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ON THE USE OF HIGH-FREQUENCY ECONOMIC INFORMATION TO ANTICIPATE THE CURRENT QUARTER GDP: A STUDY CASE FOR MEXICO

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ABSTRACT

A method for anticipating quarterly estimates of 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, the model predicts the quarterly GDP based on three different approaches: production side, expenditure side, and principal components extracted from a set of strategic indicators. This model, considered a purely econometric system with no personal data adjustment, allows us to forecast the current quarter GDP and its price deflator using monthly information on economic activity, financial markets, futures prices and forwards, and expectations.

Keywords: GDP; Econometric system; Mexico; Forecasting model

I.- INTRODUCTION

The high-frequency forecasting methodology is based on the technique of the Current Quarter Model for the U.S. economy developed at the University of Pennsylvania. In applying this methodology to the case of Mexico, we have included market expectations and futures prices to incorporate the effects of news and recent

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developments on the future performance of the economy. In addition, we can also use market expectations as the instrumental variables to perform simulations of policy-induced changes.

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. 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. High-frequency indicators can be used to establish initial conditions for the structural model without any subjective personal judgment.

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 the 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). The third approach is based on the Principal Components methodology, and uses a set of strategic monthly indicators, closely related to real GDP, to estimate their main independent sources of variation. Future values for the monthly indicators are obtained from ARIMA equations.

We thus have three different estimates of the quarterly GDP obtained by 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. 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 model for the GDP price deflator also includes futures prices, forward rates and market expectations in order to capture the changes in news, rumors and political and social events that affect the expected values of key prices. This is particularly relevant for a developing country, like Mexico, in which agent and market expectations are more sensitive, given the memory of dramatic crisis episodes in the past.

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.

II.- THE HIGH-FREQUENCY FORECASTING MODEL FOR REAL GDP

The High-Frequency Forecasting Model to anticipate the quarterly GDP is based on three different approaches: production side, expenditure side, and principal components of strategic indicators.

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 Principal Components methodology uses a set of strategic monthly indicators, closely related to real GDP, to extract the main sources of variation and correlate them to GDP. The Principal Components are 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.

These three approaches will give us three different estimates of the quarterly GDP, computed independently. The anticipated current quarter GDP is the average of the three independent estimates obtained.

1.- The Principal Components Model

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. 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 variables exhibiting maximal variance[1/]. 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, 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, and 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.

a).- Selecting the Strategic Indicators

[1/] An early use of principal components in econometrics was done by Stone (1947). He used the NIPA

Empirically, 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 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. The fifteen monthly indicators are: Manufacturing Production Index (IMI), Construction Industry Index (ICI), Industrial Production Index (IPI), Gross Fixed Investment Index (GFII), Real Wholesale Sales Index (WSI), Real Retail Sales Index (RSI), Index of Man-Hours Worked in Manufacturing (HOUR), Index of Real Average Wages in Manufacturing (WAR), Employment Rate (EMR%), Maquiladora Real Exports (MAQR), Volume of Crude Oil Exports (EXOV), Real Money Supply: M1 (MSR), Real Interest Rate (IRR), Real Exchange Rate (ERR), Real Tourism Balance (TOUR).

Given that the monthly series show seasonal and trend components, we proceed to adjust them in order to remove those components. This filtering process will allow us to work with just the residuals that represent the variation of each indicator which is not explained neither by seasonality nor by trend.

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frame to compute principal components from interdependent blocks, but not for forecasting purposes.

b).- Estimation of the Principal Components

In a set of strategic indicators, the answer to the question of “how many independent sources of variation are there?” is given by the principal components method[2/]. In other words, we can say that in the regression of Y on a number of independent variables X_1, X_2, …., X_m, we wish to find some linear functions (Z’s) among the X’s which in some sense capture most of their variablility[3/]. The Z’s are the principal components or the linear combinations of the X’s with the highest variance.

In Table 1, we present the Eigenvalues for the fifteen principal components (PC’s), 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 1. 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 almost 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.

[2/] Maddala (1992).
[3/] Dhrymes (1970).

