



**NINTH ANNUAL CONFERENCE ON
ECONOMETRIC MODELLING FOR AFRICA**

**30 June
to
2 July 2004**

**The Generalized Dynamic Factor Model:
Forecasting Inflation rate in France
with Business Surveys**

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Abstract

This paper recommends a new forecasting technique that uses a large panel of business surveys. The Generalized Dynamic Factor Model *à la* Forni *et al.* (2003a) is employed to obtain the common components from a large panel of business surveys in France. We use the common component to forecast inflation rate in France. The results obtained from out-of-sample time series suggest that this novel approach outperforms the Random Walk model.

* This work was in part carried out when I visited the European I Department of the International Monetary Fund as a Summer Intern. I am very grateful for their hospitality and support. I would like also to thank Mario Forni and Lucrezia Reichlin for making their codes available. The author is grateful to Francisco Nadal-De Simone and Luc Everaert for their useful insights and comments.

1. Introduction

Policy makers, businessmen, households, and academics are interested in forecasting economic variables for various reasons. For example, recent economic crises have shown the urgency of predicting such events ahead of time. This concern has been a focus of many researchers for a long time. Different approaches that have been suggested so far suffer from insufficiency of information due to some constraints in respect of econometrics model building.

In this paper we propose a novel approach that uses a large panel of time series, in so doing we benefit from availability of information; hence, we improve the forecasting performance of the model. This approach departs from the popular, VAR model, in that the latter is limited as to the number of variables to include in the model. By using a large cross-section there is a risk of running out of degrees of freedom.

We use the Generalized Dynamic Factor Model (GDFM) *à la* Forni *et al.* (2003a) to forecast inflation rate in France with business surveys. The French National Institute of Statistics (INSEE) publishes monthly or quarterly surveys obtained directly from economic agents. Economic actors give their opinions regarding the overall economic situation. The survey questionnaires deal with the past, present, and future prospect of economic performance. Business surveys are appropriate tool for forecasting and analyzing economic behaviour. Since opinions of economic agents exhibit similar patterns as the business cycles and other economic indicators, it is possible to extract common component of each variable in the panel. This allows us to clean the data from measurement errors as well as variable-specific component. We then used the common component of inflation rate to predict inflation in France. It is difficult to use national account variables because most of them are available only on a quarterly basis or with some delay in respect to the reference period.

From the empirical results, it appears that GDFM outperforms RW model in in-sample and out-of-sample time series. The RW model often is used as a benchmark technique in finance and economics because of its high performance.

The rest of the paper is organized as follows. The next section reviews some of the literature on the application of Dynamic Factor Model in economics. Section 3 describes the Generalized Dynamic Factor Model and the underlying assumptions. In section 4, we discuss the data transformation as well as the estimation of results. We compare the forecasting performance of GDFM with the random walk (RW) model in an out-of-sample forecasting exercise. Section 5 concludes and proposes avenues for further research.

2. Literature review

Dynamic factor models are increasingly being used in economic modelling because they exploit information for a large panel of time series. They are largely used in modelling economic indicators. Forni et al. (2001), Stock and Watson (1999), and Quah and Sargent (1993) use factor analysis approach to extract unobserved economic indices that capture the comovement of many variables. In addition to several works done by Forni et al, and Stock and Watson, Fukuda (2001) and Nadal-De Simone (2002) use the Stock and Watson approach to construct a new composite index of coincident economic indicators in Japan and Europe respectively.

Dynamic factor models are also used in information synthesizing. Bernanke and Boivin (2001) use Stock and Watson approach to study the state of an economy where an expert system aggregate diverse information and provide benchmark policy instead of using the Fed sets of monetary policy. This approach allows summarizing information contained in large data sets into few factors.

Furthermore, factor models are useful in studying business cycles. Business cycles of many economies in the world seem to be synchronized since the globalization era. The main source of such synchronization is that most of world economies are affected by common shocks, such as the oil price, and financial crises. The intuition behind this

approach is that common shocks that underlie comovements of large economic variables are determined by a small number of fundamental unobserved factors. Gregory and Head (1999), Forni and Reichlin (1998), Kose, Otrok and Whiteman (2003), and Forni et al (2000b) use dynamic factor models to model cross-section correlations of business cycles between countries. Similarly, many studies as such as Yang (2003), Cipollini and Kapetanios (2003), and Mody and Taylor use dynamic factor models to study the source, the nature, and the extent to which contagions have affected the world economy, especially emerging market economies, most recently.

