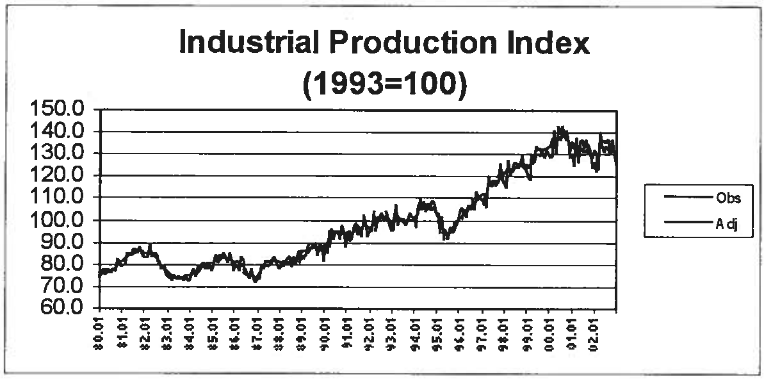
Graph III.1
(1980.01-2002.12)



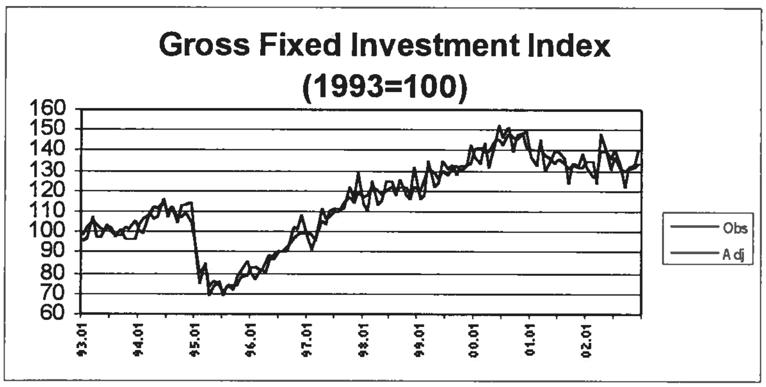
Graph III.2
(1980.01-2002.12)



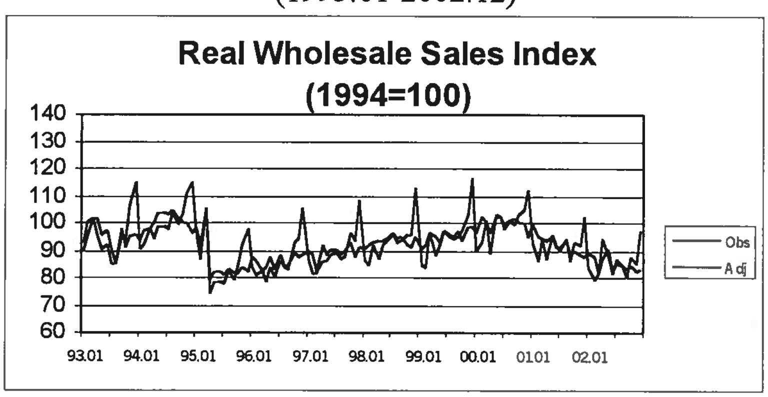
Graph III.3
(1980.01-2002.12)



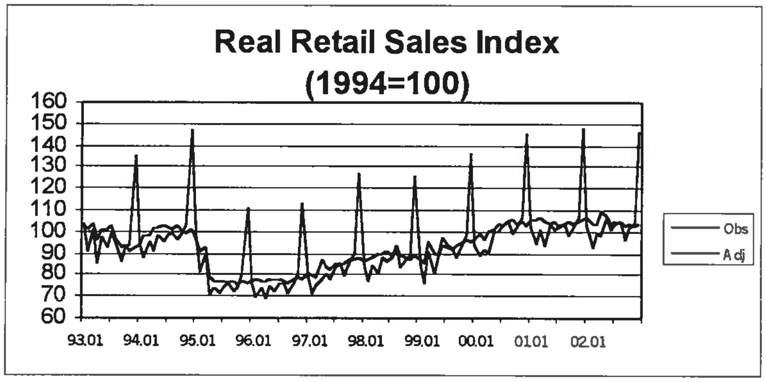
Graph III.4
(1993.01-2002.12)



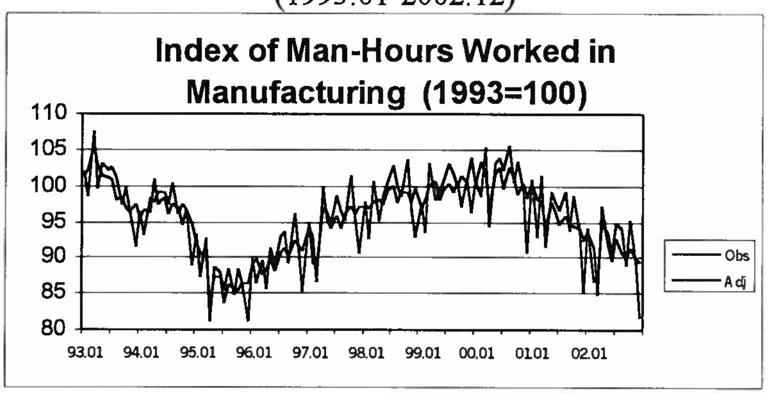
Graph III.5
(1993.01-2002.12)



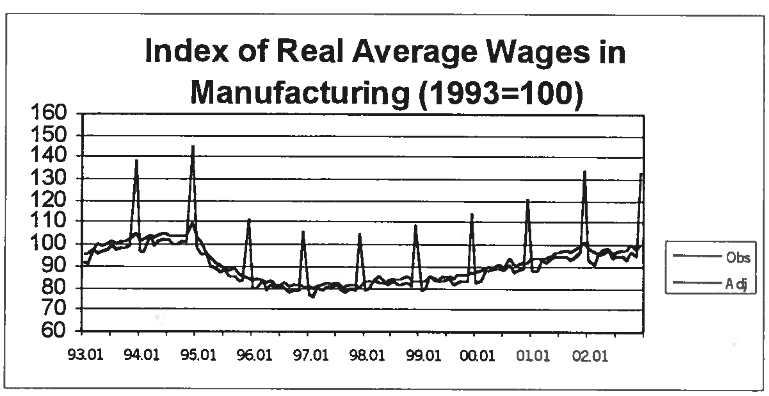
Graph III.6
(1993.01-2002.12)



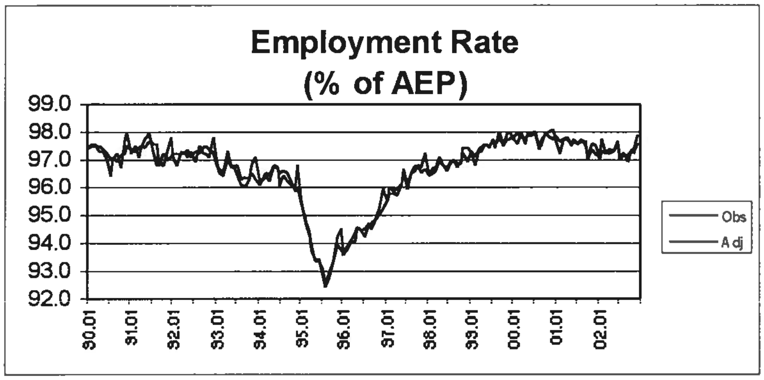
Graph III.7
(1993.01-2002.12)



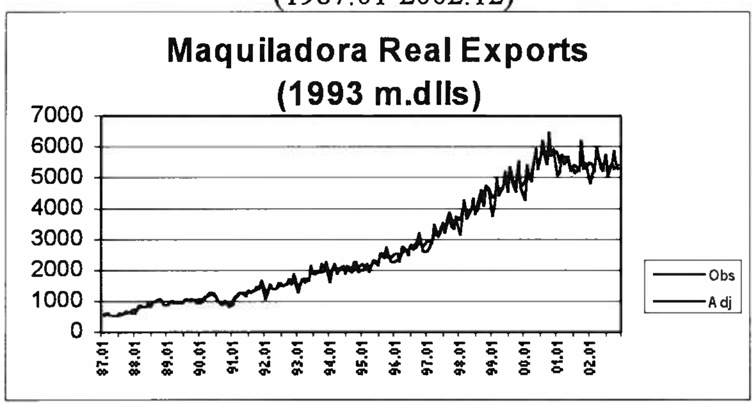
Graph III.8
(1993.01-2002.12)



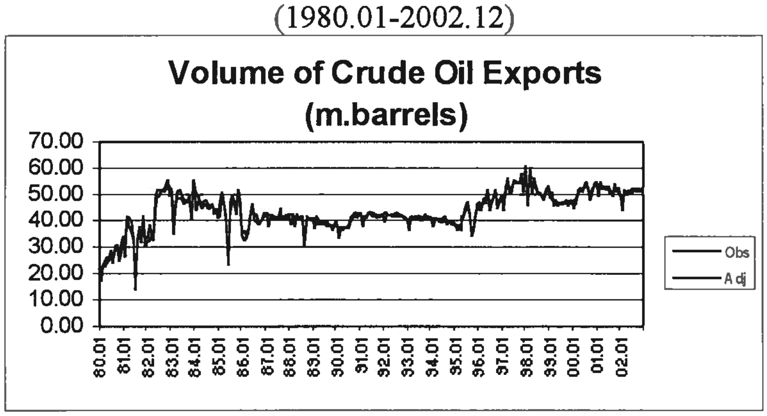
Graph III.9
(1990.01-2002.12)



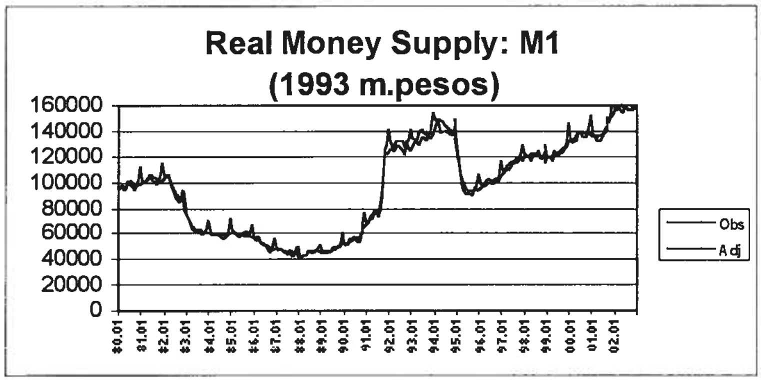
Graph III.10
(1987.01-2002.12)



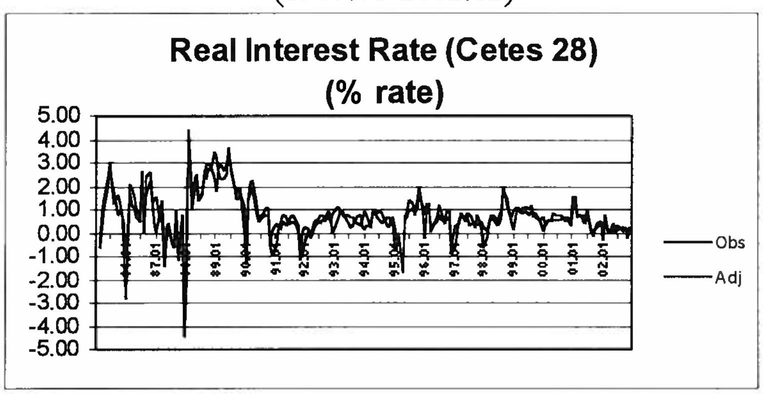
Graph III.11
(1980.01-2002.12)



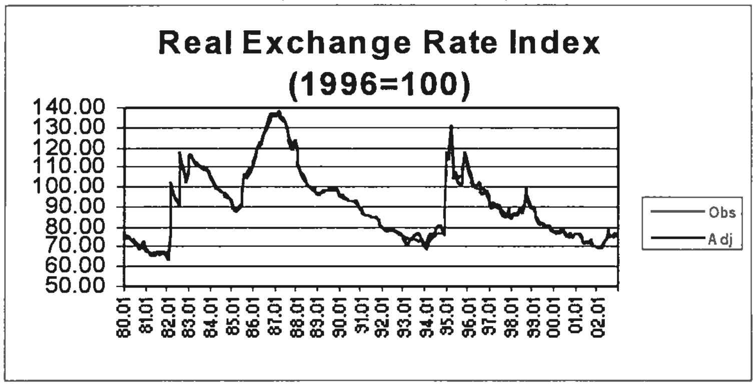
Graph III.12
(1980.01-2002.12)



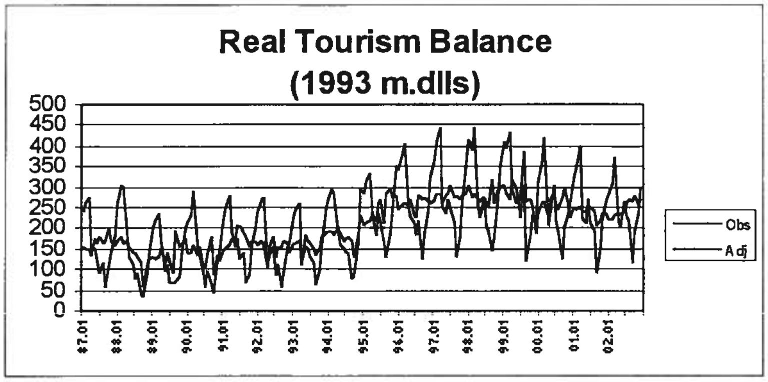
Graph III.13
(1985.01-2002.12)



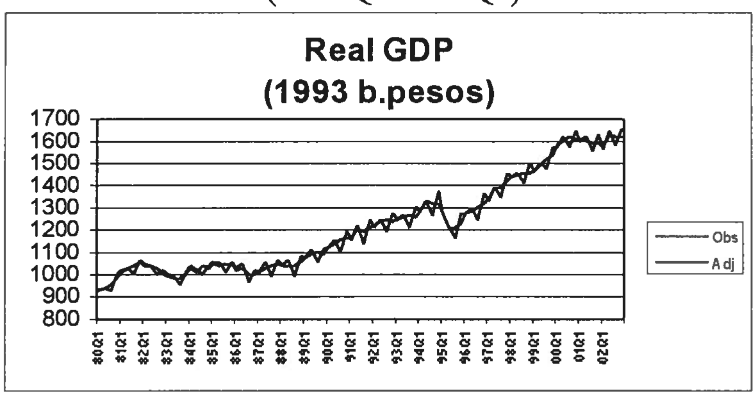
Graph III.14
(1980.01-2002.12)



Graph III.15
(1987.01-2002.12)



Graph III.16
(1980.Q1-2002.Q4)



B.- Filtering the Strategic Indicators

Commonly, economic data at high-frequency intervals are highly intercorrelated. They have common cyclical components. In particular, if we select a set of major indicators, each of which has to do with a specific variable (as in the case of real GDP), we can see the intercorrelation. In this case, we selected a set of fifteen indicators, each of which tells us something about GDP movements.

The presence of high serial correlation in the set of main indicators represents both a benefit and a cost. It is a benefit because we can use it to forecast dynamically, but it is a cost because it introduces inefficiency in parameter estimates. High correlation across different series of economic data can be partially explained by two factors: seasonality and trend. As we saw in the previous graphs, almost all the indicators chosen show both seasonal movement and trend, with the apparent exception of real interest rate, real exchange rate and exports of oil.

In order to deal with these two serial problems in our set of major indicators, and clean them up to get better parameter estimators, we need to filter these series. With respect to seasonality, we can either use officially seasonally adjusted series or introduce our own adjustments. Given that most of the Mexican economic data are not seasonally adjusted, we use the X11 methodology to adjust our main indicators.

With respect to the second serial problem, we need to "detrend" our series, i.e. take out the trend component. This can be done by regressing each indicator on a smooth function of time, and then compute the residuals from them. These residuals represent the variation of each indicator which is not explained by the trend. Of course, for this detrending process we use the series seasonally adjusted.

The regressions were obtained using monthly data for the last nine years (1994-2002). The sample starts in 1994 with the peso crisis, when the data show more regular seasonal and trend components. Almost all the regressions show that the trend component is significant, as shown by the summary statistics in Table III.1. It is important to notice that the series show two different trends, a downward trend from 1994-95 and an upward trend from 1996-2002. In order to incorporate these two different trends in the equations, we include a dummy variable starting in 1996 (dum96). As we can see in Table III.1, the variable Trend captures the downward trend from 1994-96, whose estimated coefficients are almost all negative. On the other hand, the variable Trend96, which is the product of the variable Trend and dum96, captures the upward trend from the period 1996-2002, and the estimated coefficients are almost all positive. In general terms, the regressions show a correlation higher than 0.50, with the exceptions of real interest rate (irr), man-hours worked in manufacturing (hour), and wholesale sales (wsi).

This filtering process of our main economic indicators, is implemented for each variable prior to the computation of principal components.

TABLE III.1

Estimated Regressions with Respect to Time

Equation	Estimated Coefficients			t-Statistics		R-Squared
	Constant	Trend	Trend96	Trend	Trend96	
IMI	72.4	-0.03399	0.07250	2.1	4.4	0.88
ICI	458.2	-0.22738	0.25571	12.7	14.1	0.76
IPI	129.3	-0.06252	0.09790	4.2	6.5	0.88
GFII	552.2	-0.27456	0.33998	8.9	10.9	0.82
WSI	275.3	-0.13573	0.13952	6.3	6.4	0.28
RSI	375.2	-0.18584	0.23861	12.1	15.4	0.87
HOUR	182.9	-0.08943	0.09221	5.9	6	0.34
WAR	241.5	-0.11876	0.15179	11.1	14.0	0.88
EMR%	52.0	-0.02378	0.02821	9.3	10.9	0.77
MAQR	-224.7	0.11646	0.00650	3.2	0.2	0.93
EXOV	12.0	-0.00417	0.01064	0.2	0.5	0.73
MSR	639.3	-0.31459	0.38327	20.5	24.7	0.93
IRR	-580.3	0.29113	-0.32541	1.5	1.7	0.03
ERR	-51424.2	25.8240	-30.2241	11.3	13.1	0.76
TOUR	-504.643	0.25564	-0.27312	6.8	7.2	0.56
GDP	111.9	-0.04903	0.08650	3.1	5.4	0.94

Notes: All series are seasonally adjusted and the equations were estimated in logs using OLS, with the - exception of real interest rate and real exchange rate.
All regressions use monthly data with the exception of GDP which is quarterly.

III.3.-THE MODEL OF PRINCIPAL COMPONENTS FOR ESTIMATING REAL GDP

A.- Estimation of Principal Components

Having a set of strategic economic indicators, the principal component method gives an answer to the question: "How many independent sources of variation are there?"[10/]. For example, in the regression of Y on a number of independent variables X_1, X_2, ..., X_m, we wish to find some linear functions of the X's which in some sense capture most of their variablility[11/].

Consider the linear functions Z's of the independent variables X's[12/].

$$
\begin{array}{l}
Z_1 = a_1 X_1 + a_2 X_2 + \ldots\ldots\ldots + a_m X_m \\
Z_2 = b_1 X_1 + b_2 X_2 + \ldots\ldots\ldots + b_m X_m \\
\ldots \quad \ldots \quad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \\
Z_m = \ldots \qquad \ldots \qquad \ldots \qquad \ldots
\end{array}
$$

The principal component method extracts these linear functions (Z's) choosing the a's and b's so that the variances of Z's are maximized. Therefore, the principal components Z's, which are the linear combinations of the variables X's, have the highest variance. Z_1 is called the first principal component with the highest variance, Z_2 is the second principal component with the next highest variance, but uncorrelated with Z_1, and so on. At the end, we will have a set of m principal components that accounts for the total variation of the X's.

The orthogonality property of the components is an important characteristic because it allows us to avoid the multicollinearity problem in the regression of Y on Z's, instead of Y on X's.