TABLE 1
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

Note: The period covered is from Jan 1994-Dec 2003.
The Eigenvalues show the largest Characteristic Root of successive correlation matrices.

c).- The Equation for Real GDP

From the previous chart (Table 1), the Cumulative R-Squared says 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.

We compute quarterly data for the principal components by averaging each monthly component per quarter. The regression covers the period from the first quarter of 1994 to the fourth quarter of 2003, and is estimated using OLS. The GDP series is also adjusted by seasonality and trend (GDPD).

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

$$+ 0.00125\ PC5 - 0.00285\ PC6 - 0.00020\ PC7 + 0.00495\ PC8$$

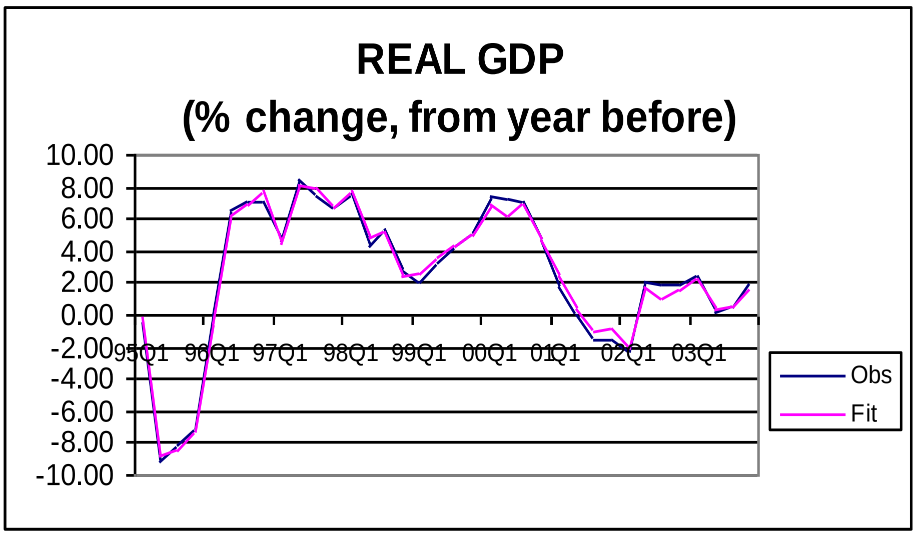
(1.2) (3.0) (0.2) (3.9)

$R^2 = 0.99$ D.W. = 1.88 $F_{9,30} = 216.3$

We retain components 2, 5, and 7 in the equation because they may prove to be statistically significant with the passage of time. The R-Squared shows that the variation in all eight principal components accounts for 99% of the variation of the real 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 of the sample (2003). The Graph 1 below shows the observed (obs) and fitted (fit) GDP growth rates.

Graph 1



2.- The Production Side Model

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 general 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 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 also 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.

a).- The Equation for Total GDP

The General Economic Indicator (GEI) is a compound index constructed by INEGI, on a monthly basis, and it incorporates information on output of the different activities from the main economic sectors: agriculture, industry and services. The index covers almost 85% of the total production activity in the economy. The computation of the monthly GEI follows the same methodology of the National Accounts for computing the quarterly GDP. Therefore, the monthly GEI can be taken as a short-term indicator of total economic activity.

Using information from the first quarter of 1993 to the fourth quarter of year 2003, we calculated the regression between the annual changes of the quarterly GDP (GDPQ%) and the quarterly GEI (GEI%), and we obtained the following results[4/].