Kabundi (2004), Stock and Watson (2002), Forni et al. (2003b), Favero and Marcellino (2001), and Aris, Banerjee, and Marcellino (2001) demonstrate how dynamic factor models are successful in forecasting economic variables. They improve the forecasting performance because of their ability to aggregate information from hundreds of economic variables. Kabundi (2004) compares the forecasting power of GDFM with the random walk (RW) model, and the results show the former outperforms the latter in in-sample as well as out-of-sample time series.

Finally, factor models are very helpful to examine cross-section cointegration in nonstationary data. Banerjee, Marcellino, and Obsbat (2001) claim that exchange rates for the European countries share a common trend - a strong cross-section correlation. Hence, the assumption of cross-section independence is violated which means that many unit root tests are no longer applicable.

3. Methodology

In this paper we combine the static approach of Stock and Watson (2002) to the GDFM of Forni *et al.* (2000a) and Forni and Lippi (2001). The method we propose is similar to the dynamic factor model by Sargent and Sims (1977), except that in this model there is a possibility of autocorrelation between idiosyncratic components. The theoretical arguments as well as the simulations done by Forni *et al.* (2003a) suggest that such a model solves not only the end-of-sample problems caused by two-sided filtering in the estimation, but it also takes advantage of dynamic information.

In GDFM each time series is decomposed into a common component which is driven by a small number of shocks to the entire panel, and an idiosyncratic component. The intuition behind the dynamic factor model approach is to extract the common component from each series, and then use it in the prediction of economic variables. Since the second part – idiosyncratic component – plays a negligible role, it is appropriate to eliminate it and focus fully on the first part.

We first consider a restrictive dynamic factor model in which the factors are dynamic but the relation between the dynamic factors and the observable variable is static. And the generalized dynamic model *à la* Forni *et al.* (2000a) will be considered later. Instead of using these approaches as competitive, we prefer regarding them as complementary. Hence, in this paper we will combine them to improve the forecasting accuracy of the model.

3.1 The Static Factor Model

Consider:

$$x_{nt} = C_n F_t + \mathbf{x}_{nt} \quad (3.1)$$

where n , q , and T are number of time series, number of factors, and number of observations, respectively; $x_{nt} = (x_{1t} \dots x_{nt})'$ is a vector of stochastic process with zero mean and covariance stationary; $F_t = (F_{1t} \dots F_{qt})'$ is a vector of common shocks; $C_n = (C_1 \dots C_n)'$ is a vector of factor loadings, which determine the influence of common shocks F_t on series. Equation (3.1) can also be written as:

$$x_{nt} = \mathbf{c}_{nt} + \mathbf{x}_{nt} \quad (3.2)$$

where $\mathbf{c}_{nt} = (c_{1t} \dots c_{nt})'$ is a vector of common components.

The model (3.2) differs from Stock and Watson (1989) in that the latter consider a fixed number of time series, while in (3.2) n goes to infinity. Applying the law of large number in (3.2), the idiosyncratic component – which is poorly correlated – vanishes. Furthermore, the assumption of orthogonal idiosyncratic components made by Stock and Watson (1989) is highly unrealistic.

To extract the common components in this case, we use the principal component approach. Only the first q eigenvalues \mathbf{I}_{c_q} and the corresponding eigenvectors V_q are calculated from the variance-covariance matrix of x_{nt} . The common component is then defined as:

$$\mathbf{c}_{nt} = x_{nt} V_q V_q' \quad (3.3)$$

3.2 The Generalized Dynamic Factor Model

Let $S_x(\mathbf{q})$, $S_c(\mathbf{q})$, and $S_{\mathbf{x}}(\mathbf{q})$ be the spectral density matrices of x_{nt} , \mathbf{c}_{nt} , and \mathbf{x}_{nt} , respectively at frequency \mathbf{q} . The GDFM à la Forni *et al.* (2000a) is similar to the static model (3.2), but with dynamic factor loading $B_n(L)$.