We need to remember that the original set of X variables, which are main economic indicators, was chosen as the set of variables correlated with Y. Thus, multicollinearity is present among the X's. The presence of multicollinearity implies that we cannot estimate individual coefficients with good precision in the regression of Y on X's. We can, however, obtain uncorrelated linear functions (Z's) from the X's and regress Y on Z's, and then get estimates of the coefficients that are not subject to multicollinearity.

In the extraction of principal components from a set of strategic indicators we have used the software Time Series Processor (TSP).

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10 / Maddala (1992).
11 / Dhrymes (1970).
12 / A similar theoretical example is in Maddala (1992), p.284.

The following two tables (III.2 and III.3) show the TSP computational output for extracting the principal components from our set of fifteen major monthly economic indicators. The period used is from January 1994 to December 2002. The series are adjusted for seasonality and trend. They are the residuals obtained from the regressions of each indicator against time.

There are some key points to note in the tables. In Table III.2, we have the correlation matrix among all fifteen indicators, where we can see the degree of multicollinearity among them. In order to avoid the multicollinearity problem in our regression we estimate linear combinations of the original variables, which are the principal components. In Table III.3, we present the eigenvalues for the fifteen principal components, and the cumulative R-Squared. The eigenvalues are characteristic roots of successive correlation matrices. If we take an eigenvalue divided by the total number of variables (15), this is exactly equal to the fraction of the variance of the original variables accounted for by the principal components. The R-Squared column means that if we use all the fifteen principal components, we can explain the total variation of the main indicators; it is 100%, as indicated by the 1.00 Cumulative R-Squared in the last row of Table III.3. If we take component 1, however, we can explain only 51% of the total variation of the fifteen leading indicators. If we take the first two components, then we can explain 68% of the total variation, and so on. The first eight components account for 96.5% of the total variation, and we omit the remaining seven components, since they account for a small portion of the total variance

In addition, we present the graphs for the first eight principal components over time (Graphs III.17-III.24). In these graphs we can see that each of them shows a different pattern, which illustrate the fact that the principal components are the "mutually uncorrelated" linear combinations of the original strategic indicators.

TABLE III.2
Correlation Matrix

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
V1	1.00														
V2	0.75	1.00													
V3	0.98	0.86	1.00												
V4	0.86	0.93	0.92	1.00											
V5	0.84	0.77	0.86	0.83	1.00										
V6	0.61	0.72	0.67	0.76	0.76	1.00									
V7	0.96	0.70	0.94	0.83	0.81	0.55	1.00								
V8	-0.06	0.31	0.05	0.20	0.23	0.57	-0.12	1.00							
V9	0.80	0.83	0.85	0.88	0.72	0.62	0.77	0.07	1.00						
V10	0.69	0.39	0.64	0.54	0.51	0.20	0.70	-0.25	0.53	1.00					
V11	0.06	-0.04	0.04	0.08	-0.09	0.02	0.05	-0.08	-0.01	0.13	1.00				
V12	0.40	0.78	0.52	0.70	0.49	0.73	0.31	0.65	0.62	0.07	0.09	1.00			
V13	0.18	0.07	0.15	0.15	0.11	-0.01	0.23	-0.22	0.08	0.25	0.00	-0.11	1.00		
V14	-0.28	-0.50	-0.35	-0.53	-0.20	-0.28	-0.27	-0.22	-0.41	-0.19	-0.22	-0.54	-0.17	1.00	
V15	0.11	-0.07	0.06	0.01	-0.09	-0.22	0.12	-0.45	0.08	0.25	0.03	-0.23	0.14	0.11	1.00

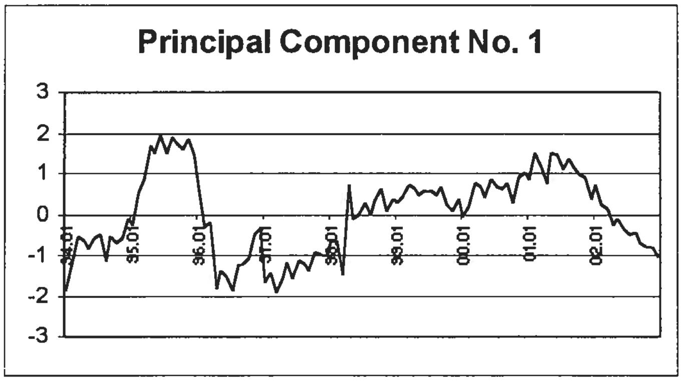
Notes: V1 = IMI, V2 = ICI, V3 = IPI, V4 = GFII, V5 = WSI, V6 = RSI, V7 = HOUR, V8 = WAR
V9 = EMR%, V10 = MAQR, V11 = EXOV, V12 = MSR, V13 = IRR, V14 = ERR, V15 =TOUR.

TABLE III.3
Principal Components

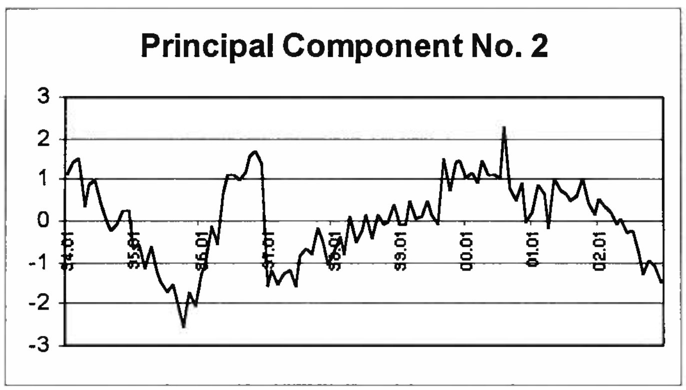
Component	Eigenvalue	Cumulative R-Squared
PC1	7.63999	0.5093
PC2	2.51296	0.6769
PC3	1.25179	0.7603
PC4	0.94832	0.8235
PC5	0.80749	0.8774
PC6	0.61960	0.9187
PC7	0.41838	0.9466
PC8	0.27278	0.9648
PC9	0.16105	0.9755
PC10	0.13258	0.9843
PC11	0.10726	0.9915
PC12	0.06776	0.9960
PC13	0.03558	0.9984
PC14	0.02321	0.9999
PC15	0.00124	1.0000

Notes: The Eigenvalue is also known as the Characteristic Root of the correlation matrix.

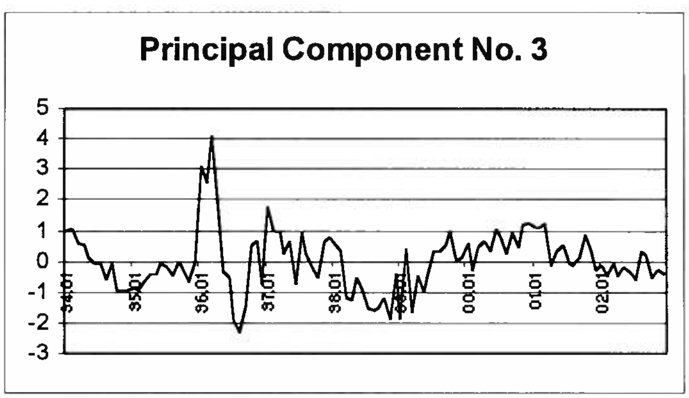
Graph III.17



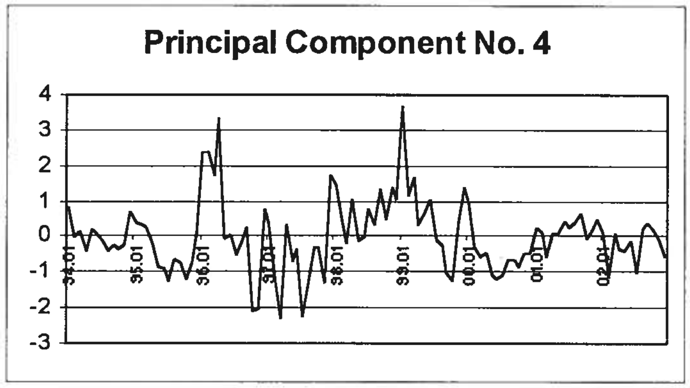
Graph III.18



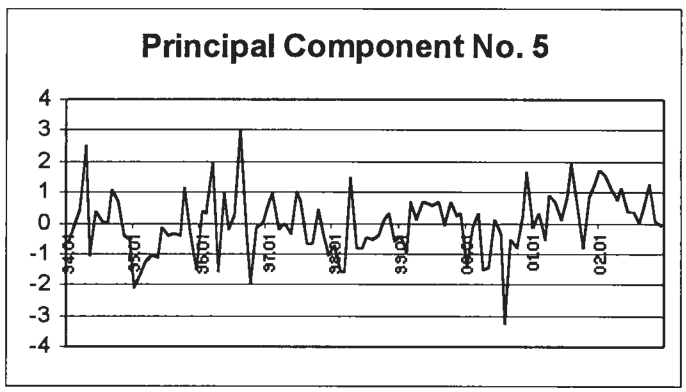
Graph III.19



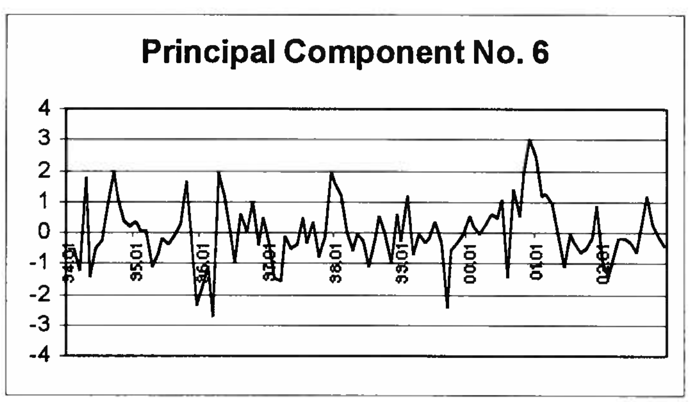
Graph III.20



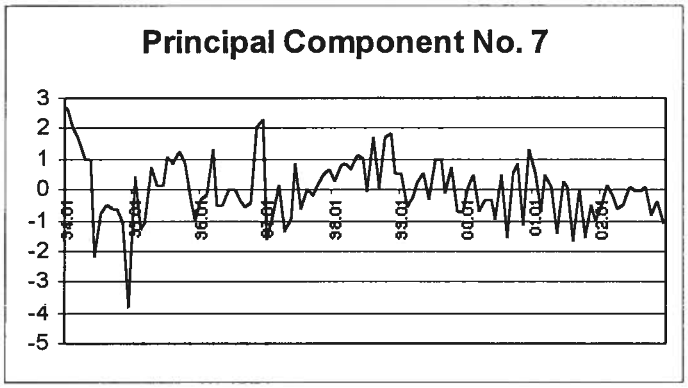
Graph III.21



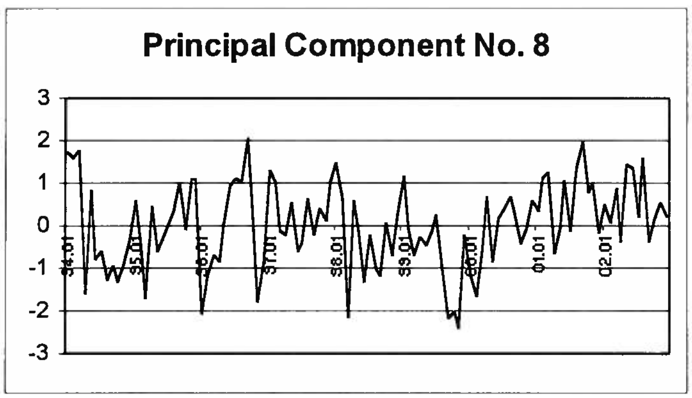
Graph III.22



Graph III.23



Graph III.24



B.- The Equation for GDP

If we regress Y on all the principal components extracted, this is exactly equivalent to using all the original set of strategic indicators X's as separate regressors. We shall use just a subset of principal components Z's in the regression of Y. In other words, regress Y on the first k principal components that substantially account for almost all the variation of the X's, and omit the m-k remaining components, which are superfluous in a correlation sense. According to the Cumulative R-Squared we have already determined that the first eight components account for more than 95% of all the variation of the original variables. Therefore, at this point we regress the real GDP on the first eight most important principal components.

In order to estimate the regression for the quarterly GDP, we need to get quarterly data for the principal components. We do that by averaging each component per quarter. The regression covers the period from the first quarter of 1994 to the fourth quarter of 2002, and is estimated using OLS with correction for autocorrelation (Cochrane-Orcutt). The GDP series is also adjusted by seasonality and trend (GDPD).

$$\underset{}{GDPD} = \underset{(998.2)}{1.00016} + \underset{(30.5)}{0.02674}\, PC1 - \underset{(0.3)}{0.00023}\, PC2 + \underset{(2.5)}{0.00198}\, PC3 + \underset{(2.5)}{0.00225}\, PC4$$

$$+ \underset{(1.2)}{0.00125}\, PC5 - \underset{(3.0)}{0.00285}\, PC6 - \underset{(0.2)}{0.00020}\, PC7 + \underset{(3.9)}{0.00495}\, PC8$$

$$R^2 = 0.99 \qquad D.W. = 1.88 \qquad F_{9,26} = 216.3$$

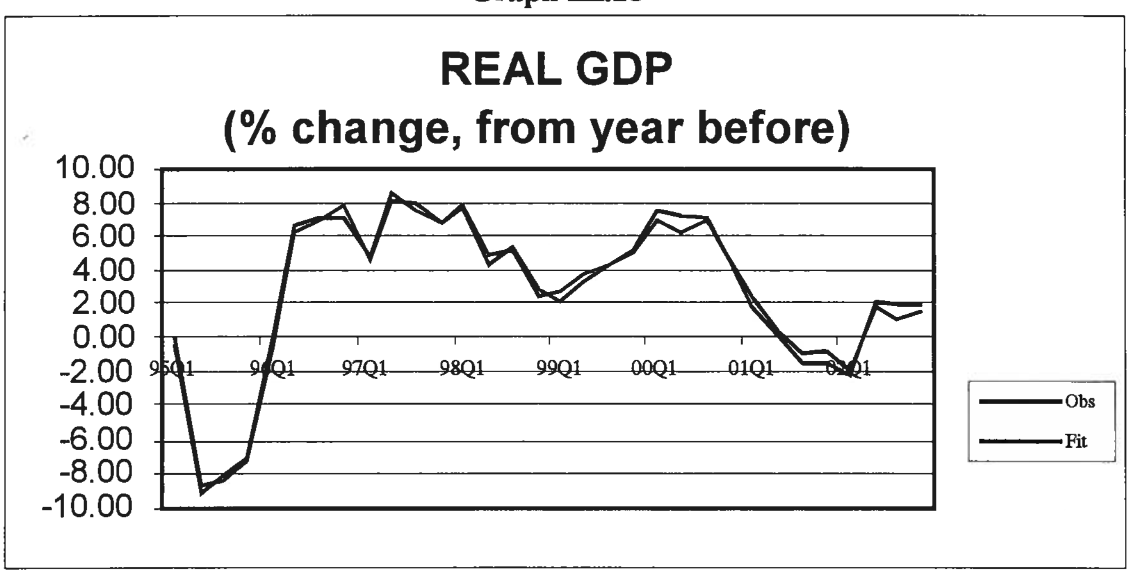
Even though components 2, 5, and 7 (PC2, PC5, PC7) are not statistically significant in explaining the variation of real GDP, we keep them in the equation because they may prove to be more important with the passage of time. The fit of the regression is good, as shown by the R-Squared = 0.99, which means that variation in all eight principal components accounts for 99% of the variation of the real GDP.

Finally, in Table III.4 we present the fitted values given by the regression, and show also the actual values for GDP. The regression is able to reproduce the historical quarterly GDP growth rate with a high degree of accuracy, in particular during the last year. The Graph III.25 below shows the observed (obs) and fitted (fit) GDP growth rate.

TABLE III.4
Real GDP
(% change, from year before)

Date	Observed	Fitted
95Q1	-0.44	-0.21
95Q2	-9.19	-8.88
95Q3	-8.03	-8.45
95Q4	-7.04	-7.27
96Q1	0.07	-0.57
96Q2	6.48	6.27
96Q3	7.13	6.96
96Q4	7.11	7.76
97Q1	4.59	4.56
97Q2	8.38	8.14
97Q3	7.48	7.87
97Q4	6.66	6.69
98Q1	7.54	7.71
98Q2	4.33	4.81
98Q3	5.28	5.23
98Q4	2.72	2.38
99Q1	2.03	2.57
99Q2	3.35	3.68
99Q3	4.29	4.24
99Q4	5.23	4.98
00Q1	7.40	6.83
00Q2	7.31	6.20
00Q3	7.02	6.83
00Q4	4.66	4.64
01Q1	1.79	2.37
01Q2	0.02	0.26
01Q3	-1.47	-1.12
01Q4	-1.53	-0.78
02Q1	-2.17	-2.14
02Q2	2.02	1.75
02Q3	1.82	0.98
02Q4	1.94	1.57

Graph III.25



III.4.- THE FORECASTS

We have used a set of fifteen strategic economic indicators, closely related to real GDP, to compute a set of principal components, which accounts for most of the variation of the original indicators, and then regress the GDP on the first eight components. This now allows us to forecast the quarterly GDP for the present year.

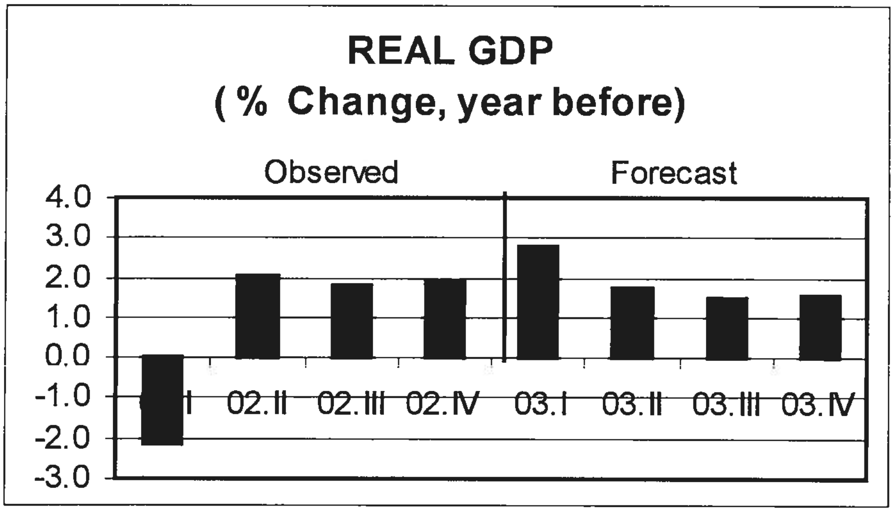
In order to get the quarterly forecast for the year 2003, we use the observed monthly information for the set of strategic indicators through December 2002. The future values of these fifteen monthly indicators are obtained using ARIMA equations for each series. We compute the corresponding principal components and use them as inputs in the regression of GDP.

The model forecasts a continuation of the economic weakness, which started at the end of last year (2002). According to the model, the economy shows a slight recovery in the first quarter of this year, but the weakness comes back in the second quarter, and stays for the rest of the year. In this way, the model predicts that the economy grows slowly with no signs of a sustained recovery during this year, as we can see in Table III.5 and Graph III.26. It is important to notice that the forecasts do not include any information regarding the developments observed during year 2003.

