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Estimation of Economic Growth in France Using Business Survey Data

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Estimation of Economic Growth in France Using Business Survey Data[1]

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Abstract

This paper proposes a new way of computing a coincident indicator for economic activity in France using data from business surveys. We use the generalized dynamic factor model *à la* Forni and others (2000) to extract common components from a large number of survey observations. The results obtained show that the resulting indicator forecasts economic activity with a relatively high degree of accuracy before the release of actual data.

JEL Classification Numbers: C33, C42, C53, E37

Keywords: Dynamic factor models, survey data, economic forecasting

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I. Introduction

Policymakers, businesses, households, and scholars are interested in forecasting economic activity. They often use economic indicators, such as the industrial production index, retail sales index, consumer confidence index, and the consumer price index to predict the business cycle. This method of prediction is very useful for medium- and long-term forecasting. In the short term, however, they are faced with a major problem of data availability, since most data are released on a quarterly basis and with some delay.

To deal with this dilemma, we use business survey data to construct a reliable short-term economic indicator index for France. The French statistics institute—Institut National de la Statistique et des Etudes Economiques (INSEE)—publishes monthly and quarterly business surveys that cover all sectors of the economy. Economic agents give opinions regarding the overall economic situation. The survey questionnaires deal with the past, present, and future prospects of economic performance. Although different, these opinions have a common factor: a coincident index.

There are many methods to measure and determine the state of the economy or stage of the business cycle. The most popular consists of combining macroeconomic indicators into a composite index. This index is computed as a weighted average of individual indicators. Another approach, developed by Stock and Watson (1989), uses the Kalman-Filter method to extract a latent variable from a large number of indicators. In this paper we use the generalized dynamic factor model (GDFM) of Forni and others (2000) to extract the common component a coincident index from business survey data.

This coincident index is used in forecasting GDP growth for France. From the empirical analysis we compare the forecasting power of GDFM with the random walk (RW) model in an out-of-sample test. The RW model has been popular in finance and economics as a result of its high forecasting performance at very short horizons.

The remainder of the paper is organized as follows. In Section II, we discuss relevant literature in the development of business cycle indices. Section III deals with the theoretical methodology of the GDFM approach. In Section IV, we discuss the data transformation as well as the estimation of results. We compare the forecasting performance of GDFM with the RW model using the root mean squared error (RMSE) and Theil’s inequality coefficient criteria. The final section concludes and provides some issues for further research.

II. Literature Review

Most studies on business cycles are based on the early work of Burns and Mitchell (1946). They found that the regularity in business cycles was explained by the comovements of economic variables. Since then, there have been many approaches to compute a business cycle index. The first and most widely used is the method that estimates the index as a weighted average of individual indicators. Mathematically we have:

$$X = \sum_{i=1}^{n} w_i I_i, \tag{2.1}$$

where X is the composite index, I_i is the i^{th} indicator index, and w_i is the weight allocated to I_i.

A second approach was initiated by Stock and Watson (1989). They argued that the comovements in many economic variables have a common factor that can be captured by a single latent variable. The Kalman-Filter method is used to calculate this unobserved variable, which serves as an economic indicator index

$$\begin{aligned} \Delta X_t &= \beta + \gamma(L)\Delta C_t + u_t \\ \phi(L)C_t &= \delta + n_t \\ D(L)u_t &= \varepsilon_t, \end{aligned} \tag{2.2}$$

where X_t denotes an $n \times 1$ vector of macroeconomic indicators, C_t is a common unobserved scalar variable, L is the lag operator, u_t and η_t are idiosyncratic movements in the indicator X_t and in C_t respectively, ε_t is a white noise error, β and δ are parameters, and $\gamma(L)$, $\Delta(L)$, and $\phi(L)$ are lag polynomials.