The GDFM is as follows:

$$x_{nt} = B_n(L) f_t + \mathbf{x}_{nt} \quad (3.4)$$

where $f_t = (f_{1t} \dots f_{nt})'$ is a vector of common factors, $B_n(L)$ is a polynomial of order s in the lag operator L . Equation (3.4) can also be written as:

$$x_{nt} = \mathbf{c}_{nt} + \mathbf{x}_{nt} \quad (3.5)$$

where $\mathbf{c}_{nt} = (\mathbf{c}_{1t} \dots \mathbf{c}_{nt})'$ is a vector of common components. The i^{th} common component is a function f_t such as:

$$\mathbf{c}_{it} = b_{i1}(L)f_{1t} + b_{i2}(L)f_{2t} + \dots + b_{iq}(L)f_{qt} \quad (3.6)$$

In a dynamic factor model analysis the following assumptions are required for the identification of common components and the consistency of their estimates.

Let I_{xq} , I_{c} , and I_{x} be dynamic eigenvalues of x_{nt} , c_{nt} , and x_{nt} , respectively, and V_n be the eigenvector of I_{xq} .

- i) The factors f_t are mutually orthogonal stationary processes at any lead and lag.
- ii) The idiosyncratic components x_{nt} are correlated both in the time dimension and in the cross-section dimension.
- iii) $I_{xq}(\mathbf{q}) \rightarrow \infty$, as $n \rightarrow \infty$, for any frequency $\mathbf{q} \in [-\mathbf{p}, \mathbf{p}]$
- iv) $I_{cj}(\mathbf{q}) > I_{c_{j+1}}(\mathbf{q})$, for any $\mathbf{q} \in [-\mathbf{p}, \mathbf{p}]$; where $j=1, \dots, q$.
- v) There exists \mathbf{k} , such that $I_{x_n}(\mathbf{q}) \leq \mathbf{k}$, for any $\mathbf{q} \in [-\mathbf{p}, \mathbf{p}]$.

In the static factor model the common shocks have a contemporaneous impact on all series. However, such assumption seems unrealistic in that economic variables are affected simultaneously by coincident, leading and lagging variables. The information of coincident variables reveals the current state of the economy, while the information of leading and lagging variables deal with future and the past economic events. Hence, combining coincident, leading and lagging variables improves the forecasting accuracy.

Letting $F_t = (f_t' \dots f_{t-s}')'$ and $C_n = (B_0 \dots B_n)$, the equation (3.1) becomes similar to dynamic model (3.4). The number of common factors of the static model is $r = q(s+1)$.

For example, a common component of dynamic model with 2 common factors and 1 lagged covariance is written as follows:

$$c_t = a_1 f_t + a_2 f_{t-1} + b_1 f_t + b_2 f_{t-1}$$

and the static model will have $r=2(1+1)$ common factors. Using the static model the common component becomes:

$$c_t = a_1 F_{1t} + a_2 F_{2t} + a_{31} F_{3t} + a_4 F_{4t}$$

where $F_{1t} = f_t$ $F_{2t} = f_{t-1}$ $F_{3t} = f_{2t}$ $F_{4t} = f_{2t-1}$

The weakness of the static approach is that it uses only information contained in the contemporaneous covariances, while neglecting lagged covariances. Thus, the static model applies equation (3.4) without taking dynamic of F_t into account. On the other hand, the shortcoming of the GDFM *à la* Forni *et al.* (2000a) is that the estimation of common components c_{nt} declines as t approaches T . It implies that GDFM is good for in-sample prediction, but it is not suitable for out-of-sample forecast.

Since the former approach is appropriate for the estimation of most recent values, while the latter is better for in-sample prediction; they can be combined to improve the forecasting accuracy of the model. Forni *et al.* (2003a) suggest using GDFM in the estimation covariances, which in turn are used in the static model for forecast. These results are better than static principal components forecasts.

4. Data transformation and empirical results

4.1. Data transformation

Qualitative business surveys¹ are informative about economic performance in that they convey a message regarding the frame of mind of economic agents. The INSEE releases

¹ Surveys are conducted asking economic agents particular questions concerning the economic outlook. These questions lead to the following answers: economic performance is expected to improve, to be stable, or to deteriorate. In order to conduct any empirical study surveys must be quantified. Their quantification is obtained by taking the balance between the positive (improve) and the negative (deteriorate) percentage of answers. Afterward indicators can be used to evaluate or predict the current performance of the economy as well as its future prospects.

monthly and quarterly surveys that cover a wide range of economic activity. Each survey has a quantitative counterpart. Business surveys are important variables for economic actors because of the information they provide about their matching part, quantitative variables; especially when the latter are not available. Economic agents use them mainly to account for either the absence of their quantitative counterparts or for long delays in respect of the reference period.