TABLE III.5
Real GDP Forecast
(% change, from year before)

Date	GDP (%)	
02.I	-2.2	Observed
02.II	2.0	
02.III	1.8	
02.IV	1.9	
Annual	0.9	
03.I	2.8	Forecast
03.II	1.7	
03.III	1.5	
03.IV	1.5	
Annual	1.9	

Graph III.26


REAL GDP
(% Change, year before)
Observed
Forecast
4.0
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
02.II
02.III
02.IV
03.I
03.II
03.III
03.IV

III.5.- REFERENCES

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CHAPTER IV

THE PRODUCTION SIDE MODEL FOR REAL GDP

IV.1.- INTRODUCTION

The total GDP and some of its main production components can be anticipated in advance of the official release. The official announcement of quarterly estimates of GDP takes place forty five days after the end of each quarter. The anticipated GDP can be forecasted as soon as key monthly information on economic activity is made available to the public by government and market sources.

The Production side model estimates quarterly GDP from the supply side using monthly information about different productive sectors of the economy. This information is collected by the National Institute of Statistics (INEGI), on a monthly basis, for the main economic sectors and put together in a global economic index which represents the performance of the aggregate production activity.

The model estimates the total GDP by using the General Economic Indicator (GEI). This monthly indicator represents almost 85% of total production, and is strongly correlated with the quarterly GDP that is eventually published. Given that the production of services is highly correlated with aggregate economic activity, we can estimate the GDP for the tertiary sector as a function of the GEI. The primary sector GDP is estimated using both strategic pieces of information, its lags and the general economic indicator. Finally, the computation of the secondary sector GDP is taken from the estimation of the industrial activity provided by the principal components model.

In this way, the Production side model provides an alternative estimate for the total GDP and its distribution among the three main production sectors: Primary, Secondary and Tertiary, mainly using monthly information on aggregate economic activity.

IV.2.- THE GENERAL ECONOMIC INDICATOR (GEI)

The General Economic Indicator (GEI) is a compound index constructed by INEGI, on a monthly basis, and it incorporates information on output from the main sectors in the economy. This index is released sixty days after the end of each month.

The monthly information on economic activity, included in this index, comes from different sectors such as: agriculture, industry and services. The general index represents almost 85% of the total productive activity in the economy. It includes basic information from the nine main divisions classified by the National Accounting methodology: agriculture, mining, manufacturing, construction, electricity, commerce, transportation, financial services, and social services. This information is collected month by month through surveys of private firms, public institutions, industrial groups and chambers of commerce[13/]

The basic monthly information on activity is processed and weighted to construct the monthly general indicator. In computing the monthly GEI, INEGI applies the same National Accounting methodology that it uses for computing the quarterly GDP.

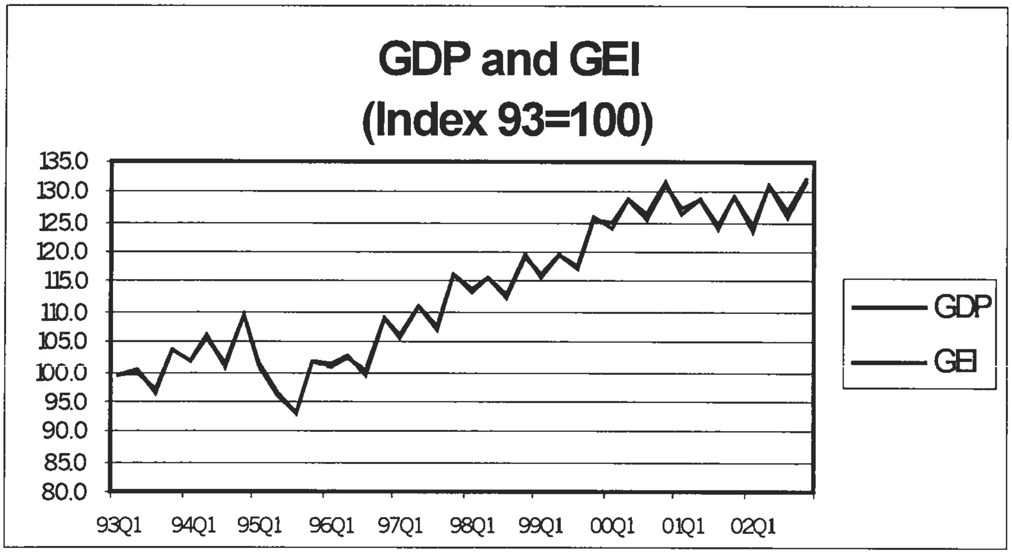
Given that the GEI reflects the monthly information on production of goods and services from the main entities in the economy, it is evidently a closely related indicator to production behavior. It also shows a high correlation with the quarterly GDP.

It is important to mention that the GEI does not incorporate as broad a universe of economic activities, as the quarterly GDP does. Therefore, the results of the quarterly GEI may differ from those of the quarterly GDP. The monthly GEI, however, can be taken as a short-term indicator of total economic activity.

The Graph IV.1 below shows the relationship between the GDP and the GEI, and we can appreciate that both quarterly series are almost the same. In fact, they show the same pattern and behavior over time, from the first quarter of 1993 to the fourth quarter of 2002.

[13/] For more references about the specific sources of information see: INEGI (2000a).

Graph IV.1



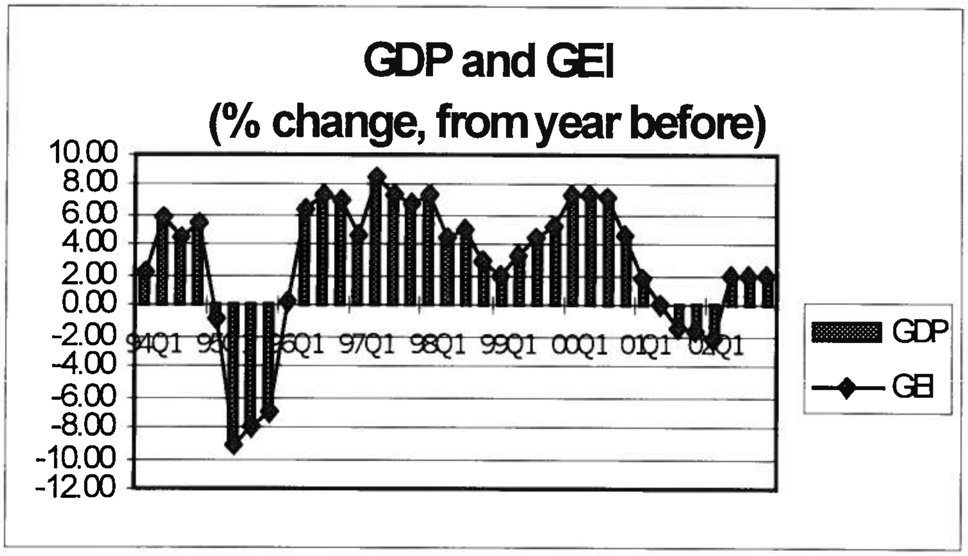
IV.3.- THE ESTIMATION OF THE PRODUCTION SIDE MODEL

On the production side, the model estimates the total GDP through the GEI, and also the sectoral distribution of GDP into primary GDP, secondary GDP, and tertiary GDP. The sectoral components are directly estimated as functions of the general index of economic activity (GEI).

The total GDP and its main components can be anticipated as soon as the monthly information on economic activity is released and made publicly available by INEGI[14/]. As we saw in the previous part, the GEI is a monthly indicator of general economic activity and it is highly correlated with quarterly GDP. It represents 85% of the total production activity. The Graph IV.2 shows a close correlation between the 4-quarter change of the quarterly GDP and of the quarterly GEI (% change, from year before).

[14/] A related work for the demand side of the U.S. GDP can be found in Payne (2000).

Graph IV.2



INEGI's computation of the monthly GEI, using the National Accounting methodology, saves us from the job of collecting the monthly production information by sectors in order to link it to the corresponding sectoral GDP. In this case, INEGI does the job and provides us with the monthly general index which we will use to estimate the total GDP and its sectoral components. In a sense, we proceed in the opposite way from that in Dr. Klein's Current Quarter Model for the U.S.[15/]. We take advantage of the GEI's existence, and first estimate the total GDP. Its supply side components are then separately estimated. The discrepancy between the overall estimate of GDP and that obtained by adding the estimates for their components is explained in terms of taxes and subsidies by sectors.

These quarterly estimates of total GDP and its sectoral components do not produce identical results because of taxes and subsidies, which can be separately estimated by sectors.

[15/] Details on the U.S. Model can be found in Klein and Park (1995), Klein and Park (1993), and Klein (1999).

Using information from the first quarter of 1993 to the fourth quarter of year 2002, we calculated the regression for the annual change of the quarterly GDP, and we obtained the following results[16/].

$$GDPQ\% = -0.01486 + 1.00426 * GEI\%$$
$$\quad\quad (0.5) \quad\quad (187.6)$$

$$R^2 = 0.999 \quad D.W. = 2.87 \quad F_{1,34} = 35199$$

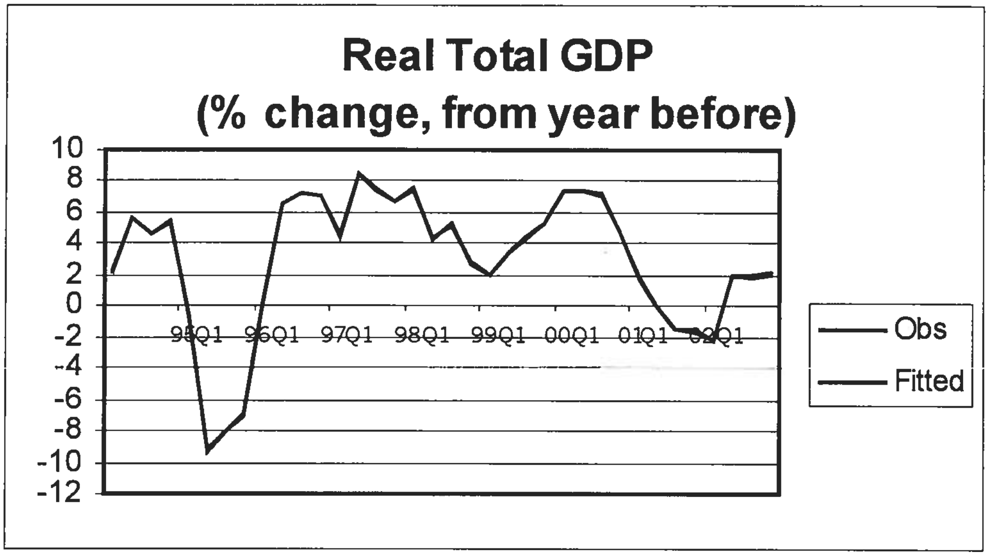
where GDPQ% and GEI% stand for the annual growth rates of the quarterly GDP and quarterly GEI, respectively.

The equation shows a good fit and the GEI is highly significant in explaining the GDP behavior. Given that the GEI includes only 85% of the total production activities (according to INEGI), we keep the constant term to attempt to capture the missing influences in the explanation of the quarterly GDP. Essentially, GDPQ and GEI have the same growth rate. The constant term is not significantly different from zero and the slope term is not significantly different from 1.0, as they should be.

From Graph IV.3 below we can see that the equation closely reproduces the annual growth rate of the quarterly GDP as a function of the corresponding growth rate of the quarterly GEI.

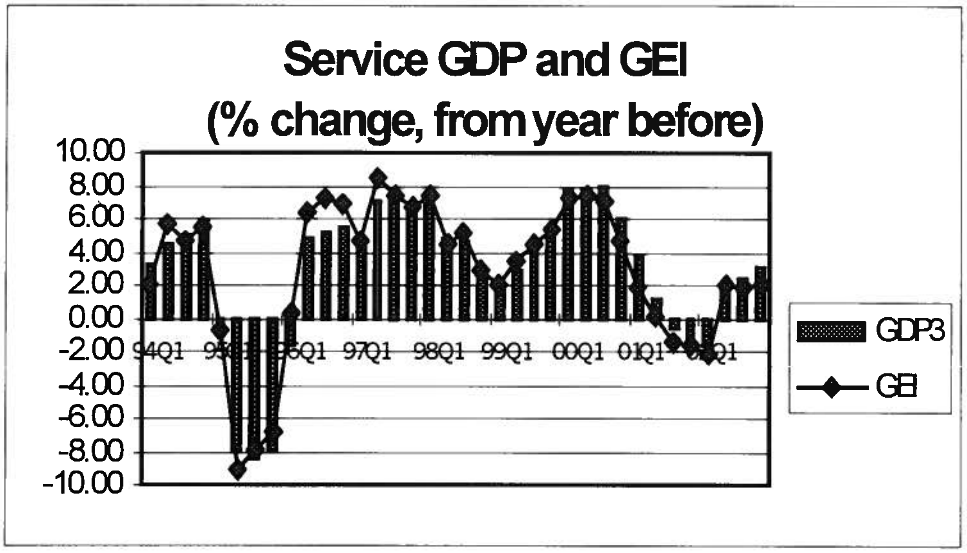
[16/] The estimation was made using Ordinary Least Squares (OLS).

Graph IV.3



Similarly, for the case of the tertiary sector we see a high correlation with the general indicator. This can be appreciated from Graph IV.4 below. This correlation can be explained, to a great extent, because the service sector represents two thirds of the total GDP and its behavior is closely related to the whole economy. In fact, the annual growth rate of the quarterly GDP of Services moves a little above or a little below the corresponding annual growth rate of the quarterly Total GDP.

Graph IV.4



We also know that the monthly GEI collects information on production from all the activities included in the service sector: commerce, transportation, financial, and social services. However, at present INEGI does not provide the corresponding GEI for the service sector. For this reason, we take the general index as the indicator that summarizes the short-term behavior of the tertiary activities.

As in the case of the Total GDP, now we estimate a regression between the annual growth rates of the quarterly GDP of Services (GDPQ3%) and the quarterly GEI (GEI%) as the explanatory variable. We use the same sample period (1993:Q1 – 2002:Q4), and we get the following results[17].

$$GDPQ3\% = \underset{(0.6)}{0.29119} + \underset{(19.8)}{0.87975} * GEI\%$$

$$R^2 = 0.98 \qquad D.W. = 1.77 \qquad F_{2,32} = 647.5$$

According to the estimates obtained, each percentage point change in the quarterly GEI explains 0.88 percentage point change in the quarterly Tertiary GDP. The equation shows a good fit as we can see in Graph IV.5 below. The estimated equation is able to reproduce quite well the historical behavior of the Service GDP, on a quarterly basis.

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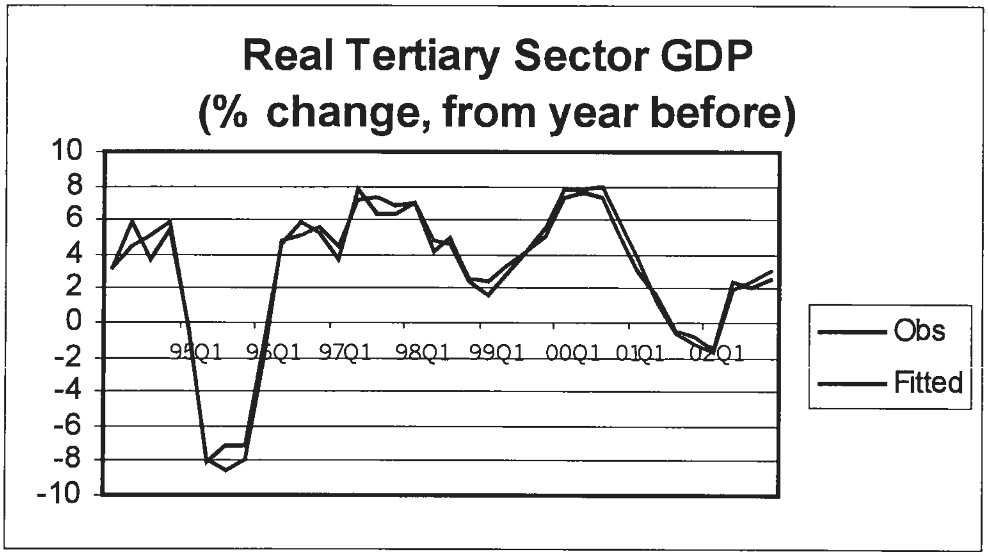
[17] Estimation given by Ordinary Least Squares (OLS), with autocorrelation correction by Cochrane-Orcutt.

Graph IV.5



The primary activities which comprise agriculture, livestock, forestry and fishing do not provide information on a regular monthly basis; just a few of them do so. In addition, the diversity of the harvest calendars makes it difficult to compute an exact measurement of the primary activities by month, and even by quarter. In fact, the quarterly primary GDP is the only activity usually subject to revisions at the end of the year[18/].

Certainly, the scarcity of monthly information for the whole primary sector and the fact that it counts for only around 5% of the total GDP, make it difficult for us to get a good estimated equation for this sector. We have, however, two reference points: the general indicator includes monthly information from some of the primary activities, and we also know that the annual harvest is usually distributed throughout the year in such a way that each quarter has a high correlation with its corresponding quarter of the previous year. Therefore, we can estimate an equation for the annual growth rate of the quarterly primary GDP (GDPQ1%) against the annual rate of the quarterly GEI (GEI%) and the lags of the primary GDP.

[18/] See details on the measurement problems of the primary sector in INEGI (2000b), and INEGI (1998).

The best estimate we have prepared for the period 1993:Q1 to 2002:Q4 is as follows[19/]:

$$GDPQ1\% = \underset{(3.0)}{4.66830} - \underset{(1.4)}{0.23215} * GDPQ1\%_{(t-1)} - \underset{(0.1)}{0.02038} * GDPQ1\%_{(t-2)}$$

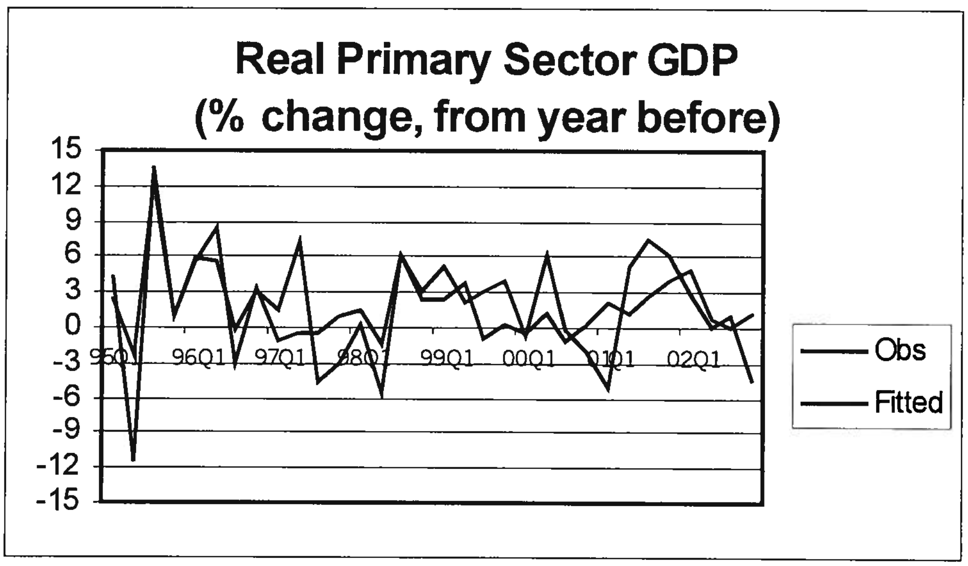
$$- \underset{(0.7)}{0.14720} * GDPQ1\%_{(t-3)} - \underset{(2.9)}{0.47368} * GDPQ1\%_{(t-4)}$$

$$- \underset{(1.1)}{0.20923} * GEI\%_{(t-1)} - \underset{(0.9)}{0.20458} * GEI\%_{(t-4)}$$

$$R^2 = 0.42 \qquad D.W. = 1.96 \qquad F_{6,25} = 2.98$$

The equation shows a relatively poor fit, but it is the best we could get, given the quality of information available. The Graph IV.6 below shows how much the equation reproduces the historical behavior of the quarterly primary GDP growth rate.