The Stock and Watson method depends on three main assumptions. First, it is essential to make an a priori distinction between coincident and leading variables. Only the former are used in the development of the index. Secondly, common components and idiosyncratic components are uncorrelated at all leads and lags. Lastly, idiosyncratic components are assumed to be mutually uncorrelated. This approach has been used in a wide range of applications. The National Bureau of Economic Research (NBER) index is based on the Stock and Watson (1989) technique. Building on several studies done by Stock and Watson, Fukada (2001), and Nadal-De Simone (2002) use this technique to construct a new composite index of coincident economic indicators in Japan and Europe respectively.

The third approach is the principal components method. It is a technique that was originally used in psychology to identify latent factors underlying the variability in the observed characteristics of agents. Stone (1947) was the pioneer in introducing the principal component analysis into econometric modeling. The notion behind this technique is that fluctuations of economic variables are determined by many unobserved factors. The technique uses all available information from a wide range of economic indicators without an a priori distinction between leading and lagging variables. Like the Stock and Watson model, common components and idiosyncratic components are not mutually uncorrelated. Unlike the previous approach, which allows for a single common component, in the current method there are as many principal components as there are indicators. Recently Lawrence Klein and Suleyman Ozmucur (2002) have used this approach to estimate the economic growth rate in China.

Lately Forni and others (2000) have expanded on the last two methods by developing a new way of computing a coincident and a leading indicator of economic activity called the GDFM. The GDFM reconciles dynamic principal components analysis with the dynamic factor model of Sargent and Sims (1977) and Geweke (1977). This method allows estimation of the index without an a priori distinction between coincident and noncoincident series. Unlike Stock and Watson's approach (1989), Forni and others (2000) point out that leading and lagging variables contribute to a better estimation of the coincident indicator. The coincident index is the weighted average of common components. GDFM differs from other methods in that it allows for a mild cross-correlation among idiosyncratic components; the opposite is a demanding restriction that seems unrealistic.

In this paper, we use Forni, and others' approach to estimate the indicator index for France. The next section deals with the theoretical framework of GDFM.

III. Methodology

In the GDFM, each time series is assumed to be composed of two sets of unobserved components: the common components, which are driven by a small number of shocks that are common to the entire panel; and the idiosyncratic components, which are specific to a particular variable and orthogonal with the common components. The notion behind the common component analysis is that only a small number of random variables determines the business cycle. Since the second part plays a negligible role in the estimation of the business cycle, it is appropriate to eliminate it and focus fully on the first part.

Assume we have n series expressed as follows:

$$x_t^i = \alpha_i(L)u_t + \varepsilon_t^i, \qquad (3.1)$$

where x_t^i is an $(n \times 1)$ vector stochastic process with zero mean and stationary covariance, $x_t^i = (x_t^{1i}, x_t^{2i}, ..., x_t^{ni})'$; $u_t = (u_t^1, u_t^2, ..., u_t^q)'$ is a $(q \times 1)$ vector of mutually orthogonal common shocks with zero mean and unit variance and with $q < n$; $\varepsilon_t^i = (\varepsilon_t^{1i}, \varepsilon_t^{2i}, ..., \varepsilon_t^{ni})'$ is a $(n \times 1)$ vector of idiosyncratic shocks; and $\alpha^i(L)$ is a $(q \times n)$ matrix of rational functions with the lag operator L. The GDFM approach allows for autocorrelation between ε_t^i variables, and the variances of ε_t^i are bounded as $i \to \infty$. Equation (3.1) is the generalized dynamic model developed by Forni and others (2000).

GDFM deals with autocorrelation by using the law of large numbers. That is, when n is large, the idiosyncratic components, which are poorly correlated, vanish. Hence, we are basically left with the common components only.[2]

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[2] See Forni and others (2000) for technical details on the GDFM.

IV. Data Transformation and Empirical Results

A. Data Transformation

Qualitative business surveys[3] are informative about economic performance in that they convey a message regarding the frame of mind of economic agents. The INSEE releases monthly and quarterly surveys that cover a wide range of economic activity. Many of the qualitative answers to surveys have a quantitative counterpart in data provided by statistical offices. Business surveys are important for economic agents who count on them for gathering information on the most likely state of economic activity before the actual data are released, or in some cases, even obtain an opinion on a sector or aspect of economic activity not yet covered by a statistical release.