We have selected 189 quarterly and seasonally adjusted French surveys ranging from the first quarter of 1991 until the first quarter of 2003.² We then aggregate them under the labels demand, labour market, orders, price, production, and services. Each sector, in turn, is divided into agro-food, consumption, automobile, intermediate, manufacturing, and total industry products.

We perform a unit root test to assess the stationarity of variables. Since the ADF (augmented Dickey Fuller) tests had been criticized for their low power, we prefer using the DFGLS test proposed by Elliott, Rothenberg, and Stock (ERS, 1996). The optimal lag length is selected using the modified AIC (MAIC) criterion. We then transform all nonstationary series by differencing. Finally, we normalize all variables by subtracting the mean from each series and dividing them by their standard deviation.

4.2. Empirical results

To estimate a dynamic model, it is necessary to determine the value for truncation s , and most importantly, the number of factors. Forni *et al.* (2000a) suggest that $s = \frac{2}{3}T^{1/3}$ performs well. Following this procedure, we have $s = 2$, which is not sufficient to describe the dynamic of inflation in France. However, it is more realistic to use $s = 4$ in order to have a higher order dynamic in our model.

² See Appendix for a complete list of variables.

Similarly, there is no formal statistical approach to determine the number of factors in Generalized Dynamic Factor Model. Bai and Ng (2002) proposed some information criteria for the selection of number of factors in large dimensional panels. We prefer the principal components method, which suggests the selection of number of factors q based on the first eigenvalues of the spectral density matrix of x_{nt} . This approach consists of adding principal components until the increase in the explained variance is less than a specific value α - here we choose $\alpha = 0.10$. Table 4.1 shows that 3 first principal components explained 84.40% of total variation.

Table 4.1: Variance Explained by the 3 first Principal Components

	1	2	3
Variance	63.37	11.00	10.00
Cumulative Variance	63.37	74.37	84.40

In this section we use GDFM to construct an inflation indicator for France with business surveys. We use the technique described in the previous section to estimate. We first employ the dynamic factor model to construct in-sample estimation of inflation. A business survey is seen as a coincident indicator when it provides contemporaneous information about the actual economic outlook; while a leading variable reflects the future prospect of the economy.

Figure 4.1: Inflation rate and Common component

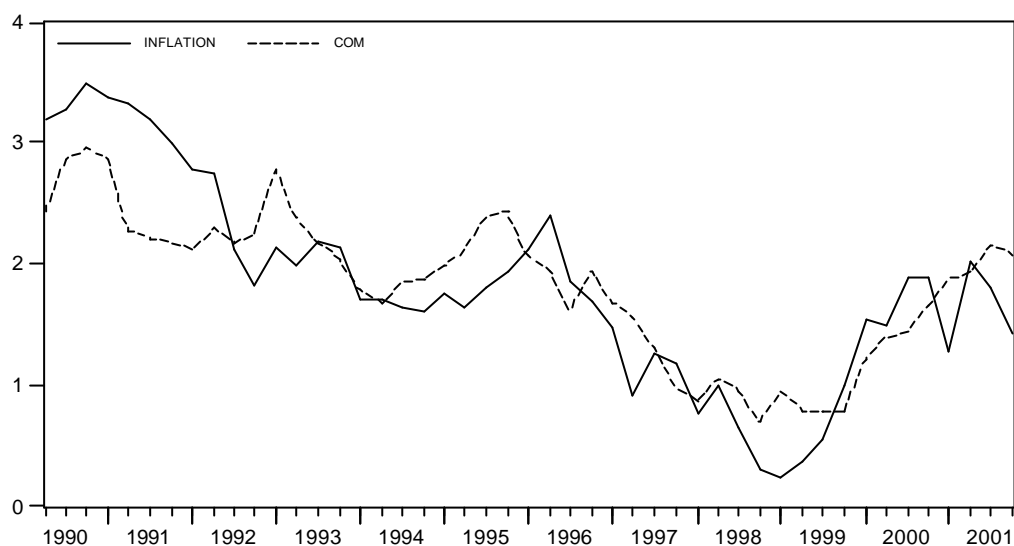


Figure 4.1 illustrates the relationship between the constructed indicator (COM) and the inflation rate in France. The common component follows the same pattern as the inflation rate, but the inflation rate seems to be lagging for most of the turning points. Table 4.2 confirms the close relationship with a statistically significant positive correlation coefficient of 0.85.