Graph IV.6



Regarding the secondary sector, we know that its time series values move exactly as those in the industrial sector. Since we already have an equation to forecast the industrial production in the Principal Components Model (Chapter III), we do not estimate a separate equation of it as a function of GEI. Therefore, future values of the industrial production index (IPI) are extrapolated by the ARIMA process introduced for IPI in Chapter III.

19/ Using Ordinary Least Squares (OLS).

IV.4.- THE FORECASTS

In order to get the quarterly forecasts for the Production side GDP, for the year 2003, we use the equations previously estimated and extrapolate the monthly values of the GEI.

In the case of the equation for the quarterly total GDP as a function of the quarterly GEI, we estimate the future monthly values of the GEI by fitting an ARIMA equation to this series and forecasting the next twelve months. We compute the quarterly GEI as a three-month average. Then we input the annual growth rate of the quarterly GEI into the GDP equation and get the corresponding annual growth of the quarterly GDP.

Similarly, we input the quarterly GEI forecasts into the tertiary GDP equation and get the quarterly forecast for the Service GDP growth rate. The same process is applied to the primary GDP equation, including its lags, and we get the corresponding forecast for the quarterly primary GDP growth.

Finally, for the secondary sector we use the monthly forecasts of the industrial production index (IPI) that we already generated with the principal components model. Then we compute the quarterly figures of the IPI as a three-month average. The IPI is exactly the indicator that INEGI uses to measure the quarterly industrial GDP. Therefore, our forecast for the annual growth rate of the quarterly IPI gives us the forecast for the annual growth rate of the secondary sector GDP.

At this point we have generated the quarterly forecasts for the Production side GDP, including the total, and its distribution among the primary, the secondary, and the tertiary sectors. It is important to notice that the sum of the three components does not give the total GDP, the difference is given by taxes and subsidies. The equations for sectoral GDP are used to distribute the total GDP among the production sectors, but the total GDP from the production side is obtained as a function of GEI.

As we can see from the results in Table IV.1, the Production side model foresees an extension of the weakness of economic activity for the whole year 2003, which started to be evident by the end of 2002. The extension of the weakness predicted by this model implies an annual GDP growth rate of 1.6% this year, which represents a slight recovery with respect to the growth of 0.9% last year. The forecast for the year 2003, by the production side, indicates an economic weakness more pronounced than that shown by the principal components approach in Table III.5 (Chapter III); but it should be noted that the results reported in this chapter include more information, not only from the production sectors but also from the principal components approach. Graph IV.7 below shows the GDP growth rate by quarters.

TABLE IV.1
Quarterly GDP by Production Side

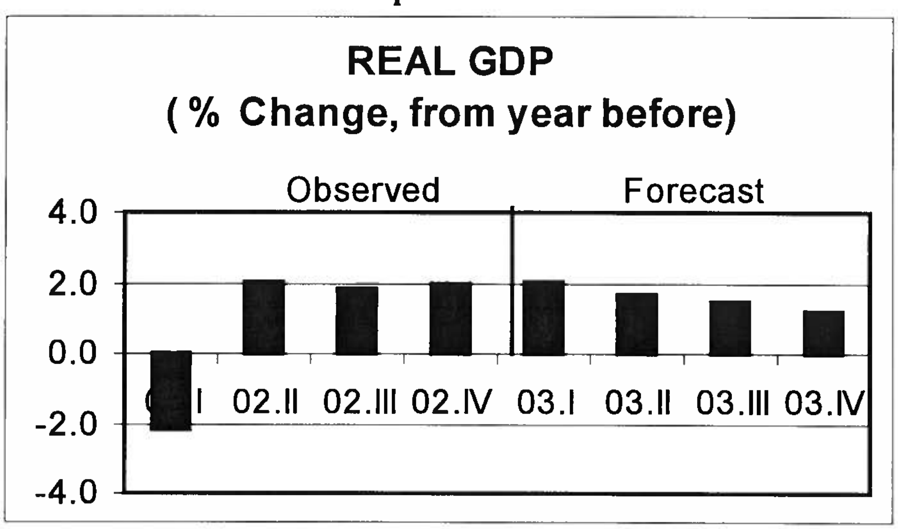
	2002I	2002II	2002III	2002IV	ANNUAL	2003I	2003II	2003III	2003IV	ANNUAL
REAL GDP (billion pesos 1993)	OBSERVED				2002	FORECAST				2003
Total GDP	1562.5	1647.3	1581.8	1655.0	1611.7	1594.5	1674.8	1605.0	1674.8	1637.3
Annual Rate (%)	-2.2	2.0	1.8	1.9	0.9	2.0	1.7	1.5	1.2	1.6
Primary Sector	79.0	83.9	74.6	94.2	82.9	82.5	86.2	77.2	98.6	86.1
Annual Rate (%)	2.9	0.0	1.0	-4.5	-0.2	4.3	2.8	3.4	4.6	3.8
Secondary Sector	387.9	422.5	415.8	406.9	408.3	391.3	426.0	418.0	408.2	410.9
Annual Rate (%)	-4.3	2.7	0.6	0.9	0.0	0.9	0.8	0.5	0.3	0.6
Tertiary Sector	969.7	1008.2	963.9	1020.4	990.6	994.3	1030.3	983.3	1038.5	1011.6
Annual Rate (%)	-1.7	1.9	2.4	3.0	1.4	2.5	2.2	2.0	1.8	2.1

Note.- The difference between the total GDP and the sum of the components is given by taxes and subsidies.

TABLE IV.2
Real GDP Forecast
(% change, from year before)

Date	GDP (%)	
02.I	-2.2	Observed
02.II	2.0	
02.III	1.8	
02.IV	1.9	
Annual	0.9	
03.I	2.0	Forecast
03.II	1.7	
03.III	1.5	
03.IV	1.2	
Annual	1.6	

Graph IV.7



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CHAPTER V

THE EXPENDITURE SIDE MODEL FOR REAL GDP

V.1.- INTRODUCTION

One of the three methods, used by National Account statisticians, to compute GDP is the Expenditure or Demand side approach, in addition to the Production and Income sides. The demand components represent the economy's absorption of the total production generated in a particular period of time. In other words, they represent the total utilization of final goods and services in an economy.

In the computation of the quarterly GDP, the statisticians in charge of the National Accounts use several monthly indicators to compute each of the demand components, which in turn are summed up to obtain the total GDP.

The quarterly GDP from the demand side can be anticipated in advance of the government release, as in the case of the production approach, through the estimation of the demand components using monthly indicators closely related to them. GDP figures are released six weeks after the end of each quarter. However, four weeks before the official release, the main monthly indicators are available for the first two months of that quarter, which will allow us to estimate the quarterly demand components and consequently the GDP with an appropriate degree of accuracy.

The Expenditure Side Model proposed here tries to use a methodology that is similar to that used by National Accountants. We collect, month-by-month, similar indicators. In the prediction of the GDP for the actual and future quarters, we use ARIMA equations to forecast the monthly indicators linked to the quarterly demand components.

In this model, we combine the use of high-frequency indicators, time series equations, and regression analysis to establish the linkage between the monthly indicators and the quarterly demand components. At the end, we try to anticipate well in advance the quarterly GDP prior to the official release.

V.2.-THE NATIONAL ACCOUNTING FRAME

The National Accounting methodology to compute the GDP is, as we noted above, based on three approaches: the Production, the Income, and the Expenditure sides. From the basic macroeconomic identity, we know that the GDP or total output is equal to the total absorption of the economy, or the total expenditure of all residents within the economy[20/].

$$GDP = Cp + Cg + I + \Delta S + X - M$$

In other words, the total expenditure on production of goods and services in an economy is equal to the sum of Private Consumption (Cp), Government Consumption (Cg), Gross Investment (I), Inventory Change (ΔS), plus Net Exports (X-M).

The statisticians in charge of the National Accounts can compute the total GDP just by computing the demand aggregates. This means, they collect information on a monthly or quarterly basis for the set of variables that account for each of the demand components. In most of the cases, they use monthly series to compute the corresponding quarterly component. In a few other cases, when the availability of information is limited or delayed, they make estimates for the third month of the quarter in order to compute the quarterly demand component[21/]. The use of estimation for the third month of the quarter is a major reason for the further revisions of quarterly and annual figures.

The National Accounting System for Mexico follows the international standards established by the UN, OECD, World Bank, and IMF, and fulfils the requirements of the National Income and Product Accounts (NIPA) manual[22/]. The National Institute of Statistics of Mexico (INEGI) releases the quarterly figures for GDP six weeks after the end of each quarter, based on the production side. However, ten weeks after the end of the quarter, INEGI releases the GDP by the demand side.

The first component of the aggregate demand is Private Consumption Expenditure, which is defined as the value of the purchases of goods and services of resident families and private institutions in the domestic and foreign markets. The computation method used by INEGI is through indexes of real sales or production.

The second demand component is Government Consumption Expenditure, defined as the current final government purchases (federal, state and local) of goods and services, plus wages and salaries of government employees. This public expenditure also includes the military, health and education sectors[23/]. The main information source is the statistics of public finance from the Ministry of Finance.

20/ See Dornbusch and Fischer (1990), pp 33-58, and Rivera-Batiz (1994), pp 265-268.
21/ An example of this estimation for the U.S. case is also mentioned in Payne (2000), pp 54-63.
22/ INEGI (1999), and Mosqueda (2000).
23/ INEGI (1999), and INEGI (2000).

The third component is Gross Fixed Investment, and represents the purchases of capital goods of the private and public sectors to increase their capital stocks. Capital goods can be national or imported, and include those for construction, machinery and equipment, and transportation. The information to compute gross investment comes from the construction sector, capital goods production, and capital spending of the public sector.

The fourth component is Exports of Goods and Services, and includes the country's sales of goods and services to the rest of the world, including gold and silver, and maquiladora exports. The main information to compute foreign sales comes from the balance of payments, and the series are deflated by price indexes adjusted by exchange rates.

The fifth aggregate of demand is Imports of Goods and Services, and represents the purchases of imported goods and services such as insurance and freight. Data also come from the balance of payments, and are adjusted by prices and exchange rate. These imports are subtracted because they constitute part of the sales recorded elsewhere.

Finally, the last component is called Inventory Change, and is defined as the difference between the volume of merchandise stocks at the beginning of the period and at the end of the period, with appropriate valuation adjustments. This concept is computed by INEGI as a residual between the total utilization of goods and services and the rest of the demand components.

The quarterly GDP figures and the demand components are presented by INEGI in constant price terms, using 1993 as the base year.

V.3.- THE ESTIMATION OF THE DEMAND COMPONENTS

The Expenditure side model is based on the National Accounting Structure and tries to follow, as closely as possible, INEGI's methodology.

In order to estimate the quarterly GDP, we need to estimate the quarterly demand components and sum them up. For the estimation of each demand component we try to use the same or similar monthly series that the statisticians of INEGI use to compute them. We form 3-month averages and link them to the corresponding demand aggregates through regressions. In other words, we construct "bridge" equations that relate National Accounts components to corresponding monthly indicators[24/]. This is done with historical data.

The bridge equations have the following structure:

$$N_{it}\% = \alpha_i + \beta_i I_{it}\% + \varepsilon_i$$

where N_{it} stands for the quarterly demand component from the National Accounts, and I_{it} is the 3-month average of the corresponding monthly indicator, both variables expressed in percentage changes with respect to the same period of the year before (%)[25/]. For example, if N_{it} represents private consumption and I_{it} is retail sales, then we can say that the percentage change of retail sales reveals in advance the percentage change of private consumption from National Accounts. If the retail sales series is exactly the monthly indicator that INEGI uses to compute private consumption, then the value of the coefficients in the regression would be:

$$\alpha_i = 0, \qquad \beta_i = 1$$

In other words, the percentage change in private consumption should be well estimated by the percentage change in retail sales. Similar correspondences are constructed between the other demand components and their corresponding monthly indicators.

PRIVATE CONSUMPTION EXPENDITURE

Private spending on consumption can be quite well explained by retail sales. The index of retail sales is published monthly and released seven weeks after the end of each month. Graph V.1 shows the close correlation between the percentage change of quarterly private consumption and the percentage change of the 3-month average of the

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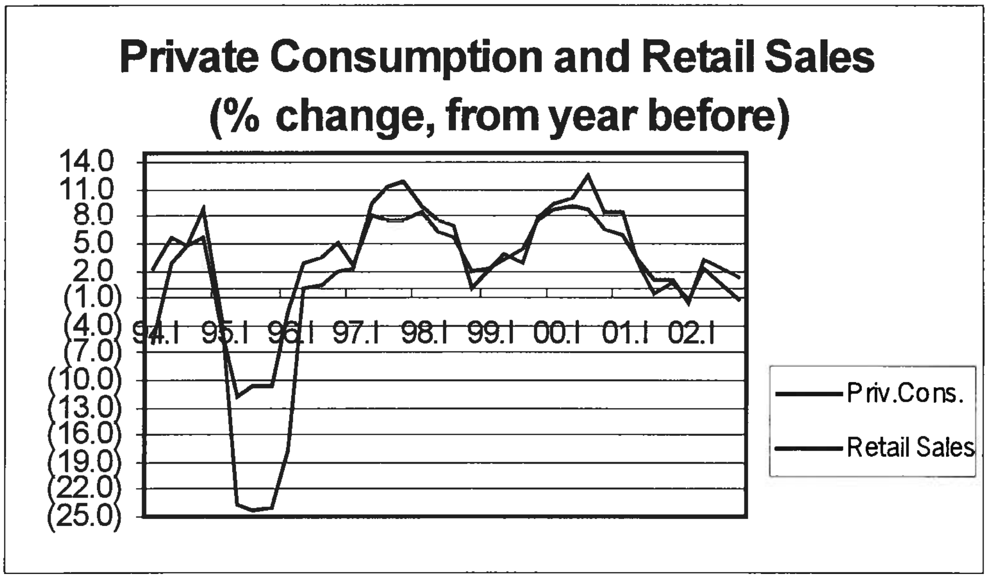
24/ For the U.S. model see Klein and Park (1995), and Klein and Park (1993).

25/ Klein and Park (1993) use the bridge equation in log-log form and compute quarter-over-quarter changes, rather than quarter-over-same quarter a-year-ago for individual variables.

retail sales index. The data sample is taken from the first quarter of 1994 to the last quarter of the year 2002.

Graph V.1



The estimated equation for the percentage change in Private Consumption (Cp%) as a function of the percentage change in Retail Sales (RSI%) shows an R-Squared of 0.92, which indicates that the retail sales index is a good predictor of private consumption. However, given that retail sales do not include services, just merchandise, then it does not explain the total change in private consumption, that is one reason why the constant term in the equation is also significant. The estimation results are as follows[26/].

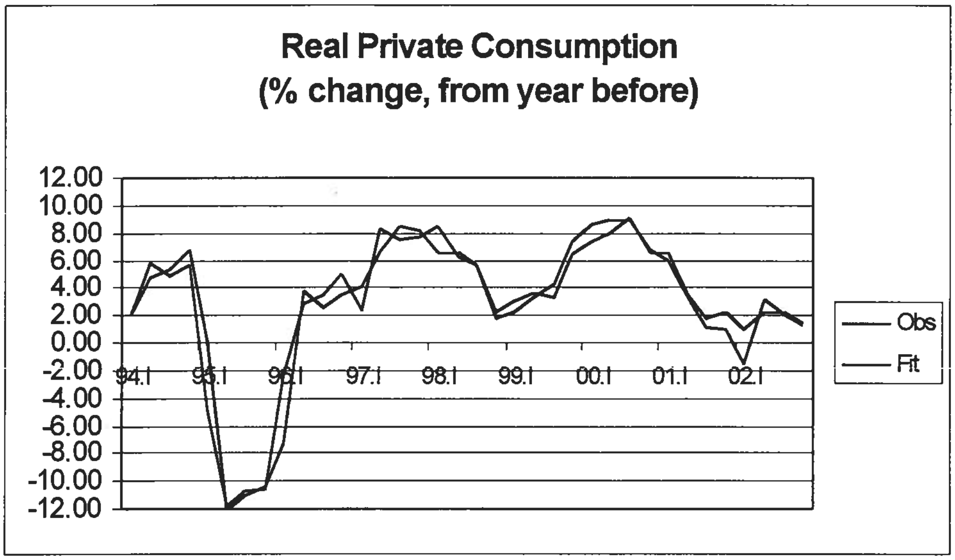
$$\underset{(5.0)}{Cp\% = 2.06952} + \underset{(11.4)}{0.51714\ RSI\%}$$

$$R^2 = 0.92 \qquad D.W. = 2.1 \qquad F_{2,32} = 186.8$$

The regression performance shows that the historical data can be explained fairly well, as it is shown in Graph V.2 below, between the observed (Obs) and the fitted values (Fit).

[26/] The regression was corrected for autocorrelation by Cochrane-Orcutt transformation.

Graph V.2



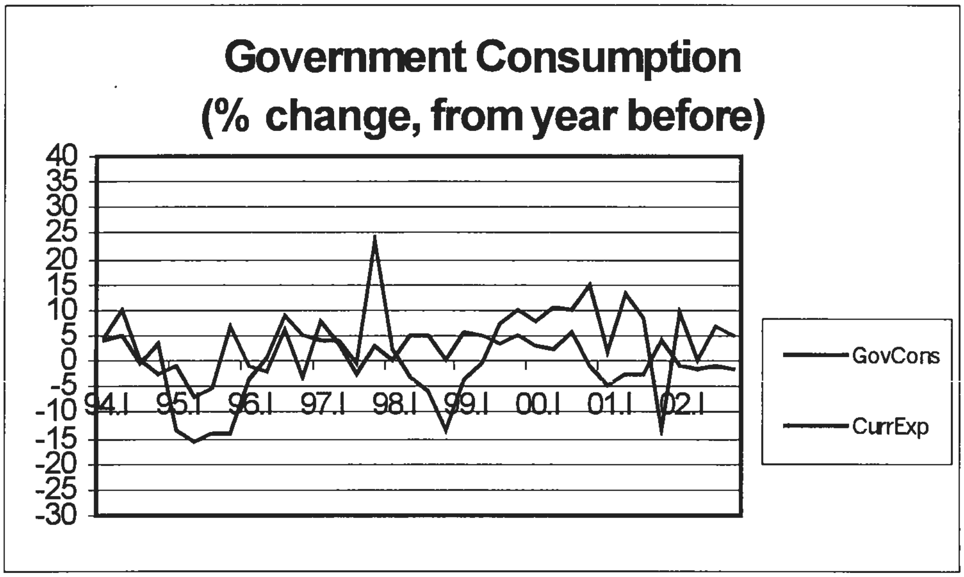
GOVERNMENT CONSUMPTION EXPENDITURE

Public consumption is the most difficult component to predict, because of the lack of monthly information in advance, and because of the different items that are considered in the primary spending of government, including the particular price index to deflate government consumption[20/]. However, the current government expenditure that comes from the public finance statistics, is the series that best represents the main items for computing public consumption. The current expenditure series includes wages, salaries, and purchases of goods and services of the three levels of government: federal, state and local. Although this series is monthly, two years ago was published only every three months. At present, this series is available every month and is provided five weeks after the end of each month by the Ministry of Finance.

The degree of correlation between government consumption from National Accounts and current government expenditure from public finance in real terms is shown in Graph V.3 below. We see that the correlation is high in some periods, and in some other periods the deviations are significant. The price index used to deflate the current government expenditure is the GDP price deflator (PDGDP).

[20/] A similar problem is found by Payne (2000) for the U.S. model.

Graph V.3



The estimation of the bridge equation for Government Consumption (Cg) as a function of the Current Government Spending (CGS) was made in log-log form, and includes the fourth lag of both the independent and the dependent variables. This log and lag structure indicates that the percentage change in public consumption expenditure should be approximately explained by the percentage change in current government expenditure in real terms. The data sample is from 1994:Q1 to 2002:Q4.