We have selected 189 quarterly seasonally adjusted French surveys spanning from the first quarter of 1991 until the first quarter of 2003.[4] We then aggregate them under the labels demand, labor 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 each series, 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.

B. Empirical Results

In this section we use GDFM to construct an economic indicator for France. We estimate the coincident indicator as discussed in the previous section by taking the average of common components of business surveys. A business survey is seen as a coincident indicator when it provides contemporaneous information about the actual state of the economy; while a leading variable reflects the future prospect of the economy. Figure 1 illustrates the relationship between the constructed indicator (COM) and the economic growth rate in France. The moving averages[5] of these variables follow the same pattern in that they have the same turning points in

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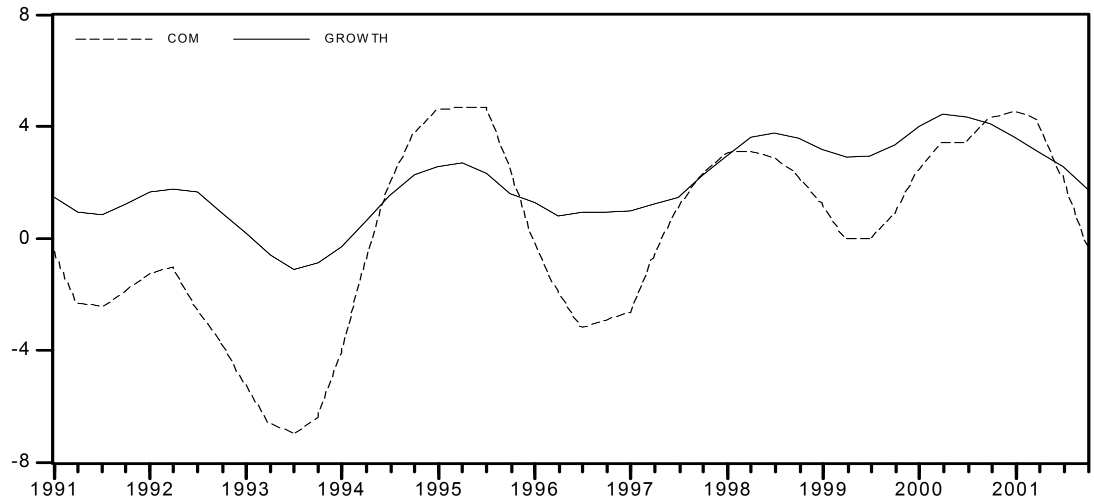
[3] Surveys are conducted asking economic agents particular questions concerning the economic outlook. These questions lead to the following answers: economic performance is expected to improve, to be stable, or to deteriorate. In order to conduct any empirical study, surveys must be quantified. Their 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.

[4] See Appendix for a complete list of variables.

[5] We used centered 5-quarter moving averages.

some periods (1991Q3, 1992Q2, 1993Q3, 1997Q1, and 1999Q3). However, the common component has a quarter lead for 1998Q2, and it lags for the rest of the turning points (1995Q3 and 2001Q1). The close relationship is confirmed by a statistically significant positive correlation coefficient of 0.86.

Figure 1: Moving Average of Common Components and Economic Growth Rate



To analyze 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 then regress the indicator on the GDP growth rate, and we obtain the following results:[6]

$$\underset{}{GROWTH} = \underset{(14.23)}{1.92} + \underset{(8.79)}{0.33COM} + \underset{(27.83)}{0.90e_{t-1}} + \underset{(37.22)}{0.98e_{t-2}} \tag{4.1}$$

$$\overline{R}^2 = 0.95 \qquad DW = 0.84$$

The results show that all variables in the model are statistically significant. The adjusted R-square, $\overline{R}^2$, is relatively high, meaning approximately 95 percent of variation in growth rate is explained by variables in the model. The White test[7] indicates that COM is uncorrelated with

[6] Variables in brackets denote t-statistics.