Table 4.2: Correlation between inflation and common component

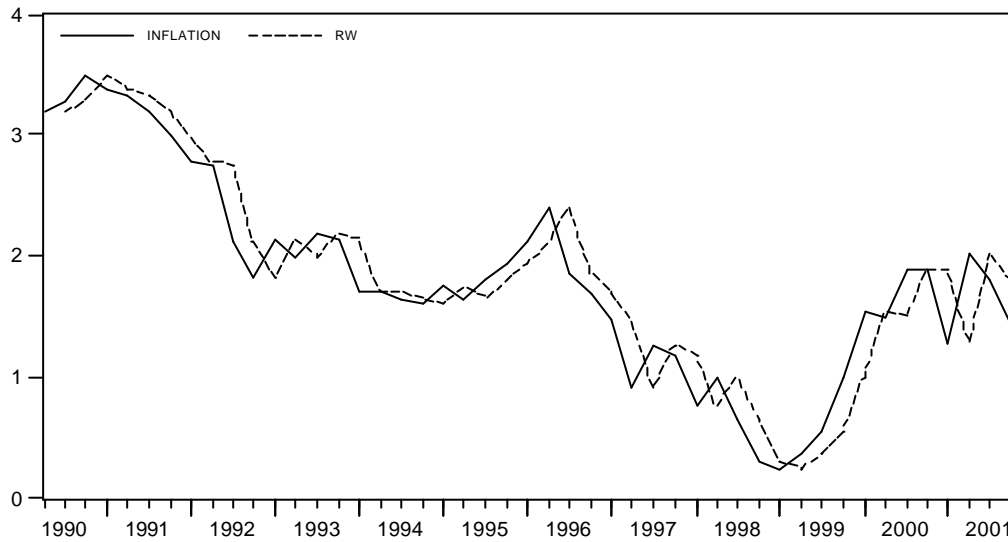
	INFLATION	COM
INFLATION	1	
COM	0.847	1

To analyse the forecasting capacity of GDFM and the RW model, we divide the time series into two sets: the in-sample set (from 1991Q1 to 2001Q4), which serves to estimate parameters in the model; and the out-of-sample set (from 2002Q1 to 2003Q1), which facilitates the evaluation of their forecasting performance.

We use the Random Walk (RW) model as benchmark to measure the forecasting ability of GDFM.

The graphical representation depicted in Figure 4.3 reveals that the RW model is lagging. Hence, it is not prudent to use the RW to forecast the economic growth rate, in that it is difficult to predict turning points ahead of time.

Figure 4.3: Random Walk



However, these findings may be misleading. A model may have a better in-sample prediction on the one hand and a poor out-of-sample prediction on the other hand. To test that possibility, we use the above models for out-of-sample simulations to determine their forecasting ability. We use the root mean squared error (RMSE) and Theil's inequality coefficients (U) criteria:

$$RMSE = \sqrt{\frac{\sum (\hat{y}_t - y_t)^2}{n}} \quad (4.1)$$

$$U = \sqrt{\frac{\sum (\hat{y}_t - y_t)^2}{n}}{\frac{\sum y_t^2}{n}} \quad (4.2)$$

where \hat{y}_t is the predicted value at time t , y_t is the actual value at time t , n is the sample size. The smaller the RMSE and U ($0 \leq U \leq 1$), the better the forecast performance of the model. The closer U is to zero, the better the forecasting power of the model. Similarly, the model with a lower value of RMSE and U has a higher forecasting performance than the other.

Table 4.3: Forecast performance statistics

	In-sample		Out-of-sample	
	RMSE	U	RMSE	U
COM	0.453	0.226	0.333	0.166
RW	0.305	0.155	0.413	0.222

Table 4.3 illustrates the forecasting performance of different models. The RW model outperforms GDFM in in-sample sets. In out-of-sample forecast, the GDFM is the best model. Hence, it is suitable to use GDFM in forecasting inflation rate.