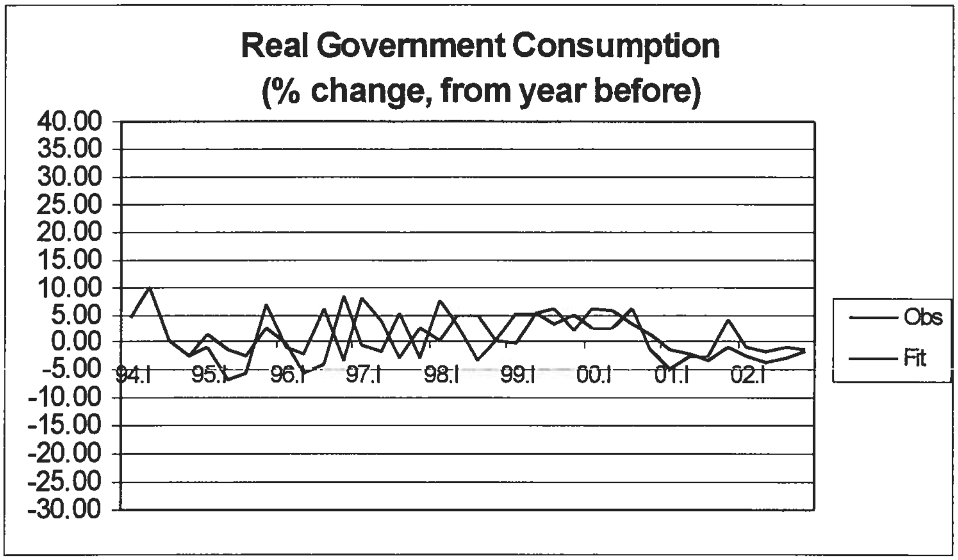
$$\text{Log}(Cg) = \underset{(1.9)}{0.15328}\ \text{Log}(CGS/PDGDP) - \underset{(2.0)}{0.18288}\ \text{Log}(CGS/PDGDP)_{t-4}$$

$$+ \underset{(260.3)}{1.00338}\ \text{Log}(Cg)_{t-4}$$

$$R^2 = 0.94 \qquad D.W. = 1.8 \qquad F_{2,33} = 249.8$$

The regression shows an R-Squared of 0.94, which indicates that after all, changes in current government expenditure can be a predictor of the changes in public consumption. However, in the graph of the goodness of fit (Graph V.4), we see that the regression fit shows higher deviation at the beginning of the period, and a little bit closer at the end.

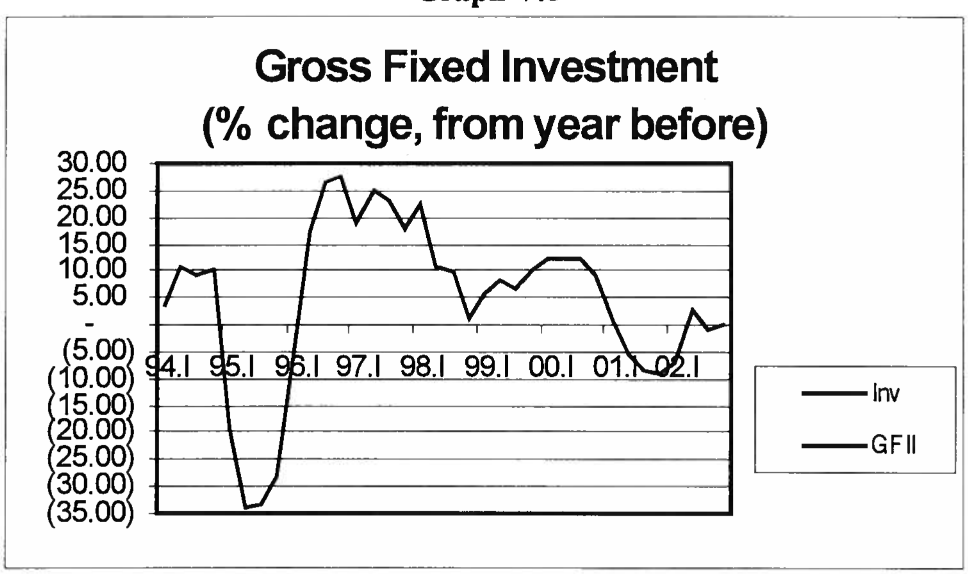
Graph V.4



GROSS FIXED INVESTMENT

The formation of fixed capital is the easiest component to estimate, thanks both to the availability of monthly series and to the fact that INEGI publishes the monthly indicator for investment that represents 100% of the quarterly gross fixed investment from National Accounts. The monthly index of investment includes machinery and equipment (national and imported), and construction in real terms. INEGI's release of the monthly indicator takes place nine weeks after the end of each month. In Graph V.5 below, we can see that the correlation between the two series is nearly perfect.

Graph V.5



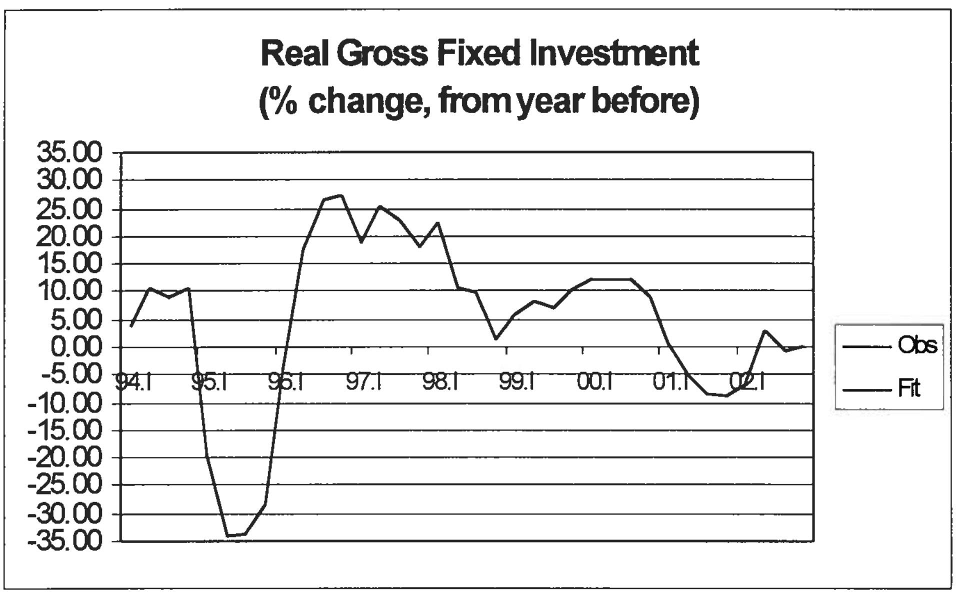
As expected, the estimated equation gives a coefficient of almost 1 for the coefficient of the index of fixed investment, and an R-Squared of 1. Which means that the percentage change of the 3-month average of the monthly Gross Fixed Investment Index (GFII%) accounts for the total percentage change of the quarterly Gross Fixed Investment from the National Accounts (I%). The data sample covers the same period, from 1994:Q1 to 2002:Q4.

$$I\% = \underset{(4570.1)}{0.99954}\ GFII\%$$

$$R^2 = 1.00 \qquad D.W. = 1.5$$

Certainly, the regression fits closely to the observed data, as we can see in Graph V.6 below, in which the two curves coincide with one another for the whole period.

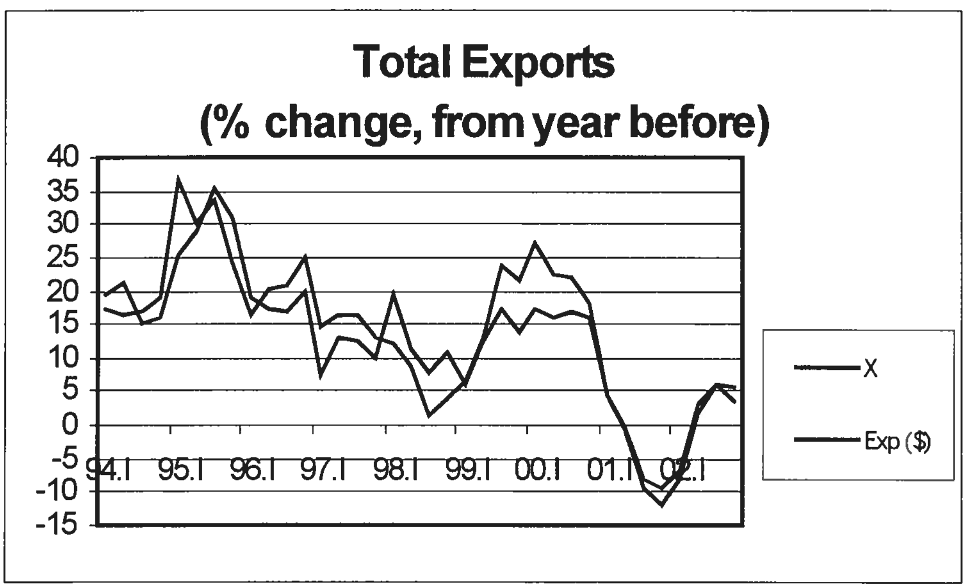
Graph V.6



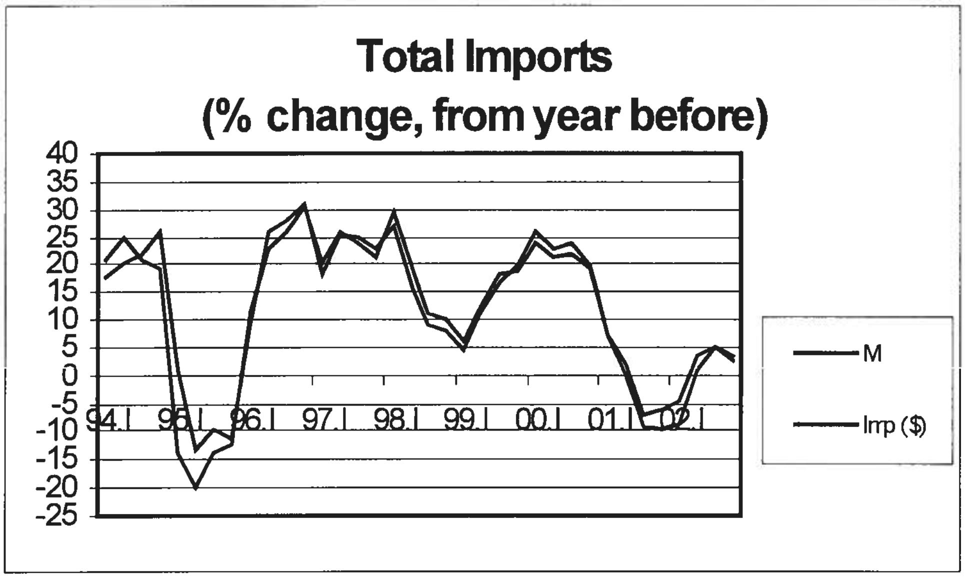
NET EXPORTS

For the case of Exports and Imports of Goods and Services, the main source of data is the balance of payments. The dollar value of Total Exports and Imports of goods are the monthly indicators closely linked to the corresponding demand components from National Accounts. Although exports and imports from the balance of payments do not include services, they account for most of the variation of the corresponding National Account components. Services from the balance of payments are released only quarterly; so they do not help too much. Preliminary figures of monthly exports and imports in dollars are released four weeks after the end of each month, and revised figures are released six weeks after the end of the corresponding month. After different computations with different price indexes and exchange rates, we found that the best monthly indicators closely linked to the corresponding demand components are exports and imports in dollar terms. One explanation could be that the effects of prices and exchange rates mutually cancel deviations. Therefore, the percentage changes of total exports and total imports in dollars are the best predictors of the percentage changes in exports and imports of goods and services in pesos from National Accounts, as we can see in Graphs V.7 and V.8 below.

Graph V.7



Graph V.8



The estimated equation for the Export component says that the percentage change of the 3-month average of Exports of goods in dollars (EXP%) is related to the percentage change of quarterly Exports of Goods and Services (X%). For the case of Imports, the percentage change of the 3-month average of Imports of goods in dollars (IMP%) is related to the percentage change of quarterly Imports of Goods and Services from National Accounts (M%). The period used in the regression is the same as before: 1994:Q1-2002:Q4[28]. We include a Dummy variable to capture the high expansion period after the financial crisis of 1995.

$$X\% = 7.37901 + 0.70044\ EXP\% - 5.58370\ DUM9699$$
$$(2.3) \qquad (8.3) \qquad (2.0)$$

$$R^2 = 0.91 \qquad D.W. = 1.92 \qquad F_{3,31} = 99.1$$

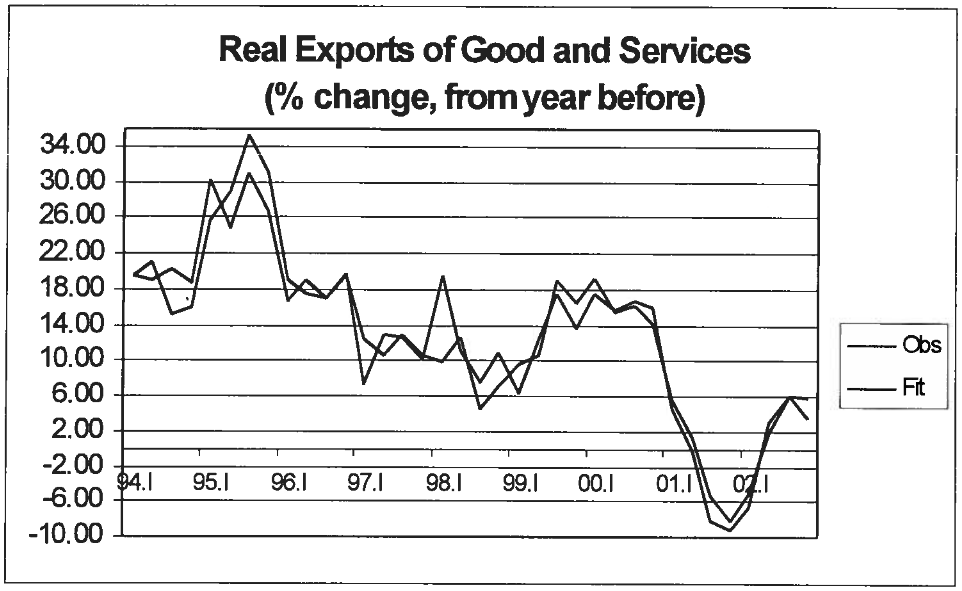
$$M\% = -4.84358 + 0.93949\ IMP\% + 6.04284\ DUM9699$$
$$(2.5) \qquad (16.8) \qquad (2.8)$$

$$R^2 = 0.97 \qquad D.W. = 1.63 \qquad F_{3,31} = 330.9$$

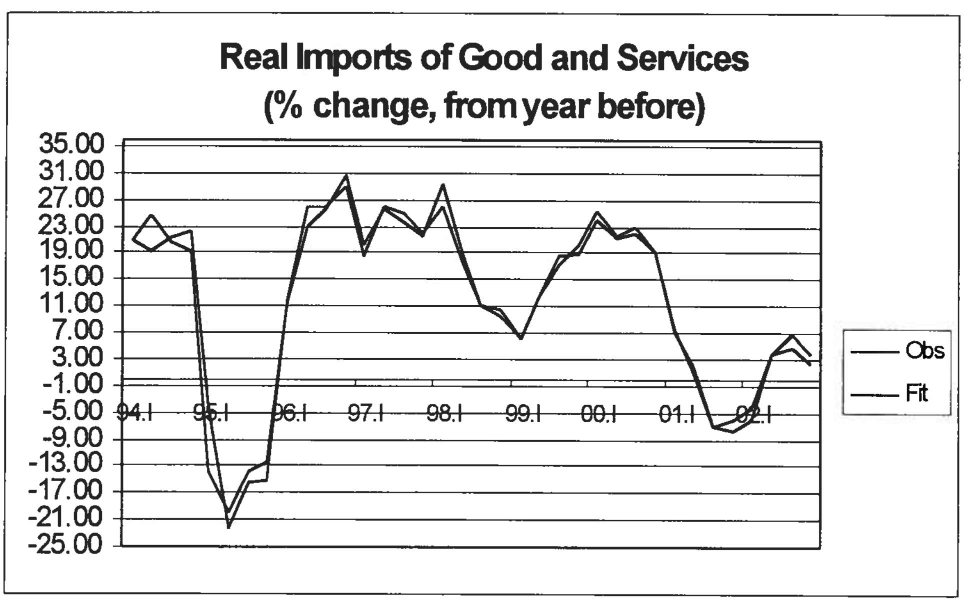
[28] / The OLS estimation was corrected by the Cochrane-Orcutt transformation.

The goodness of fit for both regressions are 0.91 and 0.97, respectively given by the R-Squared. Both regressions show that the historical data can be well explained by the monthly series for goods in dollar terms. The fit seems to be closer for the case of Imports, as can be seen in the following two graphs.

Graph V.9



Graph V.10



INVENTORY CHANGE

The Change in Inventories (ΔS) is also difficult to forecast well because of the absence of monthly information, their volatility, and because it is computed as a residual between the total utilization of goods and services and the rest of the demand components. The only source we have is the quarterly release of the series made by INEGI ten weeks after the end of each quarter. We can see, however, that inventories have a historical trend, which can be used to explain its future movements. We assume that the explanatory measures of the actual change in inventories are the values of inventories in the last four quarters. The estimated regression takes the form of an autoregressive model that includes the last four lags[29/]. Our data sample covers the same period as before.

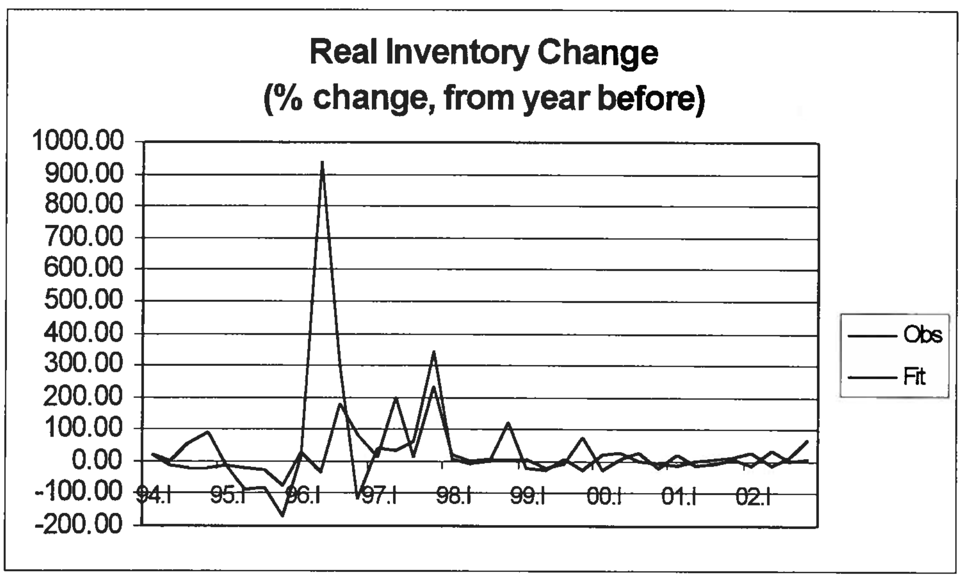
$$\Delta S = -\underset{(2.1)}{0.22888}\,\Delta S_{t-1} - \underset{(1.0)}{0.10749}\,\Delta S_{t-2} - \underset{(1.4)}{0.12931}\,\Delta S_{t-3} + \underset{(6.7)}{0.70499}\,\Delta S_{t-4}$$

$$+ \underset{(2.7)}{36463.0}\,DUM9699$$

$$R^2 = 0.77 \qquad D.W. = 2.0 \qquad F_{6,29} = 16.1$$

The fit of the regression is 0.77, given by the R-Squared; and we see how the fit is closer at the end of the period, as shown by Graph V.11.