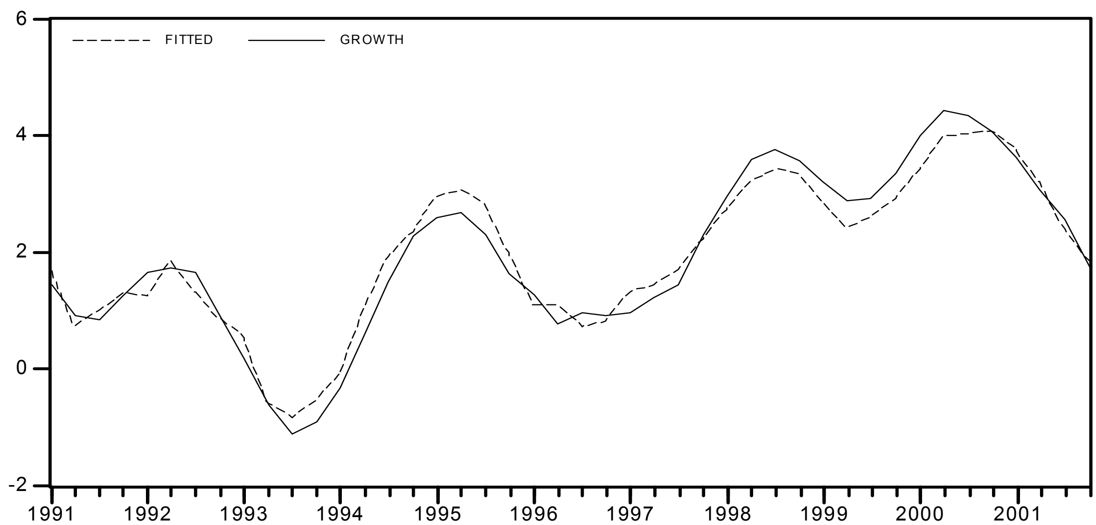
[7] We use the White test to verify the presence of heteroscedasticity in the model. P-value of F-statistics is 0, which is greater than the critical value of 0.05 indicates the absence of heteroscedasticity in the model.

error term. The Durbin Watson suggests the presence of autocorrelation in the model. We use the New-West method to adjust the standard error of coefficients, hence, correcting the model for autocorrelation. Equation (4.1) becomes:

$$\underset{}{GROWTH} = \underset{(8.72)}{1.92} + \underset{(6.64)}{0.33COM} + \underset{(25.30)}{0.90e_{t-1}} + \underset{(47.09)}{0.98e_{t-2}} \tag{4.2}$$

Figure 2 shows how well the computed indicator predicts the economic growth rate in France. It is evident that the constructed indicator is a "coincident" indicator since it predicts contemporaneous change in GDP with a high degree of accuracy. However, as most surveys used in its estimation are available on average 6 weeks before the release of GDP data, the indicator might be better referred to as a leading indicator of its quantitative counterpart.

Figure 2: Moving Average of Economic Growth Rate and Regression Line



We use the RW model as benchmark to measure the forecasting ability of GDFM. Two RW models are selected, the traditional model and the “realistic model.” In the first model economic growth rate depends on its lagged value. This is the traditional RW model (RWO), which represents the optimist view. However, the first estimate of GDP growth in France is only published 42 or 43 days after the period it refers to, the provisional estimate is released 50 days after the reference period, and the final estimate 90 days after. This means agents might not have the lagged value of GDP available to construct the model. Hence, the realistic approach will be to use a two-period lag model such as in equation (4.4).