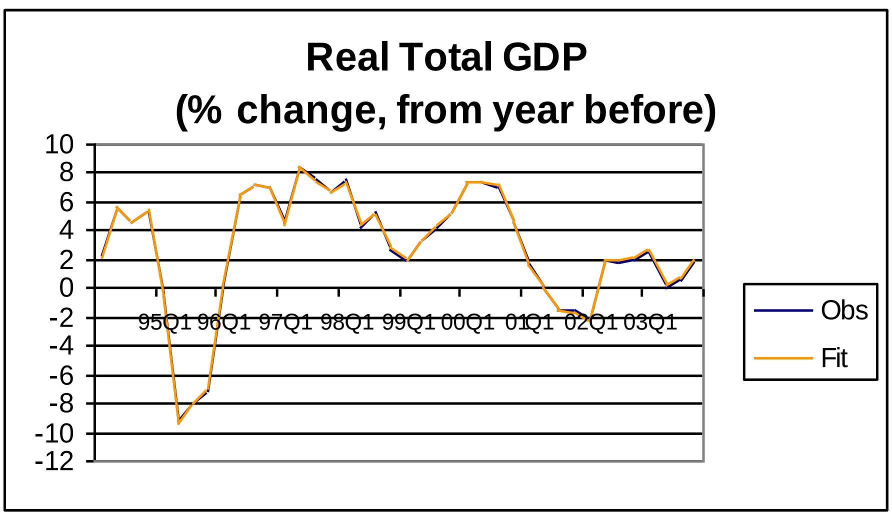
$$GDPQ\% = -0.01486 + 1.00426 * GEI\%$$
$$(0.5) \qquad (187.6)$$

$$R^2 = 0.999 \qquad D.W. = 2.87 \qquad F_{1,38} = 35199$$

As we can see, the GEI is highly significant in explaining the GDP behavior. 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.

The equation closely reproduces the annual growth rate of the quarterly GDP as a function of the corresponding growth rate of the quarterly GEI, as shown by the graph.

Graph 2



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

b).- The Sectoral Distribution of GDP

Two of the three sectoral components of GDP are directly estimated as functions of the general index of economic activity (primary and tertiary sectors), while the secondary sector equation is taken from the principal components model that we already estimated: the industrial production index (percentage change).

The equations for the primary and tertiary sectors were estimated in annual growth rates (%) as functions of the general indicator, and some lags in the case of the primary sector. The sample period used is the same as in the total GDP (1993:Q1-2003:Q4). GDPQ1 stands for the primary sector GDP, and GDPQ3 is the tertiary sector GDP.

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

$$R^2 = 0.98 \qquad D.W.= 1.77 \qquad F_{2,36} = 647.5$$

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

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

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

$$R^2 = 0.42 \qquad D.W.= 1.96 \qquad F_{6,29} = 2.98$$

The fit of the equation for the tertiary sector is good enough. The poor fit for the primary sector equation is explained by the lack of information for primary activities on a monthly basis, by the irregular harvest calendar for the year, and by the fact that it counts for only 5% of the total GDP. However, this is the best estimation we could get.

As we already mentioned, we do not need to estimate a regression for the secondary sector, because we already have an equation for the industrial sector in the principal components model.

At this point we have generated the model for the Production side, including the total GDP, 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.

3.- The Expenditure Side Model

The Expenditure Side Model computes the total GDP through the estimation of the demand components using monthly indicators closely related to them. This model follows the same methodology of the National Accounts to compute the GDP by the demand side. We try to collect similar monthly indicators to establish the linkage between them and the quarterly demand components. Once the demand components are estimated, we sum them up to obtain the total GDP.

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

a).- The Conceptual Framework

From the basic macroeconomic identity, the GDP or total output is equal to the total absorption of the economy, or the total expenditure of all residents within the economy[5/].

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

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).

Private Consumption Expenditure is defined as the value of the purchases of goods and services of resident families and private institutions in the domestic and foreign markets. Government Consumption Expenditure includes the current final government purchases (federal, state and local) of goods and services, plus wages and salaries of government employees. Gross Fixed Investment represents the purchases of capital goods of the private and public sectors to increase their capital stocks. Exports of Goods and Services consist of the country's sales of goods and services to the rest of the world, including gold and silver. Imports of Goods and Services represent the purchases of imported goods and services such as insurance and freight. Finally, Inventory Change 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.

b).- Estimation of the Demand Components

[5/] See Dornbusch and Fischer (1990), pp 33-58, and Rivera-Batiz (1994), pp 265-268.

For the estimation of each demand component we try to use the same or similar monthly series that the statisticians 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[6/].

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 (%)[7/]. Suppose that I_{it} represents retail sales and N_{it} is private consumption, then if the value of the coefficients in the regression were: $\alpha_i = 0$, and $\beta_i = 1$, we can say that the percentage change in private consumption should be well estimated by the percentage change in retail sales.