Figure 4.5: Inflation, Common Component, and Random Walk

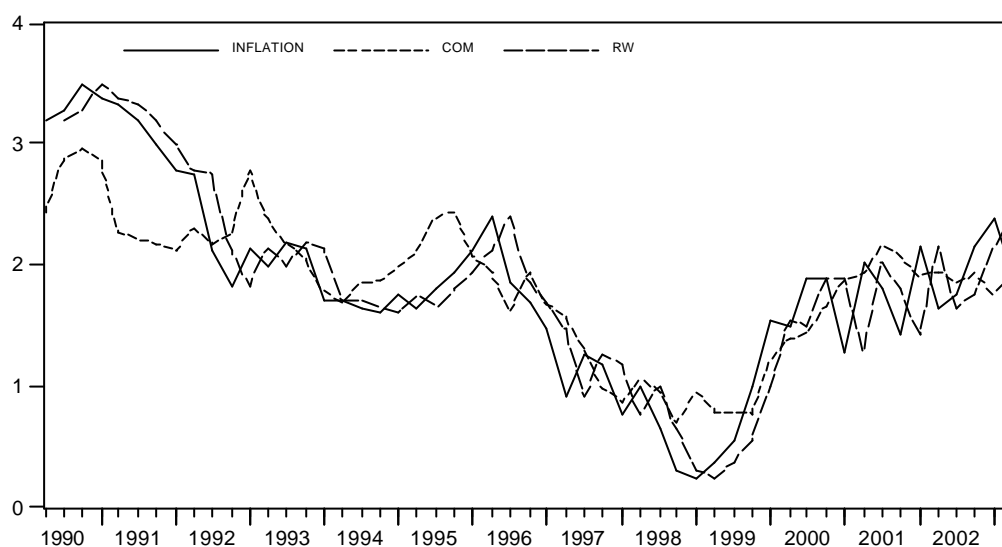


Figure 4.5 shows that the common component model does not estimate fluctuations in inflation from 2000 until 2003. The common component appears to be smoother than the inflation series. We assume that the volatility in inflation for this specific period is caused by an idiosyncratic component from specific periods.

5. Conclusion

This paper proposes a new way of forecasting the inflation rate in France, exploiting information from a large panel of business surveys. The method is based on the dynamic factor model proposed by Forni *et al.* (2003a), which is a combination of a static factor model and a dynamic factor model. We compare the forecasting performance of the GDFM to two Random Walk models. The results reveal that the constructed common component is a good estimate of the inflation rate in France in out-of-sample forecasting. It implies that the opinion of economic agents has a high predictive power for economic performance in France.

Further work includes improving the short-term prediction of output growth using monthly surveys and national account series, since most economic variables are only available on a

quarterly basis. Also, in computing latent factors, e.g., common to opinion of agents, one can determine to which extent economic agents are rational in their decision-making processes.

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Appendix: Data description

This appendix lists all the variables used in this paper to construct the economic indicator in France. All surveys use quarterly, seasonally adjusted data from INSEE. Data is transformed after being tested for unit roots using Elliott, Rothenberg, and Stock (ERS, 1996) unit root test. The transformation code: 0 = no transformation, and 1 = first difference. We have a panel of 218 variables in total from 1991Q1 to 2003Q1.

Data Description	DFGLS
Demand	
Demand - Recent Trend - Total Industry	0
Demand - Recent Trend - Manufacturing	1
Demand - Recent Trend - Agro-food	0
Demand - Recent Trend – Consumption	1
Demand - Recent Trend - Automobile Industry	0
Demand - Recent Trend – Equipment	0
Demand - Recent Trend - Intermediate	0
Foreign Demand - Recent Trend - Total Industry	1
Foreign Demand - Recent Trend - Manufacturing	1
Foreign Demand - Recent Trend - Agro-food	0
Foreign Demand - Recent Trend - Consumption	0
Foreign Demand - Recent Trend - Automobile	0
Foreign Demand - Recent Trend - Equipment	1
Foreign Demand - Recent Trend - Intermediate	0
Foreign Demand - Prospect - Total Industry	1
Foreign Demand - Prospect - Manufacturing	0
Foreign Demand - Prospect - Agro-food	0
Foreign Demand - Prospect - Consumption	0
Foreign Demand - Prospect - Automobile	0
Foreign Demand - Prospect - Equipment	1
Foreign Demand - Prospect - Intermediate	0
Demand in service sector - Enterprises	1
Demand in service sector -Excluding Interim	0
Demand in service sector - Total Service	0
Demand in service sector - Private	1
Demand in service sector -Interim	0
Labor Market	
Employment - Recent Trend - Total Industry	1
Employment - Recent Trend - Manufacturing	0