Graph V.11

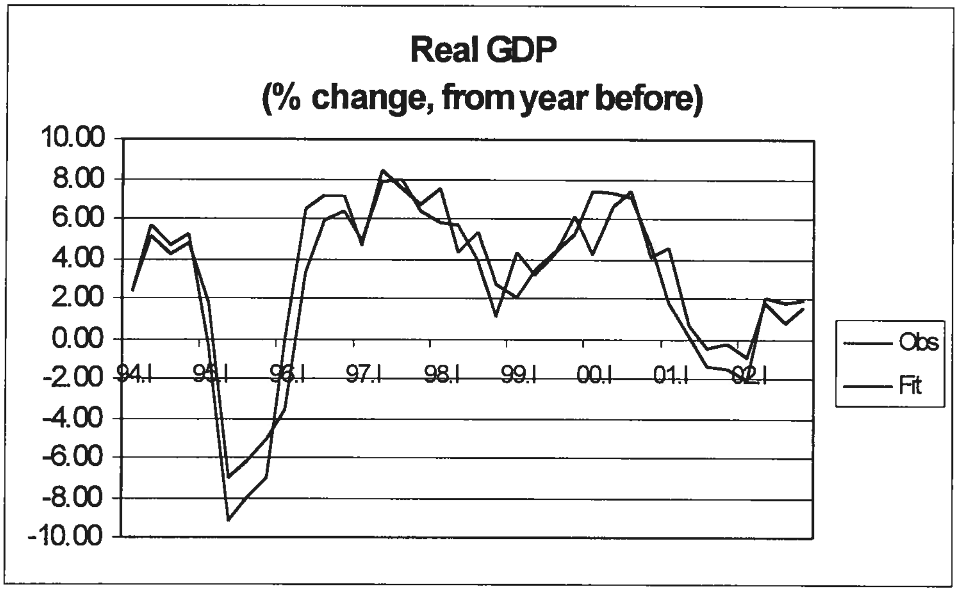


29 / The OLS estimation was corrected by the Cochrane-Orcutt transformation.

REAL TOTAL GDP

Finally, once we have estimated all the demand components, we add them up and get the total GDP in real terms for each quarter. The performance of the estimated quarterly GDP is quite good, as we can see in Graph V.12 below. The larger deviations between the observed and fitted values, in some periods, can be explained by the poor estimation of public consumption expenditure and inventory change. Generally speaking, however, we could say that the estimation of the demand components allows us to reproduce the historical trend of the observed quarterly GDP figures.

Graph V.12



Note.- The estimated GDP (Fit) was obtained as the sum of all the Demand components.

V.4.- THE FORECASTS

Having set up the equations for all the demand components (expenditure side), as functions of monthly indicators, we proceed to forecast the performance of the economy for the present year (2003) computing the quarterly GDP from the sum of the demand components.

We use ARIMA equations to obtain the future values of the monthly indicators that are linked to the corresponding National Account components, and use observed data through December 2002. The monthly forecasts are obtained for the whole year 2003, and we compute their 3-month average.

The quarterly forecasts for the GDP through the demand components are shown in Table V.1. In general terms, we can say that the Expenditure side model predicts a continuation of the weakness of the Mexican economy during the whole year 2003. The predicted annual GDP growth rate is 1.7%, which results in a growth much lower than the original official goal of 3.0% for the year. In table V.2 and Graph V.13 below we see the trajectory of the economy along the year.

TABLE V.1

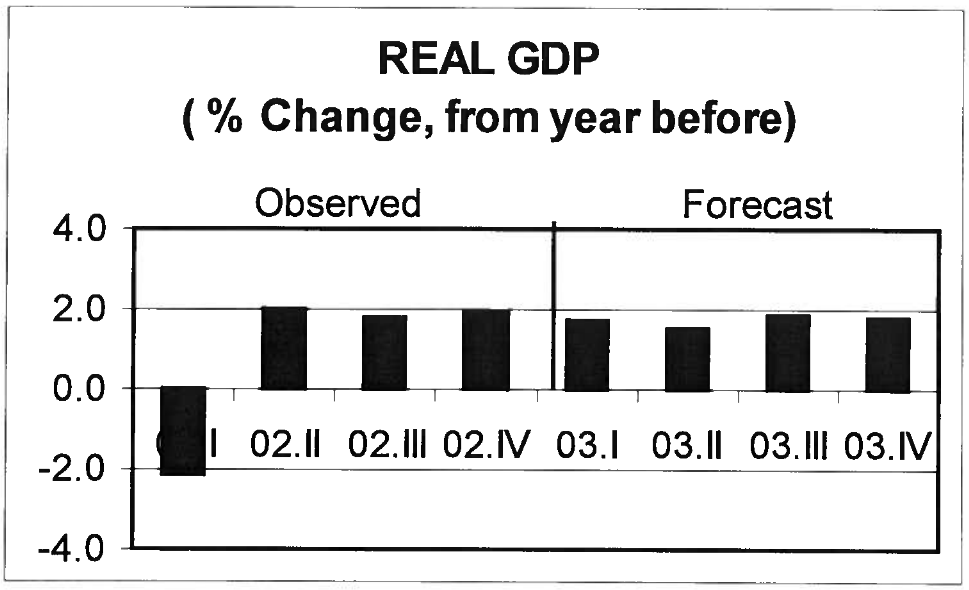
Quarterly GDP by Expenditure Side

	2002.I	2002.II	2002.III	2002.IV	ANNUAL	2003.I	2003.II	2003.III	2003.IV	ANNUAL
REAL GDP (billion pesos 1993)	OBSERVED				2002	FORECAST				2003
Total GDP	1562.5	1647.3	1581.8	1655.0	1611.7	1589.2	1671.9	1611.4	1684.9	1639.4
Annual rate (%)	-2.2	2.0	1.8	1.9	0.9	1.7	1.5	1.9	1.8	1.7
Private Consumption	1085.2	1186.6	1148.3	1183.9	1151.0	1098.0	1203.7	1168.3	1207.4	1169.4
Annual rate (%)	-1.6	3.1	2.0	1.2	1.2	1.2	1.4	1.7	2.0	1.6
Government Consumption	142.7	158.0	124.2	187.4	153.1	144.5	159.8	124.9	187.7	154.2
Annual rate (%)	-1.1	-1.7	-0.8	-1.3	-1.3	1.3	1.2	0.6	0.2	0.8
Gross Fixed Investment	299.9	322.1	307.4	314.4	310.9	304.1	326.3	310.6	316.5	314.4
Annual rate (%)	-6.9	2.8	-0.8	0.0	-1.2	1.4	1.3	1.0	0.7	1.1
Inventory Change	80.4	32.7	46.7	39.6	42.4	84.8	31.1	48.8	40.1	51.2
Annual rate (%)	26.8	-13.1	11.1	70.7	-7.8	5.5	-4.9	4.7	1.2	20.8
Exports	504.7	569.6	564.3	567.8	551.6	538.4	601.2	592.6	593.6	581.4
Annual rate (%)	-6.7	3.1	6.0	3.4	1.4	6.7	5.5	5.0	4.6	5.4
Imports	550.4	621.6	609.0	638.2	604.8	580.7	650.2	633.8	660.4	631.3
Annual rate (%)	-4.5	3.5	4.8	2.5	1.5	5.5	4.6	4.1	3.5	4.4

TABLE V.2
Real GDP Forecast
(% change, from year before)

Date	GDP (%)	
02.I	-2.2	Observed
02.II	2.0	
02.III	1.8	
02.IV	1.9	
Annual	0.9	
03.I	1.7	Forecast
03.II	1.5	
03.III	1.9	
03.IV	1.8	
Annual	1.7	

Graph V.13



Note.- Total GDP was obtained as the sum of all the demand components.

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CHAPTER VI

THE PRINCIPAL COMPONENTS MODEL FOR THE GDP PRICE DEFLATOR

VI.1.- INTRODUCTION

As in the case of the quarterly real GDP, we can expect to anticipate in advance the short-term movements of the GDP prices. Using the monthly flow of information for strategic price indicators, it should be possible to predict the quarterly GDP deflator through the application of a Principal Components Model and the supplementary use of futures prices, forward rates and expectations given by markets and agents in the economy.

The Principal Components Model uses monthly indicators of strategic prices to extract their main sources of variation, in order to explain the variation of the quarterly GDP price deflator. Once the GDP deflator equation is set up as a function of the independent sources of variation of the monthly prices (Principal Components), we use ARIMA equations to obtain the monthly forecasts of the main prices or related indicators, and we also introduce futures prices and expectations for relevant variables such as exchange rates, interest rates, oil price, and inflation at the consumer level.

The relevance of including futures, forwards and expectations in our model derives from the fact that daily News, Rumors, and Political and Social Events immediately influence the expected values of key prices. Certainly, the change in expectations, given bad or good News, modifies the future values of strategic prices in the economy, and this in turn influences key economic variables. In this way, market expectations will allow us to simulate the future impact of recent developments in the economy without making subjective assumptions.

It is important to notice that the 2003 forecast for the GDP price deflator, closely approaches to the official inflation target when we introduce into the model the day-to-day fluctuations of futures, forwards and expectations. This is particularly relevant for a developing country in which agent and market expectations are more sensitive to News, given the memory of dramatic crisis episodes in the past.

The GDP price deflator model combines the use of ARIMA monthly forecasts with the change in expectations of agents and markets regarding future values of strategic prices.

VI.2.- SELECTING THE STRATEGIC PRICE INDICATORS

In order to construct the Principal Components Model, we need to select a set of monthly indicators deemed to be closely related to the GDP price deflator. We choose monthly series of different prices that reflect the short-term movement of the general price index in the whole economy. In a sense, the quarterly movement of the GDP deflator can be predicted using monthly values of leading prices in the economy, which are among the most important determinants of the GDP prices.

As it was stated in a previous paper[30/], and in Chapter III, the Principal Components methodology is based on pure statistical correlation among variables; therefore, we need to select those key prices that mainly influence the general price in the economy. These highly correlated prices come from different sectors and markets such as consumers and producers, foreign exchange, money, stock exchange, labor and oil markets.

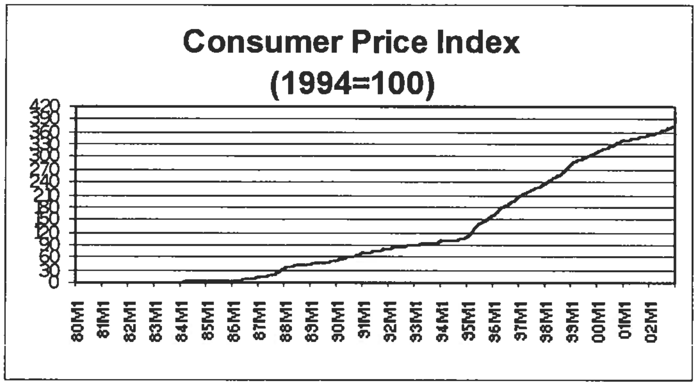
We have selected ten of the most important prices as determinants of the GDP deflator. They are monthly series, highly correlated, and used to compute the Principal Components.

1) Consumer Price Index (CPI)
2) Producer Price Index (PPI)
3) Nominal Exchange Rate (ERN)
4) Nominal Interest Rate (IRN)
5) Nominal Money Supply (MSN)
6) Oil Price (OPN)
7) Stock Exchange Index (SEI)
8) Nominal Minimum Wage (MWI)
9) Import Price Index (IMPP)
10) Average Industrial wages (WRM)

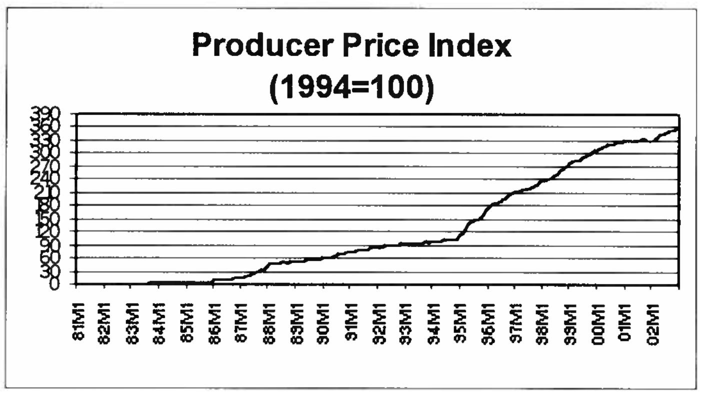
Looking at the graphs below, we can see that the individual variables show an increasing trend in the period of the 80s to the year 2002, with the exception of interest rate and oil price. During this period, Mexico experienced three main economic crises, in which inflation and devaluation were the common denominator. This highly inflationary period is well reflected in the increasing trends of nominal variables. During this period, however, we can distinguish three different trends on each graph. The first period goes from 1980 to 1987, in which the nominal variables show a relatively steady trend. The second goes from the late 80s to mid 90s with a steeper trend. And the third comes from mid 90s to the year 2002, during which the series show even a higher slope. Although this last period has been one of decreasing annual inflation, the consolidation of stabilization and structural reform has allowed the economy to succeed in achieving sustainable economic growth. Certainly, higher economic growth with declining inflation during the second half of the 90's, helped to account for more real growth in those years.

[30/] Klein and Coutiño (1999).

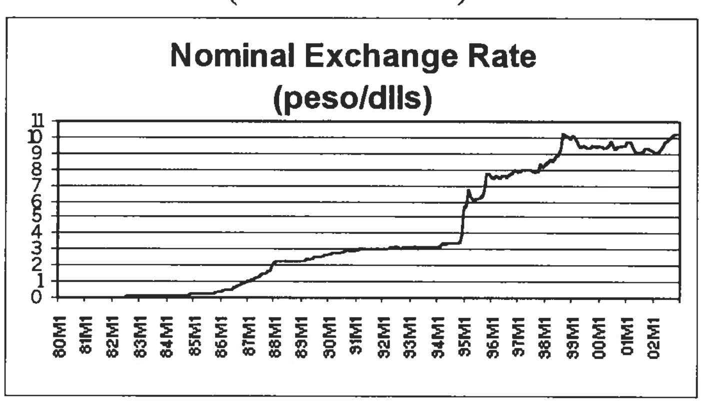
Graph VI.1
(1980.01-2002.12)



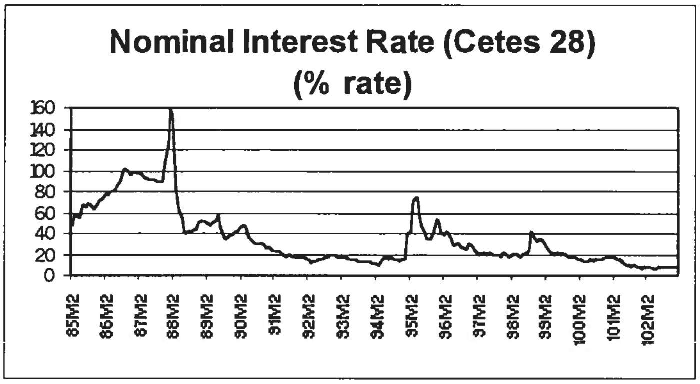
Graph VI.2
(1981.01-2002.12)



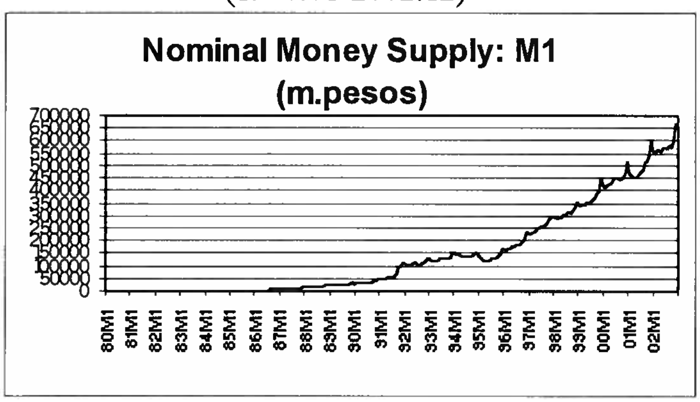
Graph VI.3
(1980.01-2002.12)



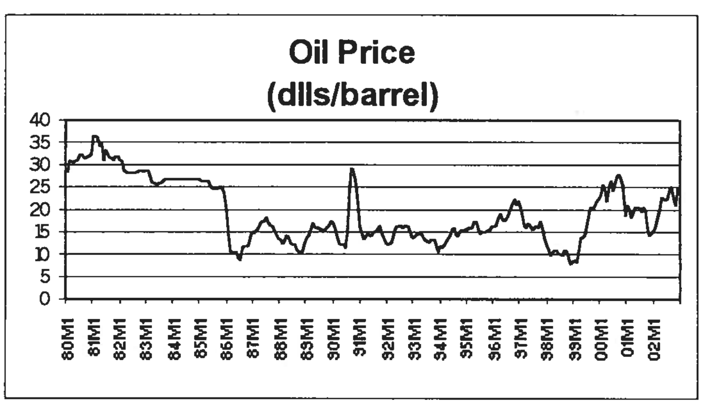
Graph VI.4
(1985.02-2002.12)



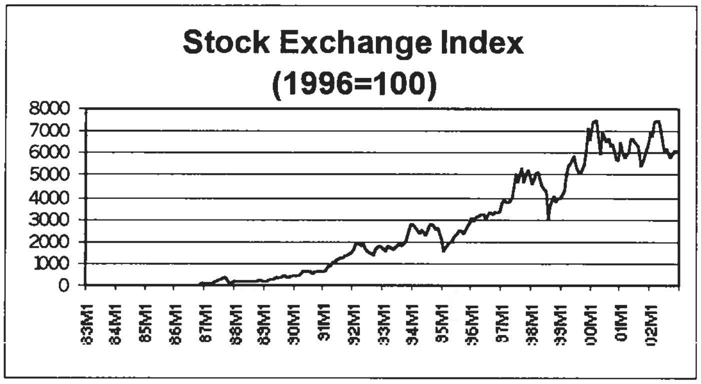
Graph VI.5
(1980.01-2002.12)



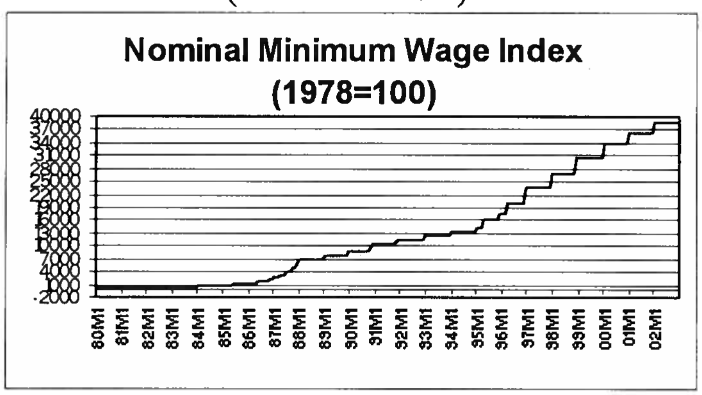
Graph VI.6
(1980.01-2002.12)



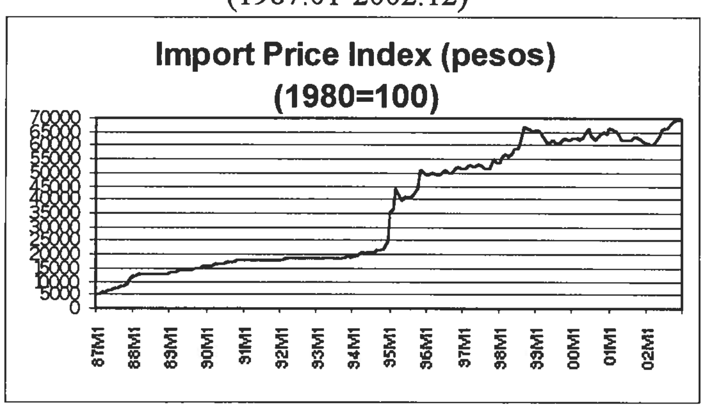
Graph VI.7
(1983.01-2002.12)



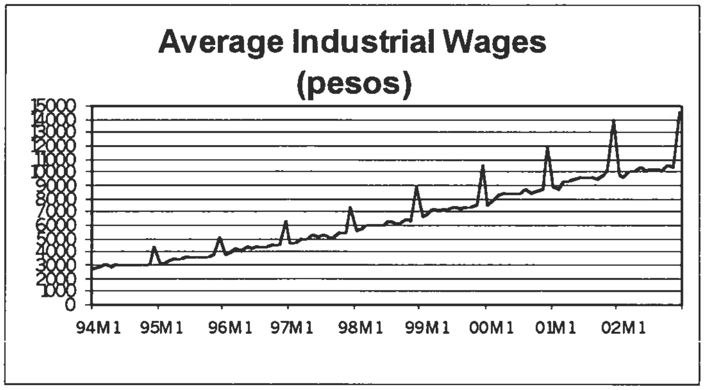
Graph VI.8
(1980.01-2002.12)



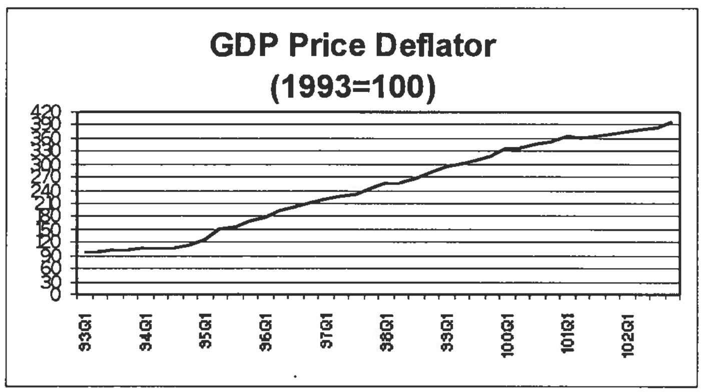
Graph VI.9
(1987.01-2002.12)



Graph VI.10
(1994.01-2002.12)



Graph VI.11
(1993.Q1-2002.Q4)



VI.3.- THE PRINCIPAL COMPONENTS MODEL

The Principal Components methodology is the same as explained in Chapter III, but the substance is different.