Private Consumption Expenditure

Private spending on consumption can be quite well explained by retail sales. The index of retail sales is published monthly, and its 3-month percentage change (RSI%) shows a close correlation with the percentage change of quarterly private consumption (Cp%). The data sample is taken from the first quarter of 1994 to the last quarter of the year 2003.

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

[7/] Klein and Park (1993) use the bridge equation in log-log form and compute quarter-over-quarter

$$Cp\% = 2.06952 + 0.51714\ RSI\%$$
$$\quad (5.0) \qquad (11.4)$$

$$R^2 = 0.92 \qquad D.W. = 2.1 \qquad F_{2,36} = 186.8$$

The regression performance shows that the historical data can be explained fairly well, as it is shown by the R-Squared statistic.

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[8/]. 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 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.

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

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

$$R^2 = 0.94 \qquad D.W. = 1.8 \qquad F_{2,37} = 249.8.$$

changes, rather than quarter-over-same quarter a-year-ago for individual variables.

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

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 the monthly indicator for fixed investment represents 100% of the quarterly gross fixed investment from National Accounts. Therefore, the estimated equation of the percentage change of the Gross Fixed Investment (I%) as a function of the 3-month average of the monthly indicator of Fixed Investment (GFII%) gives a coefficient of almost 1 for the slope, and an R-Squared of 1.

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

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

Net Exports of Good and services

In 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. We found that the dollar value of exports and imports (EXP and IMP) are the best determinants of the corresponding demand components in real terms (X and M), given that the effects of prices and exchange rates mutually cancel deviations. The equations were estimated in percentage changes (%).

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

$$R^2 = 0.91 \qquad D.W. = 1.92 \qquad F_{3,35} = 99.1$$

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

$$R^2 = 0.97 \qquad D.W. = 1.63 \qquad F_{3,35} = 330.9$$

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. 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.

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

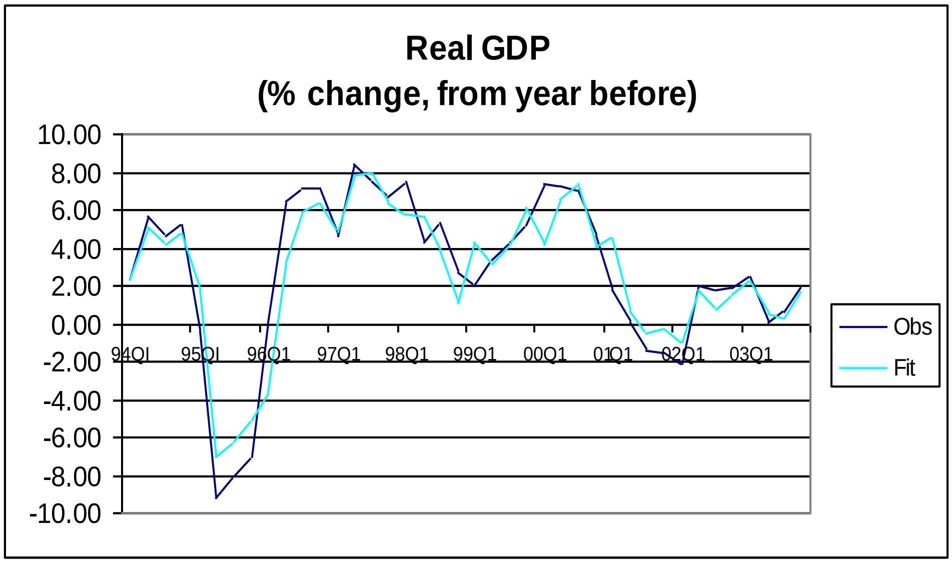
$$+ 36463.0\ DUM9699$$
$$(2.7)$$

$$R^2 = 0.77 \qquad D.W. = 2.0 \qquad F_{6,33} = 16.1$$

Total Real 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 3 below.

Graph 3



III.- THE PRINCIPAL COMPONENTS MODEL FOR THE GDP PRICE DEFLATOR

Using the monthly flow of information for strategic prices, 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. As in the case of the quarterly real GDP, we can expect to anticipate in advance the short-term movements of the GDP prices.