Employment - Recent Trend - Agro-food	0
Employment - Recent Trend - Consumption	1
Employment - Recent Trend - Automobile	1
Employment - Recent Trend - Equipment	0
Employment - Recent Trend - Intermediate	0
Hours worked - Prospect - Total Industry	0
Hours worked - Prospect - Manufacturing	0
Hours worked - Prospect - Agro-food	1
Hours worked - Prospect - Consumption	1
Hours worked - Prospect - Automobile	0
Hours worked - Prospect - Equipment	0
Hours worked - Prospect - Intermediate	0
Hours worked - Recent Trend - Total Industry	0
Hours worked - Recent Trend - Manufacturing	0
Hours worked - Recent Trend - Agro-food	0
Hours worked - Recent Trend - Consumption	1
Hours worked - Recent Trend - Automobiles	1
Hours worked - Recent Trend - Equipment	0
Hours worked - Recent Trend - Intermediates	0
Employment - Prospect - Total Industry	1
Employment - Prospect - Manufacturing	1
Employment - Prospect - Agro-food	0
Employment - Prospect - Consumption	1
Employment - Prospect - Automobiles	0
Employment - Prospect - Equipment	1
Employment - Prospect - Intermediates	0
Recruitment Difficulties - Equipment	1
Recruitment Difficulties - Intermediate	1
Recruitment Difficulties - Manufacturing	1
Recruitment Difficulties - Total Industry	1
Salary Rate Evolution - Agro-food	1
Salary Rate Evolution - Consumption	0
Salary Rate Evolution - Equipment	1
Salary Rate Evolution - Intermediate	1
Salary Rate Evolution - Manufacturing	0
Salary Rate Evolution - Total Industry	1
Salary Rate Evolution - Automobile	0
Employment - Recent Trend - Service Sector - Enterprises	0
Employment - Prospect - Service Sector -Enterprises	0
Employment - Recent Trend - Service Sector - Enterprises Excluding Interim	0
Employment - Prospect - Enterprises Excluding Interim	1
Employment - Recent Trend - Total Sector	0
Employment - Prospect - Total Sector	1
Employment - Recent Trend - Service Private	1
Employment - Recent Trend - Interim	0

Employment - Prospect -Interim 0

Orders

Orders in weeks of production - Agro-food 0
Orders in weeks of production - Consumption 0
Orders in weeks of production - Automobiles 1
Orders in weeks of production -Equipment 0
Orders in weeks of production - Intermediates 0
Orders in weeks of production - Manufacturing 1
Orders in weeks of production - Total Industry 1

Price

Selling Price - Past - Total Industry 1
Selling Price - Past - Manufacturing 0
Selling Price - Past - Agro-food 0
Selling Price - Past - Consumption 0
Selling Price - Past - Automobile 0
Selling Price - Past - Equipment 1
Selling Price - Past - Intermediate 0
Selling Price - Past Variation - Total Industry 0
Selling Price - Past Variation - Manufacturing 0
Selling Price - Past Variation - Agro-food 1
Selling Price - Past Variation - Consumption 0
Selling Price - Past Variation - Automobile 1
Selling Price - Past Variation – Equipment 1
Selling Price - Past Variation - Intermediate 0
Selling Price - Future Variation - Total Industry 0
Selling Price -Future Variation - Manufacturing 0
Selling Price - Future Variation - Agro-food 1
Selling Price - Future Variation - Consumption 0
Selling Price - Future Variation - Automobile 1
Selling Price - Future Variation - Equipment 1
Selling Price - Future Variation - Intermediate 0
Selling Price of Exports - Past - Total Industry 0
Selling Price of Exports - Past - Manufacturing 0
Selling Price of Exports - Past – Agro-food 0
Selling Price of Exports - Past - Consumption 0
Selling Price of Exports - Past - Automobile 1
Selling Price of Exports - Past - Equipment 0
Selling Price of Exports - Past - Intermediate 0
Selling Price of Exports - Past Variation- Total Industry 0
Selling Price of Exports - Past Variation- Manufacturing 0
Selling Price of Exports - Past Variation- Agro-food 1
Selling Price of Exports - Past Variation - Consumption 0
Selling Price of Exports - Past Variation - Automobile 0
Selling Price of Exports - Past Variation - Equipment 1