Given that the set of strategic indicators shows high correlation with the variable to be predicted, not only as high-frequency economic data but also as nominal variables, then we should remove the trend from each series. The trend component is one of the main explanations of the presence of high serial correlation. The series do not show a seasonal component except for the industrial wage rate and minimum wages. We "detrend" the series only by removing the linear chronological trend component as we did previously in the case of the real GDP model.

The detrending process is done by regressing each series as a semi-log linear function of chronological time, for the period from January 1994 to December 2002. The computed residuals represent the variation of the original series which is not explained by trend. The results obtained for each equation against time are summarized in Table VI.1 below. The trend component is highly significant for all equations, but comparatively less significant for oil price (OPN) and interest rate (IRN), as shown by the t-statistics. In fact, all the regressions show a high correlation between the trend and the dependent variable, as is shown by the R-Squared. The R-Squared is always higher than 0.60 with the exception of the interest rate and oil price, which are only loosely or nonlinearly related to time.

TABLE VI.1

Estimated Regressions with Respect to Time

Equation	Estimated Coefficients		t-Statistics	R-Squared
	Constant	Trend	for Trend	
CPI	-308.3	0.15700	35.5	0.92
PPI	-287.7	0.14667	30.6	0.90
ERN	-196.6	0.09939	13.5	0.63
IRN	283.8	-0.14055	8.5	0.40
MSN	-375.1	0.19399	53.9	0.96
OPN	-87.4	0.04514	4.6	0.17
SEI	-272.6	0.14057	22.4	0.83
MWI	-255.4	0.13286	45.1	0.95
IMPP	-201.8	0.10642	13.8	0.64
WRM	-313.2	0.16106	44.7	0.95
PDGDP	-298.2	0.15196	21.2	0.93

Notes: All equations were estimated in logs using OLS.
All regressions use monthly data with the exception of PDGDP which is quarterly.

Having detrended series, we proceed to compute the principal components from the set of ten strategic prices. As before, we use TSP software for the extraction of the mutually independent linear combinations of strategic prices, which have the highest variance. We have chosen the set of principal components that account for most of the total variation of the set of detrended variables, following the same procedure discussed in Chapter III.

In Table VI.2 we present the correlation matrix of the complete set of detrended variables. We can see how the degree of correlation varies among the ten variables. It is important to notice that the matrix does not show the correlation among the original strategic prices, but the correlation among the variables that represent the part of the variation of the strategic prices that is not explained by the trend; i.e. the detrended variables. That is why we see some negative correlation coefficients between some prices.

In Table VI.3 we get the Eigenvalues of the principal components, and the cumulative R-Squared. The Eigenvalues are the largest characteristic roots of the successive correlation matrices. If we take the eigenvalue of a particular principal component divided by the total number of variables, then we get the fraction of the total variance that is explained by that principal component, which is expressed by the R-Squared. In Table VI.3, we also see that the first seven principal components explain 99.6% of the total variation of the set of variables (R-Squared), and the remaining three principal components account for only a marginal 0.4%.

The following graphs show the seven first principal components, and we see how effectively they represent the uncorrelated linear combinations of the original variables. Certainly, they show totally different patterns individually.

TABLE VI.2
Correlation Matrix

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
V1	1.00									
V2	0.99	1.00								
V3	0.85	0.89	1.00							
V4	0.45	0.52	0.76	1.00						
V5	0.28	0.18	-0.11	-0.34	1.00					
V6	-0.15	-0.05	-0.11	-0.09	-0.27	1.00				
V7	0.44	0.38	0.04	-0.31	0.62	0.10	1.00			
V8	0.89	0.85	0.65	0.32	0.44	-0.24	0.50	1.00		
V9	0.83	0.89	1.00	0.76	-0.15	-0.07	0.03	0.63	1.00	
V10	0.33	0.32	0.25	0.15	0.47	-0.12	0.23	0.31	0.24	1.00

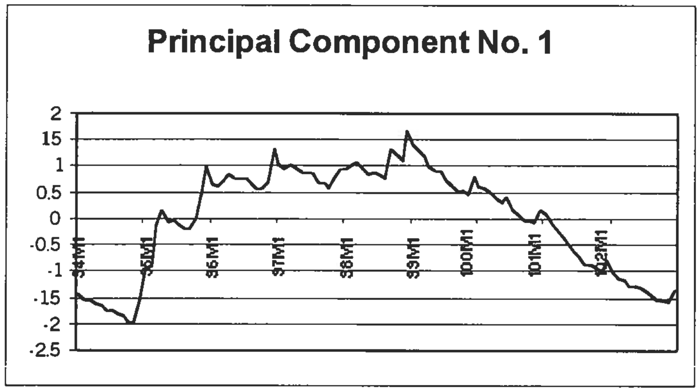
Notes: V1 = CPI, V2 = PPI, V3 = ERN, V4 = IRN, V5 = MSN,
V6 = OPN, V7 = SEI, V8 = MWI, V9 = IMPP, V10 = WRM.

TABLE VI.3
Principal Components

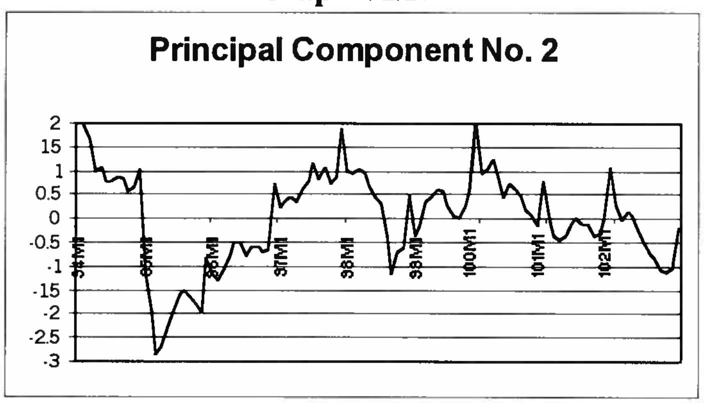
Component	Eigenvalue	Cumulative R-Squared
PC1	5.0455	0.5046
PC2	2.3286	0.7374
PC3	1.1352	0.8509
PC4	0.8253	0.9335
PC5	0.2518	0.9586
PC6	0.2236	0.9810
PC7	0.1472	0.9957
PC8	0.0410	0.9998
PC9	0.0011	0.9999
PC10	0.0007	1.0000

Note: The Eigenvalues show the largest Characteristic Root of successive correlation matrices.

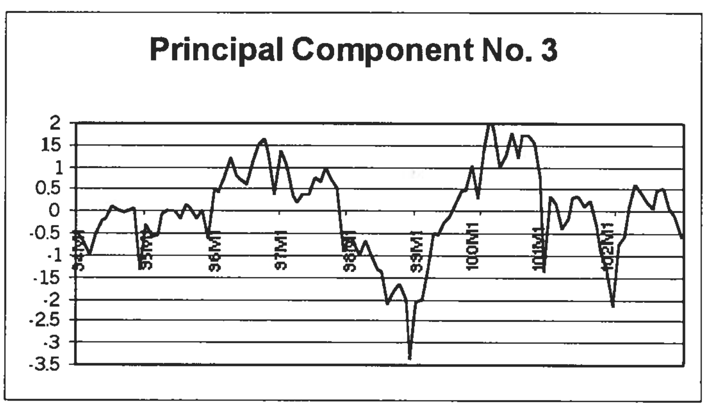
Graph VI.12



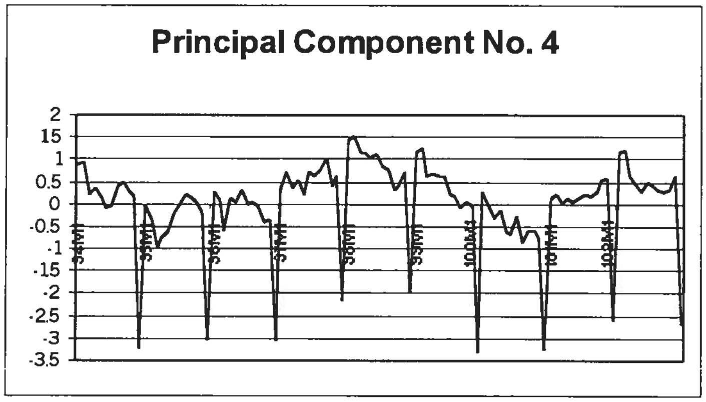
Graph VI.13



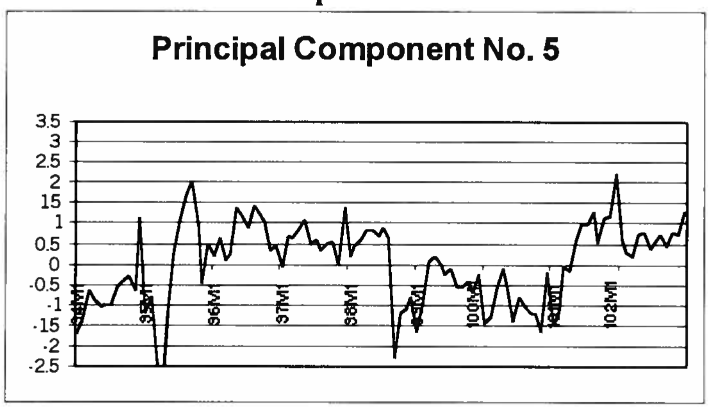
Graph VI.14



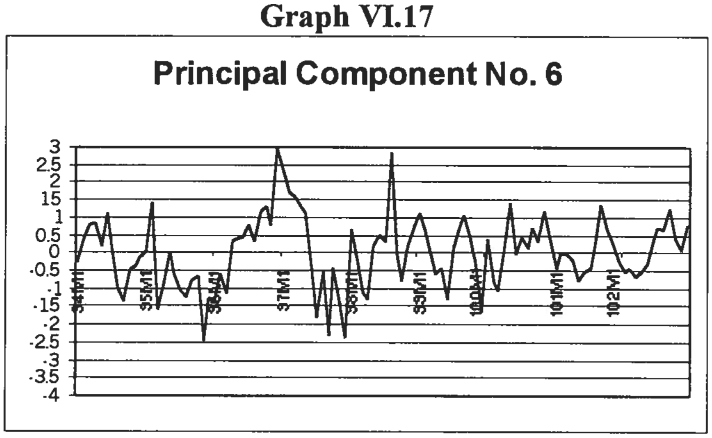
Graph VI.15



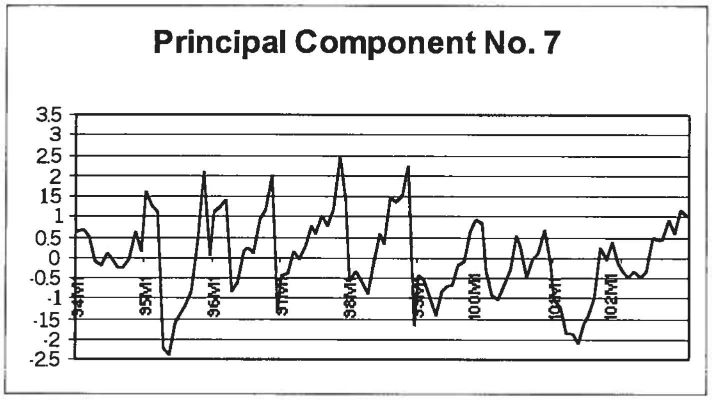
Graph VI.16



Graph VI.17



Graph VI.18


Principal Component No. 7
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
94M1
95M1
96M1
97M1
98M1
99M1
100M1
101M1
102M1

VI.4.- THE EQUATION FOR THE GDP PRICE DEFLATOR

In the previous section, we determined that the first seven principal components explain 99.6% of the total variation of the set of detrended price variables. Thus, we use the first seven principal components in the regression with the GDP price deflator as the dependent variable. In this way, the GDP deflator is a function of the first seven mutually uncorrelated sources of variation of the set of detrended strategic prices.

Given that the GDP deflator is a quarterly series, then we form the 3-month average of each principal component to get the corresponding quarterly series. The regression covers the period from 1994:Q1 to 2002:Q4, and it was estimated using OLS[31/]. The series of the GDP price deflator was also detrended (PDGDPD), and we use a Dummy variable in the regression to account for the international financial crisis in Asia, Latin America, and Russia.

$$
\begin{aligned}
PDGDPD = & \underset{(225.9)}{1.00295} + \underset{(52.9)}{0.10413}\, PC1 + \underset{(4.8)}{0.00947}\, PC2 + \underset{(5.4)}{0.01068}\, PC3 - \underset{(1.0)}{0.0028}\, PC4 \\
& + \underset{(3.4)}{0.00728}\, PC5 + \underset{(1.6)}{0.00343}\, PC6 - \underset{(2.8)}{0.00577}\, PC7 + \underset{(0.7)}{0.00361}\, DUM9699
\end{aligned}
$$

$$R^2 = 0.99 \qquad D.W. = 2.02 \qquad F_{8,27} = 518.6$$

The regression fit is tight, with an R-Squared of 0.99. All the principal components (PCs) are significant in explaining the variation of the detrended GDP deflator, with the sole exception of component four, according to the t-statistics. The estimated equation confirms that the first seven principal components account for most of the variation of the GDP price deflator in the sample period.

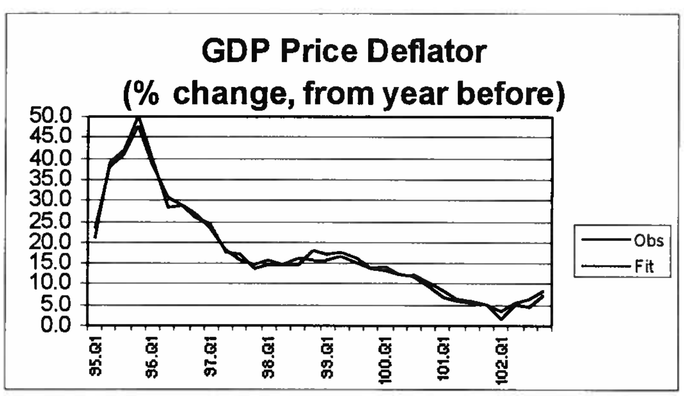
The regression approximately reproduces the historical values of the quarterly GDP deflator series, as shown in Table VI.4. This table contains the observed and fitted values given by the equation. Graph VI.19 shows how closely the regression fits the quarterly percentage change of the GDP price deflator. Both table and graph show the original series of the GDP deflator, not the detrended one.

[31 /] The numbers in parentheses are the t-statistics.

TABLE VI.4
GDP Price Deflator
(% change, from year before)

Date	Observed	Fitted
95.Q1	20.7	23.4
95.Q2	38.7	38.1
95.Q3	41.8	40.7
95.Q4	50.0	47.4
96.Q1	40.0	38.5
96.Q2	28.4	30.5
96.Q3	28.6	28.4
96.Q4	26.8	25.7
97.Q1	23.5	24.3
97.Q2	18.1	17.6
97.Q3	15.6	17.0
97.Q4	14.6	13.7
98.Q1	15.4	14.4
98.Q2	14.8	14.5
98.Q3	16.1	14.7
98.Q4	15.5	18.2
99.Q1	15.8	16.9
99.Q2	16.6	17.3
99.Q3	14.9	16.1
99.Q4	13.5	13.4
100.Q1	14.3	13.3
100.Q2	12.2	12.1
100.Q3	12.1	11.6
100.Q4	10.4	9.3
101.Q1	8.1	6.6
101.Q2	6.5	6.0
101.Q3	6.1	5.2
101.Q4	5.1	4.7
102.Q1	1.6	3.5
102.Q2	4.8	5.5
102.Q3	4.4	6.4
102.Q4	7.4	8.1

Graph VI.19



VI.5.- THE ROLE OF FUTURES, FORWARDS AND EXPECTATIONS

To forecast the GDP prices for the whole year 2003, we use the previous equation of the GDP deflator as a function of the principal components. In order to do this, we require the future values of the set of strategic prices to get forecasts of the principal components, themselves.

Within the set of monthly strategic prices, we can detect the influence of variables that cannot be easily forecasted by ARIMA equations because of the high volatility of expectations, the existence of controlled prices, or simply because some prices are largely determined by events in world markets. This subset of variables requires special treatment that should include expectations, futures and forwards in their forecasts.

We use two methodologies in forecasting the set of monthly strategic prices. The first is a subset of ARIMA equations for the following variables: producer price, money supply, stock exchange index, minimum wage, import price, and industrial wages. The second is the use of futures prices and forward rates as well as expectations for variables like: oil price, exchange rate, interest rate, and consumer price. The improvement of the monthly forecasts is significant with the introduction of changes in expectations into the future values of the second subset of variables.

Expectations are highly sensitive in an economy that has been hit by consecutive financial and economic crises. The memory of dramatic crisis episodes in developing countries makes agent and market expectations immediately responsive to news, rumors, and political and social events, and this in turn influences the expected values of key economic variables. In addition, in a world of highly developed technology in communication and information, news items are instantly transmitted to the farthest corners of the earth. So, the contagion effects on financial markets are instantaneous around the world, making expectations more sensitive to changes in news and political events [32/].

The day-to-day fluctuations in expectations, in response to news, can provoke unusual movements in prices and rates in an economy. News is an important component of the process of formation of expectations regarding the future values of key economic prices. Given that news changes are sudden and unanticipated, the changes in prices can also be dramatic from day-to-day.

In this way, news, political shakeups, social disruptions, and rumors, can give rise to substantial actions in exchange markets, inflation expectations and even in forward and futures prices. Actually, there is also a feedback among markets; changes in expectations of future inflation can be reflected immediately in the foreign exchange market and in

[32/] More details about the effects of News on exchange markets can be found in Rivera-Batiz (1994), pp.567-569, and in Tivegna (2000) pp. 1-44.

domestic interest rates as well[33/]. All this has to do with the process of expectation formation in which agents try to incorporate the day-to-day information and hints that may provide insights about the future level of relevant variables in the economy.