Certainly, daily news, rumors, and political and social events are immediately reflected in futures prices, forwards and expectations, which in turn influence the expected values of key prices. Market expectations also allow us to simulate the future impact of recent developments in the economy without making subjective assumptions.

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.

1.- Selecting the Strategic Price Indicators

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.

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. Those series are: Consumer Price Index (CPI), Producer Price Index (PPI), Nominal Exchange Rate (ERN), Nominal Interest Rate (IRN), Nominal Money Supply (MSN), Oil Price (OPN), Stock Exchange Index (SEI), Nominal Minimum Wage (MWI), Import Price Index (IMPP), Average Industrial Wages (WRM).

The monthly series do not show seasonal components, but we can distinguish a strong increasing trend during the sample period (1980-2003).

2.- Estimation of the principal Components

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 only remove the trend from each series, given that they do not show the seasonal component. Having the series detrended, we proceed to compute the principal components or the mutually independent linear combinations of strategic prices, which have the highest variance.

In Table 2 we present the Eigenvalues of the principal components, and the cumulative R-Squared. We can 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%.

TABLE 2

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 period covered is from Jan 1994 -Dec 2003.
The Eigenvalues show the largest Characteristic Root of successive correlation matrices.

3.- The Equation for the GDP Price Deflator

We use the first seven principal components in the regression with the GDP price deflator as the dependent variable, given that they explain 99.6% of the total variation of the set of variables. 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.

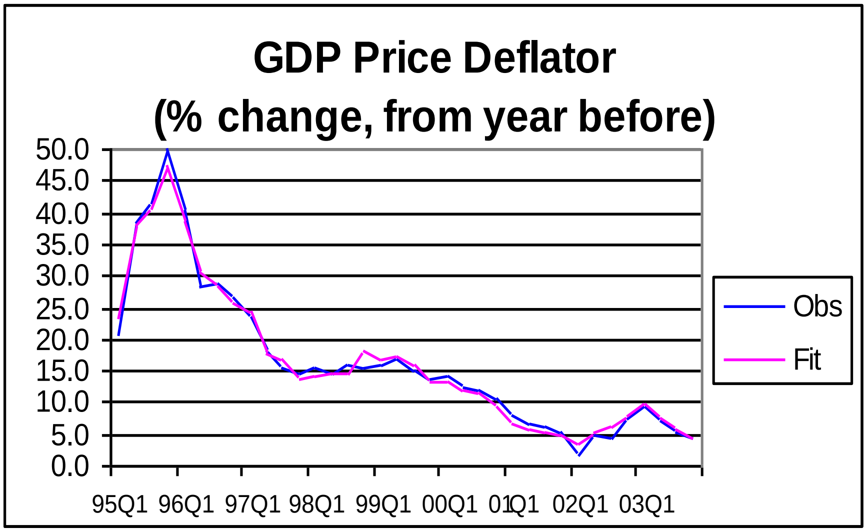
We form the 3-month average of each principal component (PC) to get quarterly series to be correlated with the quarterly GDP. The series of the GDP price deflator was also detrended (PDGDPD), and we use a Dummy variable in the regression to account for the international financial crisis in Asia, Latin America, and Russia.

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

$$R^2 = 0.99 \qquad D.W. = 2.02 \qquad F_{8,31} = 518.6$$

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 (1994:Q1-2003:Q4). The regression approximately reproduces the historical values of the quarterly GDP deflator series.

Graph 4



4.- Futures, Forwards and Expectations as determinants in the Forecast of Key Prices

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 [9/].

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 domestic interest rates as well[10/]. All this has to do with the process of expectation

[9/] 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.

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

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.

We incorporate expectations, futures, and forwards into our forecasts of the GDP price deflator through four variables: inflation, interest rate, oil price and exchange rate. Historical data for futures prices and expectations are not available for long periods. Therefore, we use futures, forwards and expectations as monthly forecasts only. In the case of the exchange rate, we use the forward rates traded at the Chicago Mercantile Exchange (CMEX); 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; and finally, for the case of oil prices, we collect futures prices for light crude oil traded daily at the New York Mercantile Exchange (NYMEX).