The optimistic approach of RW (RWO) model gives the following results:

$$GROWTH = GROWTH_{t-1} \quad (4.3)$$
$$(30.69)$$
$$R^2 = 0.88$$

Given the delays in the publication of real GDP data referred to above, a more realistic approach of the RW model (RWR) is as follows:

$$GROWTH = GROWTH_{t-2} \quad (4.4)$$
$$(15.73)$$
$$R^2 = 0.57$$

From Figures 2, 3, 4, equations (4.1), (4.3), and (4.4), it is obvious that model in equation (4.1) outperforms the random walk (RW) models. The graphical representation depicted in Figures 3 and 4 reveals that the RW models (i.e., even the optimistic RWO) are 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 3: Random Walk Optimistic

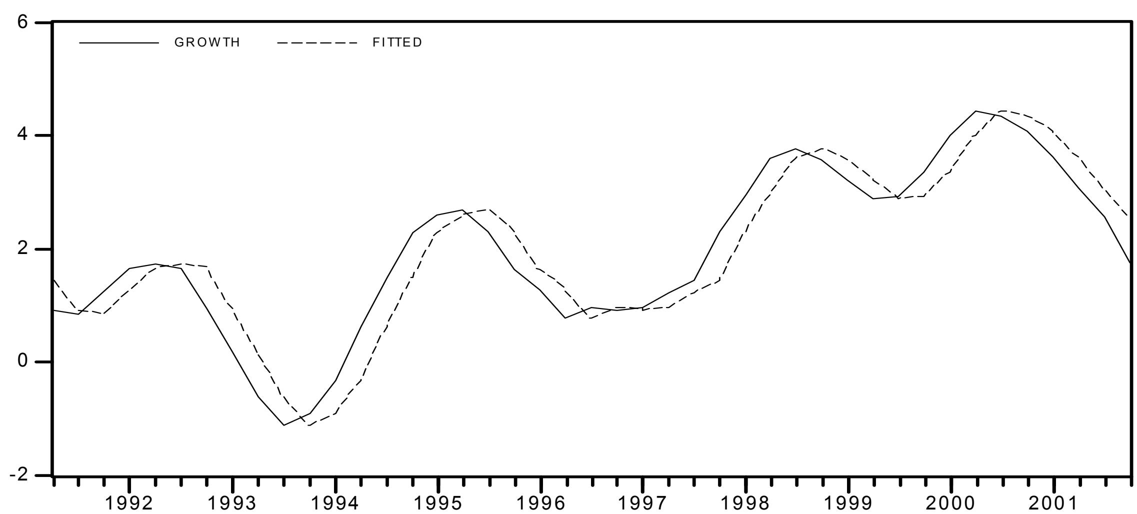
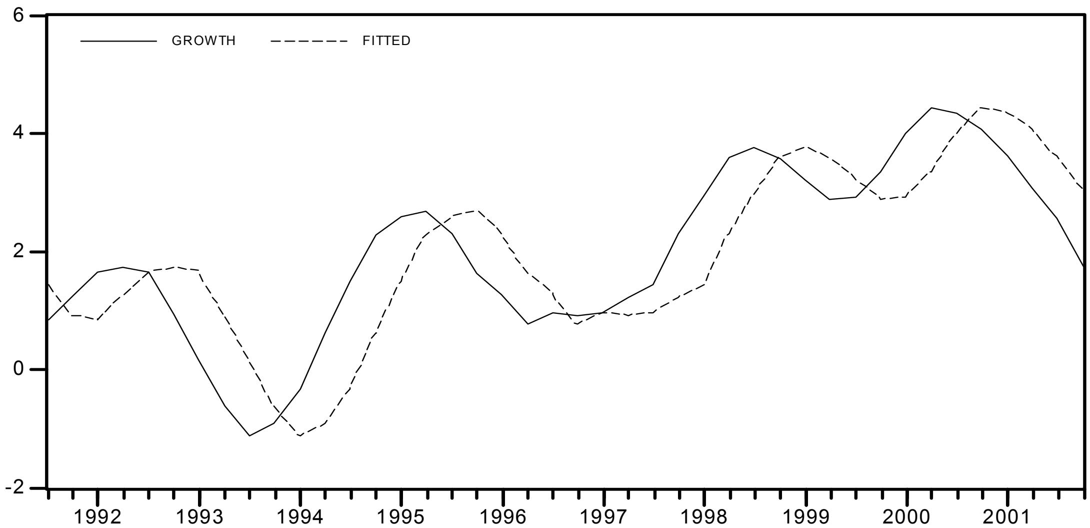