This qualitative information is difficult to incorporate in a mechanical ARIMA equation. That is why we resort to the futures and forward markets and agent expectations to get the corresponding forecasts, which incorporate additional relevant information affecting the future values of key prices. But also, the inclusion of market expectations in our model allows us to capture the effects of recent developments on the future performance of the economy. Given that market expectations will reflect the impact of recent shocks, our model can be used as a simulation tool without making assumptions about the future. That is, using market expectations, the model can simulate the future of the economy without subjective human intervention.

In the case of the exchange rate, we use the forward rates traded at the Chicago Mercantile Exchange (CMEX), which is mostly based on the "covered interest parity rule" [34/]. As it is well known, the forward exchange rate tends to reflect the spot exchange rate that most investors anticipate will prevail at the point of maturity of the contract. In this sense, the forward rate is a good estimate of the market expectations.

For the case of interest rates and inflation at the consumer level, we take the agents' expectations collected by the survey of the Bank of Mexico. The survey-based-approach tries to capture the expectations of experts involved in financial markets and economic analysis firms through the collection of their forecasts. The experts' forecasts are collected monthly by questionnaire and reported as averages. These forecasts are assumed to show the average market expectation of future values for inflation and interest rates.

Finally, for the case of oil prices, we collect futures prices for light crude oil traded daily at the New York Mercantile Exchange (NYMEX), and then get the one-month average for the year ahead. The crude oil quotation taken as a reference for the Mexican mix is the West Texas Intermediate (WTI), which maintains an almost constant difference with the Mexican mix. In this case, the oil price for Mexico is given by the international market, and it is quoted for future delivery at the NYMEX. It should be stressed that the future time horizon for these four variables is simply one year.

Through these four variables (inflation, interest rate, oil price and exchange rate), we incorporate expectations, futures, and forwards into our forecasts of the GDP price deflator. Historical data for futures prices and expectations are not available for long periods. Therefore, we use futures, forwards and expectations as monthly forecasts only.

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33 / A technical example on how exchange rate is sensitive to expectations is found in Obstfeld and Rogoff (1996), pp. 529-530.

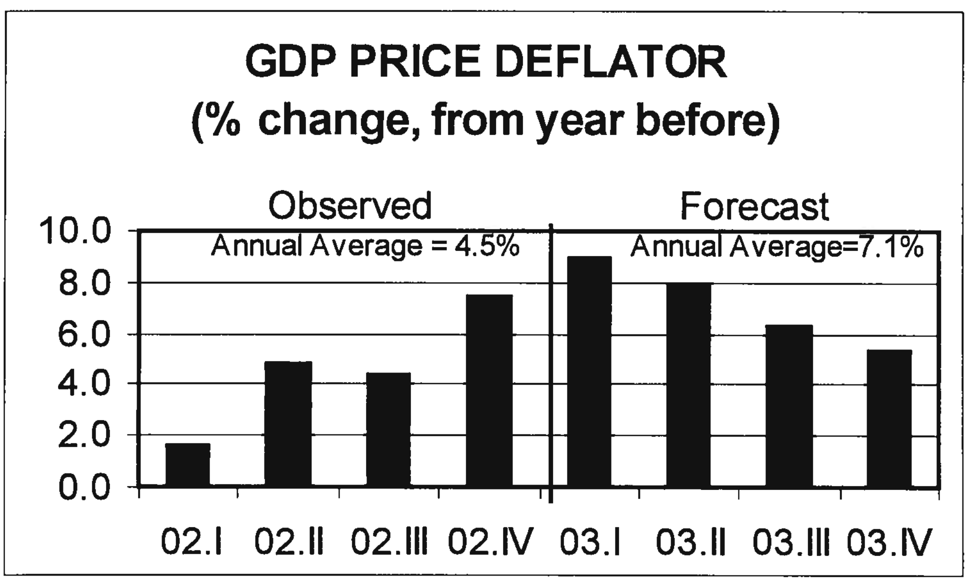
34 / More explanations about the Parity Rule can be found in Rivera-Batiz (1994), pp. 129-131, and Obstfeld and Rogoff (1996), pp. 526-530.

In Table VI.5 and in Graph VI.20 below, we present the forecast of the quarterly GDP price deflator for the year 2003, in which we use a combination of both, ARIMA equations and futures, forwards prices, and expectations to get the monthly forecasts of the set of strategic prices. We can see that the 2003 forecast tends to be higher not only than the last year's inflation but also than the official target of 3.0%. This is due, in a great extent, to the deterioration of expectations at the beginning of this year.

TABLE VI.5
GDP Price Deflator Forecast
(% change, year before)

Date	PDGDP (%)	
02.I	1.6	Observed
02.II	4.8	
02.III	4.4	
02.IV	7.4	
Annual	4.5	
03.I	8.9	Forecast
03.II	7.9	
03.III	6.3	
03.IV	5.3	
Annual	7.1	

Graph VI.20



Note: The quarterly forecast for the GDP deflator was obtained using the monthly forecast of strategic indicators from ARIMA equations, futures prices, forwards and expectations.

VI.6 .- REFERENCES

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CHAPTER VII

RESULTS AND CONCLUSION

Having constructed models for three different approaches (Principal Components of major indicators, Production by sectors, and Expenditure by components) to estimate the quarterly GDP and its price deflator, in anticipation of the official release, we face the issue of using these different sources of information. These three methods for computing the GDP are mainly independent of each other. They use different sources of information, which generate independent errors. Our final estimated result for the quarterly GDP is specified as a simple average of the three independent estimates. This should allow us to reduce the variability of prediction error.

To get the GDP forecast with the three models; we need to get the future values of all the monthly indicators involved in each model. This is done by using ARIMA equations on one hand, and futures, forwards and expectations on the other hand. Then, we form the 3-month averages and use them as inputs in each of the three different models.

The exercise we perform in this note aims to estimate the GDP for the first quarter of year 2003, whose official release we already know[35/]. We construct two estimates for the first quarter. The first uses observed monthly data up to the first month of the quarter. The second uses observed data up to the second month of the quarter. These two estimates will allow us to see how well the forecast approaches the official figure, insofar as we include more relevant monthly information in each step.

The official figure for the quarterly real GDP is released six weeks after the end of each quarter. The official release for the GDP Price Deflator is given seven weeks after the end of each quarter.

We note that the results obtained in the following two exercises are different from those obtained in previous chapters because in these two exercises we are using additional monthly information to forecast the first quarter GDP. It is also important to mention that these exercises do include information regarding the expectations that agents and markets had at the beginning of the year (2003).

[35 /] This release is subject to possible future revision by government.

EXERCISE 1

The first exercise computes the GDP for the first quarter of 2003 including observed monthly information through January 2003, which is mostly available by mid-March. In other words, we get the first estimate of GDP eight weeks before the official release and include information for the first month of the quarter.

For the case of the Price Deflator, by mid-March, we already have most of the indicators for February and just a few for January, which is expected to improve the estimate of prices. The first estimate of the GDP Price Deflator for the first quarter is made nine weeks before the official release.

Table VII.1 below summarizes the estimation of the Real GDP and its Price Deflator for the first quarter with the three methods, and uses monthly information through January 2003.

TABLE VII.1

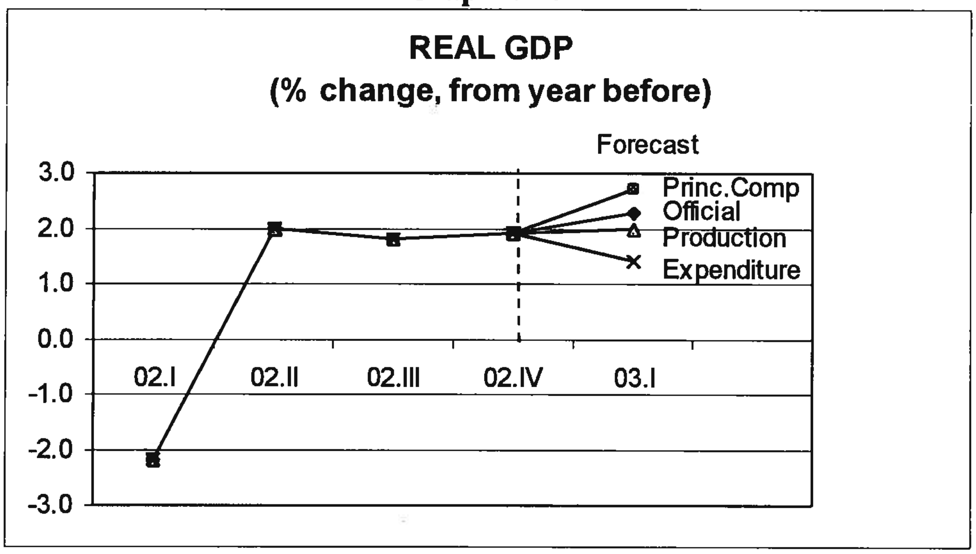
Exercise 1: Quarterly Forecast 2003:Q1

	2002.I	2002.II	2002.III	2002.IV	2003.I
	OBSERVED				FORECAST
REAL GDP (billion 1993 pesos)					
By Principal Components	1562.5	1647.3	1581.8	1655.0	1604.8
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.7
By Production Side	1562.5	1647.3	1581.8	1655.0	1594.0
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.0
By Expenditure Side	1562.5	1647.3	1581.8	1655.0	1584.7
Annual Rate (%)	-2.2	2.0	1.8	1.9	1.4
Average Real GDP	1562.5	1647.3	1581.8	1655.0	1594.5
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.0
Official Data	1562.5	1647.3	1581.8	1655.0	1597.9
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.3
GDP PRICE DEFLATOR (1993=100)					
GDP Deflator	371.1	376.8	381.6	397.0	405.2
Annual Rate (%)	1.6	4.8	4.4	7.4	9.2
Official Data	371.1	376.8	381.6	397.0	405.9
Annual Rate (%)	1.6	4.8	4.4	7.4	9.4

Note.- Shaded figures are the official release.

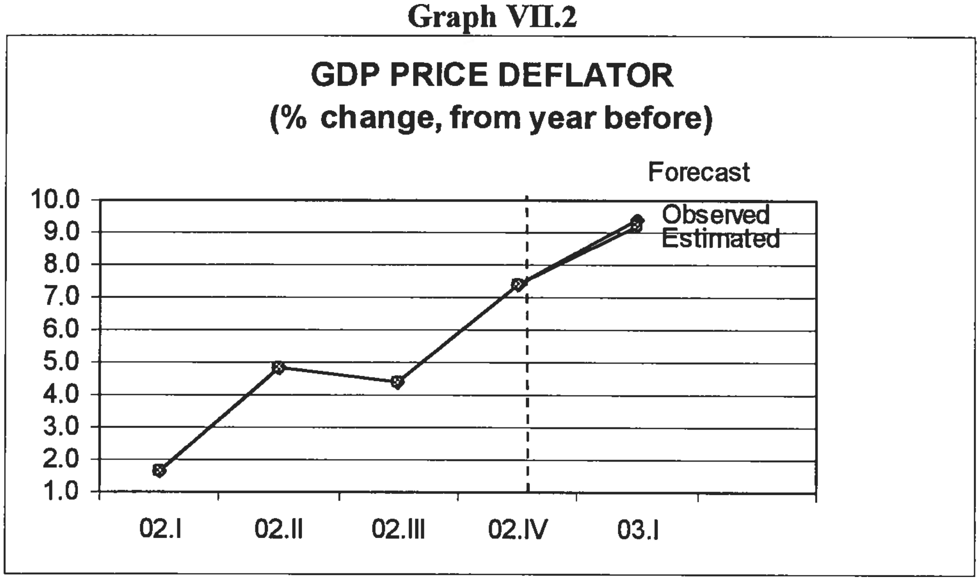
While the official figure for the first quarter growth rate of GDP is 2.3%, the average estimate from the model is as high as 2.0%. The final GDP estimate is obtained as a simple average of the three estimates given by the three different methods. The GDP estimated by the model is thus 0.3 percentage points lower than the official figure. The estimate from the Production side is the closest to the observed data, as we can see in the following graph.

Graph VII.1



In the case of the GDP deflator, the model estimate of the inflation rate is 9.2% for the first quarter, while the observed figure is 9.4%. In this case, the model also underestimates the official figure, as we see in Graph VII.2.

Graph VII.2



EXERCISE 2

The second exercise estimates the GDP for the same first quarter (2003) using observed information through February this year, which is available by mid-April. In other words, our second estimate of GDP is obtained four weeks before the official release and includes information for the second month of the quarter.

In the case of the GDP Deflator, by mid-April, we already have information through March for most prices. Therefore, our estimate is expected to be closer to the official figure. This second exercise estimate for the GDP Deflator is obtained five weeks before the official release.

Table VII.2 summarizes the results of our second estimation of GDP for the first quarter 2003, using observed information through February, and its Price Deflator using monthly information through March this year.

TABLE VII.2

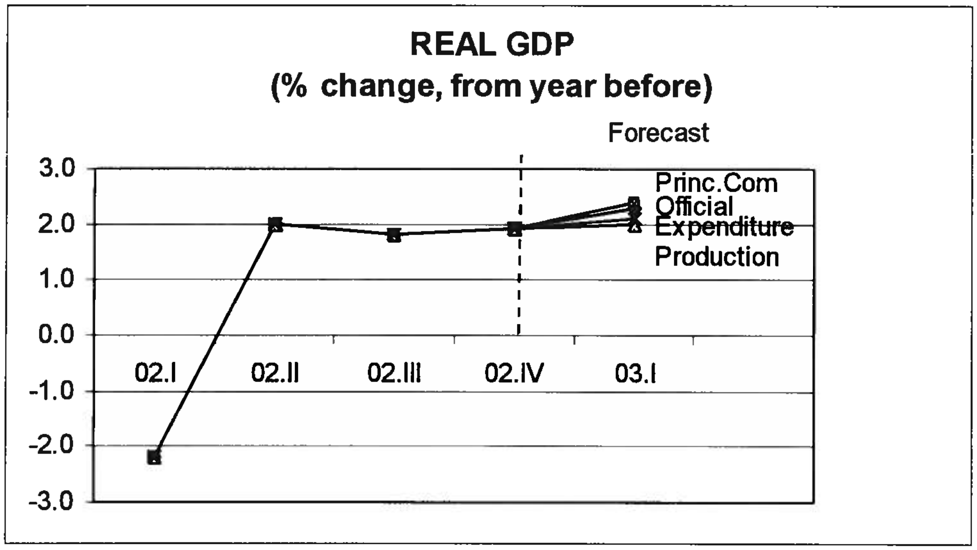
Exercise 2: Quarterly Forecast 2003:Q1

	2002.I	2002.II	2002.III	2002.IV	2003.I
	OBSERVED				FORECAST
REAL GDP (billion 1993 pesos)					
By Principal Components	1562.5	1647.3	1581.8	1655.0	1599.3
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.4
By Production Side	1562.5	1647.3	1581.8	1655.0	1593.3
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.0
By Expenditure Side	1562.5	1647.3	1581.8	1655.0	1594.8
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.1
Average Real GDP	1562.5	1647.3	1581.8	1655.0	1595.8
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.1
Official Data	1562.5	1647.3	1581.8	1655.0	1597.9
Annual Rate (%)	-2.2	2.0	1.8	1.9	2.3
GDP PRICE DEFLATOR (1993=100)					
GDP Deflator	371.1	376.8	381.6	397.0	406.4
Annual Rate (%)	1.6	4.8	4.4	7.4	9.5
Official Data	371.1	376.8	381.6	397.0	405.9
Annual Rate (%)	1.6	4.8	4.4	7.4	9.4

Note.- Shaded figures are the official release.

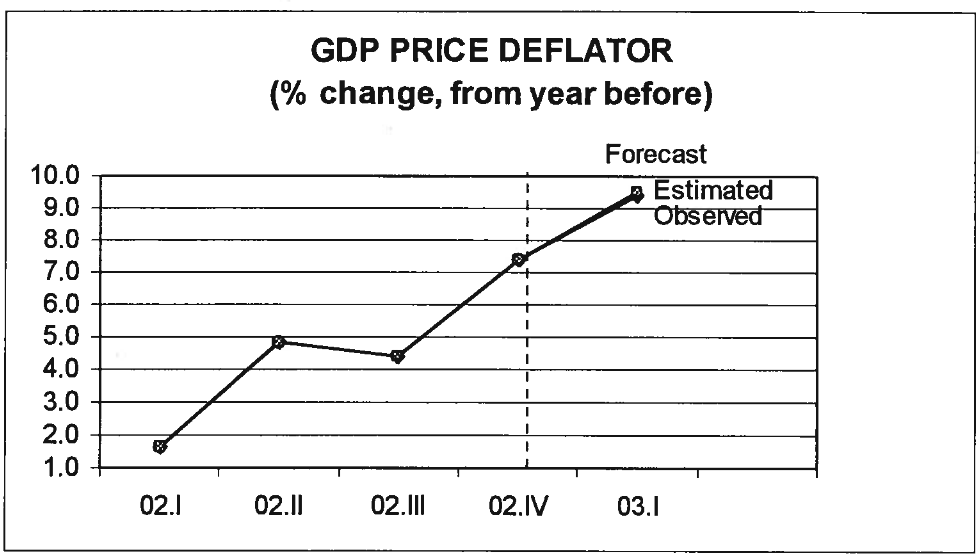
Now, we can see that the average estimate of GDP approaches the official figure of 2.3% more closely. The average estimate is 2.1%, and benefits by using information for the second month of the first quarter. In this case, the principal components model generates the closest estimate for the quarterly GDP. The graph below shows the three estimates around the official figure.

Graph VII.3



In the case of the Price Deflator, given that we have included most of the information through the third month of the quarter, the inflation estimate is much closer to the observed figure. Our estimate is 9.5%, just a little above the observed figure of 9.4%, as we can see in Graph VII.4 below.

Graph VII.4



CONCLUSION

As a general conclusion, we say that it is possible to get reasonably good estimates of the quarterly GDP and its Price Deflator in anticipation of the official release, if we use the high-frequency information closely related to them. The anticipated GDP growth rate and Inflation forecasts get closer to the observed figure, insofar as we include more relevant monthly information for production activity and prices as they are reported monthly. In other words, the model is better in anticipating the quarterly GDP just four weeks prior to the official release. The inclusion of market expectations for relevant prices, certainly improves the quality of our forecast for the GDP Price Deflator. But also, market expectations and futures prices allow us to incorporate the effects of news and recent developments on the future performance of the economy, such that we could simulate the impact of these events on the whole economy.

With this high-frequency forecasting model for the Mexican economy, we aim to provide not only the anticipation of the current quarterly GDP, but also the probable trend of the economy during the year, which could also be used to improve the predictive accuracy of structural models.

We illustrate how it pays to stay in touch with the flow of fresh reports on the economy and improve forecasting ability as the information flow progresses. This is not surprising, but what we are trying to do is to judge how much new and useful information can be extracted month-by-month. In the future, we can hope to benefit from the information flow, week-by-week, day-by-day or in the case of financial and commodity market information in real time, provided that we are successful in filtering out "noise".

There are a few lines of further research that might improve the accuracy of this model. One is the inclusion of new leading indicators, most of them not publicly available at the present, such as housing starts, factory orders, auto sales, consumer confidence, and corporate profits. Another line of research to consider is the inclusion of monthly information for changes in inventories, which could be collected by surveys. These monthly data for inventories could improve the demand side forecast, where its equation has not a very good fit given its residual computation from national accounts. Finally, the availability of longer historical series for futures prices, forwards and expectations might be an interesting exercise to perform in order to improve the high frequency forecasts. Market expectations could also be used as the instrumental variables to perform simulations of policy-induced changes.

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