At the end, 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 to anticipate the GDP deflator well in advance to the official release.

IV.- FORECAST AND CONCLUSION

We have constructed a model to estimate the quarterly GDP and its price deflator, in anticipation of the official release. While the final estimate of the real GDP is obtained as the simple average of three independent methods (principal components, production side, and expenditure side), the estimate for the GDP deflator is just the one obtained from the principal components model.

In order to test the model, we perform two forecasting exercises: last quarter of 2003 and first quarter of 2004, whose official releases are already known. The purpose of these exercises is to see how well the forecast approaches the official figures, insofar as we include more relevant monthly information. We get two estimates for each quarter, the first is obtained eight weeks before the official release, and the second is obtained four weeks before.

The future values of the monthly indicators involved in each model are obtained by using ARIMA equations and by using futures, forwards and expectations in the case of relevant prices.

1.- The High-Frequency Forecasts

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.

The first exercise tries to get two estimates of the real GDP and its price deflator for the last quarter of 2003. The first estimate is obtained eight weeks before the official release, and includes monthly information up to the first month of that quarter (October), which is mostly available by mid-December. The second estimate is obtained four weeks before the official release, and includes information through the second month of that quarter (November), which is available by mid-January.

The second exercise gets two estimates for the first quarter of 2004. The first is obtained eight weeks before the official release, and the second is obtained four weeks before. The first estimate includes monthly information up to the first month of that quarter (January), which is available by mid-March. The second estimate includes information up to the second month of that quarter (February), which is available by mid-April.

The following chart (Table 3) summarizes the forecast results. The first column indicates the month in which the forecast is made; the second column is the forecast for the last quarter of 2003 and its official release; and the third column is the forecast for the first quarter of 2004 and its official release.

As we can see in Table 3 and Graphs 5 and 6, the model anticipates the GDP growth for the fourth quarter of 2003 and the first quarter of 2004, with a good degree of accuracy. The official figure for the fourth quarter GDP growth was released in mid-February 2004, and it was 2.0%, while the model forecasted 1.7% in January and 1.5% in December. For the first quarter 2004, the official figure was released in mid-May, and it was 3.7%, while the model anticipated 3.2% in April and 3.0% in March. The model is also accurate in anticipating the GDP price deflator, as we can see in Table 4 and Graphs 7 and 8.

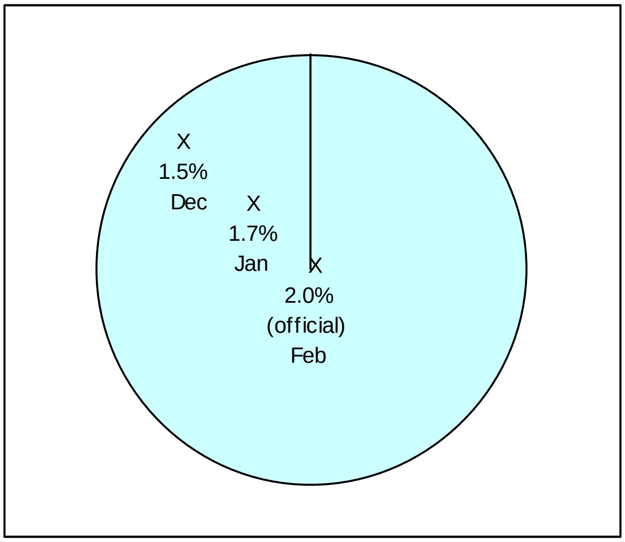
TABLE 3
REAL GDP

(% change, year before)

MONTH	2003:Q4	2004:Q1
Dec~2003	1.5	
Jan~2004	1.7	
Feb~2004	2.0	
Mar~2004		3.0
Apr~2004		3.2
May~2004		3.7

Note: Shaded figures are the official release.