Selling Price of Exports - Past Variation - Intermediate	0
Price in Service Sector - Recent Trend	1
Price in Service Sector - Future Prospect	1

Production

Production Capacity Judgment - Manufacturing	1
Liquidity Difficulties - Intermediates	1
Liquidity Difficulties - Equipment	0
Liquidity Difficulties - Automobiles	0
Liquidity Difficulties - Consumption	1
Liquidity Difficulties - Agro-food	0
Liquidity Difficulties - Manufacturing	0
Liquidity Difficulties - Total Industry	1
Production bottlenecks - Equipment	1
Production bottlenecks - Intermediates	0
Production bottlenecks - Manufacturing	1
Production bottlenecks - Total Industry	1
Production Capacity - Intermediates	0
Demand and Supply Difficulties - Agro-food	1
Demand and Supply Difficulties - Consumption	1
Demand and Supply Difficulties - Automobiles	0
Demand and Supply Difficulties - Equipment	0
Demand and Supply Difficulties - Intermediates	1
Demand and Supply Difficulties - Manufacturing	1
Demand and Supply Difficulties - Total Industry	1
Production Margin with supplementary work force - Total Industry	1
Production Margin with supplementary work force - Equipment	1
Production Margin with supplementary work force - Intermediates	0
Production Margin with supplementary work force - Manufacturing	1
Production Margin without supplementary work force - Automobiles	1
Production Margin without supplementary work force - Equipment	1
Production Margin without supplementary work force - Intermediates	0
Production Margin without supplementary work force - Manufacturing	0
Production Margin without supplementary work force - Total Industry	1
Production Margin with supplementary work force - Agro-food	1
Production Margin with supplementary work force - Consumption	1
Production Margin without supplementary work force - Agro-food	1
Production Margin without supplementary work force - Consumption	0

Service

Service to Enterprises - Past	1
Service to Enterprises - Prospect	0
Service - Total Sector - Exploitation - Past	1
Service - Total Sector - Exploitation - Prospect	0
Service - Activity -- Enterprises Excluding Interim -Past	1
Service - Activity - Enterprises Excluding Interim -Prospect	1

Service - Activity - Total Sector - Past	0
Service - Activity - Total Sector - Prospect	1
Service - Exploitation - Total Sector - Past	1
Service - Exploitation - Total Sector - Prospect	1
Service - Activity - Private Sector - Past	0
Service - Activity - Private Sector - Prospect	0
Service -Exploitation - Private Sector - Past	1
Service - Activity -- Enterprises - Interim -Past	0
Service - Activity - Enterprises - Interim -Prospect	0
Service - Exploitation - Enterprises - Interim -Past	0
Service - Exploitation - Enterprises - Interim -Prospect	0

Stocks

Stocks Level of Inputs - Industrial Products in Agro-food Industry	0
Stocks Level of Inputs - Manufacturing Products in Agro-food Industry	0
Stocks Level of Inputs - Manufacturing Products in Total Industry	0
Stocks Level of Inputs - Consumption Goods in Total Industry	0
Stocks Level of Inputs - Equipment Products in Total Industry	0
Stocks Level of Inputs - Equipment Products in Manufacturing Industry	0
Stocks Level of Inputs - Intermediate Products in Total Industry	0
Stocks Level of Inputs - Intermediate Products in Manufacturing Industry	0
Stocks Level of Inputs - Manufacturing Products in Manufacturing Industry	0
Stocks Level of Inputs - Consumption Goods in Manufacturing Industry	0
Stocks Level of Inputs - Manufacturing Products in Consumption Industry	0
Stocks Level of Inputs - Manufacturing Products in Automobile Industry	0
Stocks Level of Inputs - Manufacturing Products in Equipment Industry	0
Stocks Level of Inputs - Manufacturing Products in Intermediate Industry	0
Stocks in weeks of production - Consumption Industry	0
Stocks in weeks of production - Intermediate Industry	1
Stocks in weeks of production - Manufacturing Industry	0
Stocks in weeks of production - Total Industry	0
Stocks in weeks of production - Agro-food Industry	0
Stocks in weeks of production - Automobile Industry	0
Stocks in weeks of production - Equipment Industry	0