Graph 5
Fourth Quarter GDP Forecast (2003)



Graph 6
First Quarter GDP Forecast (2004)

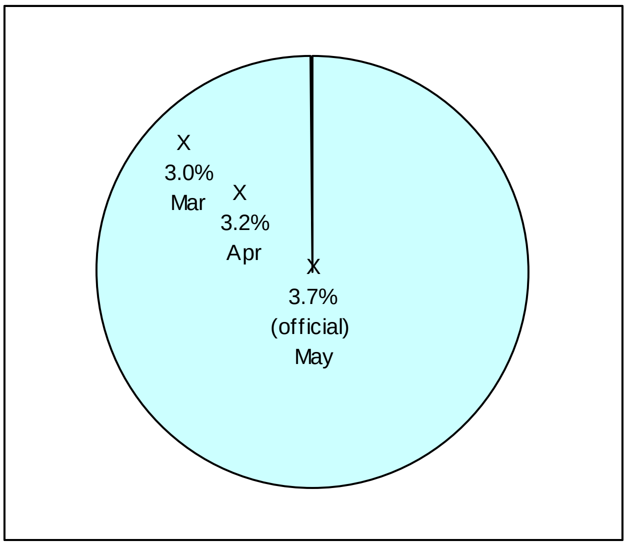
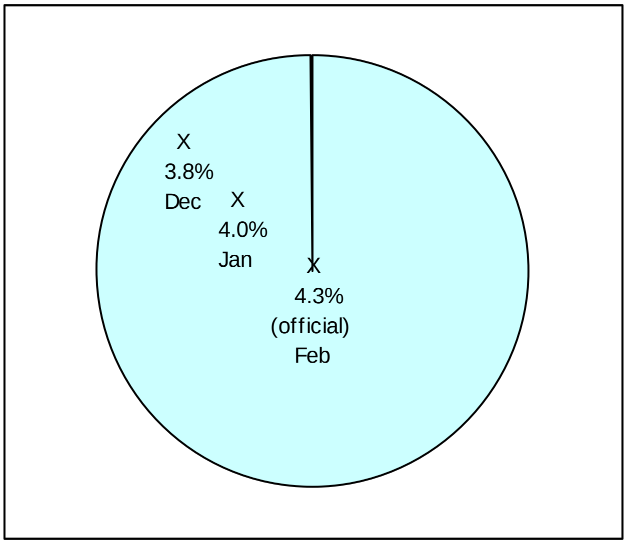


TABLE 4
PRICE DEFLATOR
(% change, year before)

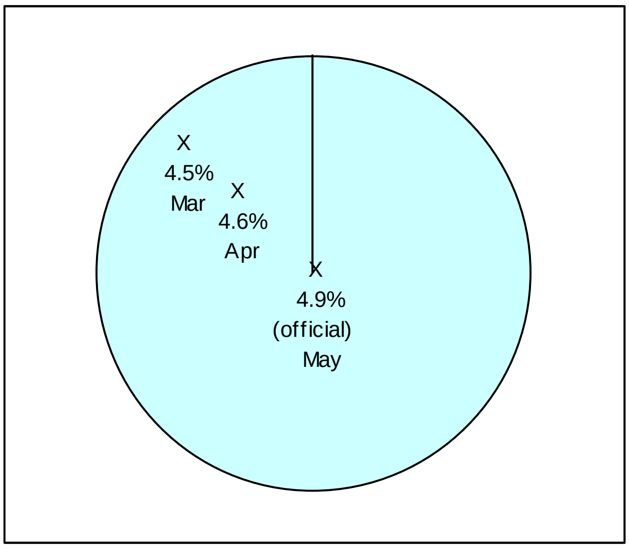
MONTH	2003:Q4	2004:Q1
Dec~2003	3.8	
Jan~2004	4.0	
Feb~2004	4.3	
Mar~2004		4.5
Apr~2004		4.6
May~2004		4.9

Note: Shaded figures are the official release.

Graph 7
Fourth Quarter GDP Deflator Forecast (2003)



Graph 8
First Quarter GDP Deflator Forecast (2004)



2.- Conclusion

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 forecast get closer to the observed figures, 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.

In addition, this high-frequency forecasting model for the Mexican economy allows us 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.

Finally, market expectations could also be used as instrumental variables to perform simulations of policy-induced changes, without subjective human intervention in the process of making assumptions about the future.

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