Figure 4: Random Walk Realistic



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:

$$RMSE = \sqrt{\frac{\sum (\hat{y}_t - y_t)^2}{n}} \tag{4.5}$$

$$U = \sqrt{\frac{\frac{\sum (\hat{y}_t - y_t)^2}{n}}{\frac{\sum y_t^2}{n}}}, \tag{4.6}$$

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, the better the forecast performance of the model. The closer U $(0 \leq U \leq 1)$ is to zero, the better the forecasting power of the model.

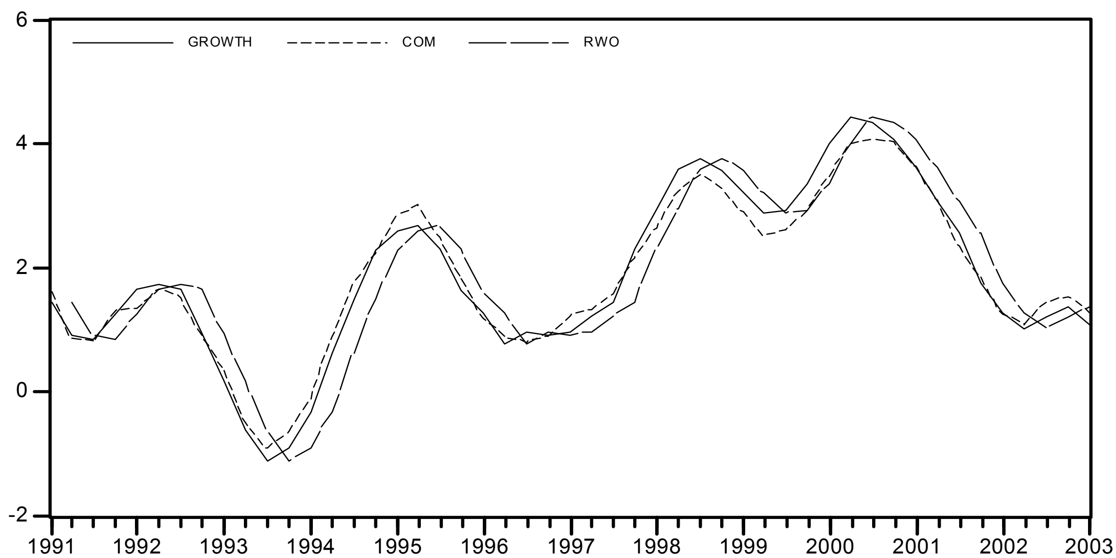
Table 1 shows that GDFM outperforms RW models for in-sample as well as in out-of-sample sets. Furthermore, the main weakness of RW models is that they predict GDP growth with a period lag.

Table 1: Forecast Performance Statistics

	In-sample		Out-of-sample	
	RMSE	U	RMSE	U
COM	0.298	0.125	0.233	0.195
RWO	0.499	0.209	0.298	0.250
RWR	0.927	0.389	0.689	0.578

Figure 5 shows that the common component model predicts the turning point in 2002Q1 in the last quarter of 2001, while the RW model predicts it a quarter later.

Figure 5: GDFM and Random Walk Model



Our next task is to analyze each component of the model in relation to the computed common component. The degree of correlation between common components of each aggregate and the economic growth rate on one hand, as well as between common components of each aggregate and the computed indicator, on the other hand, is illustrated in Table 2 and Figure 6. We compute common components of each aggregate using equation (3.1).

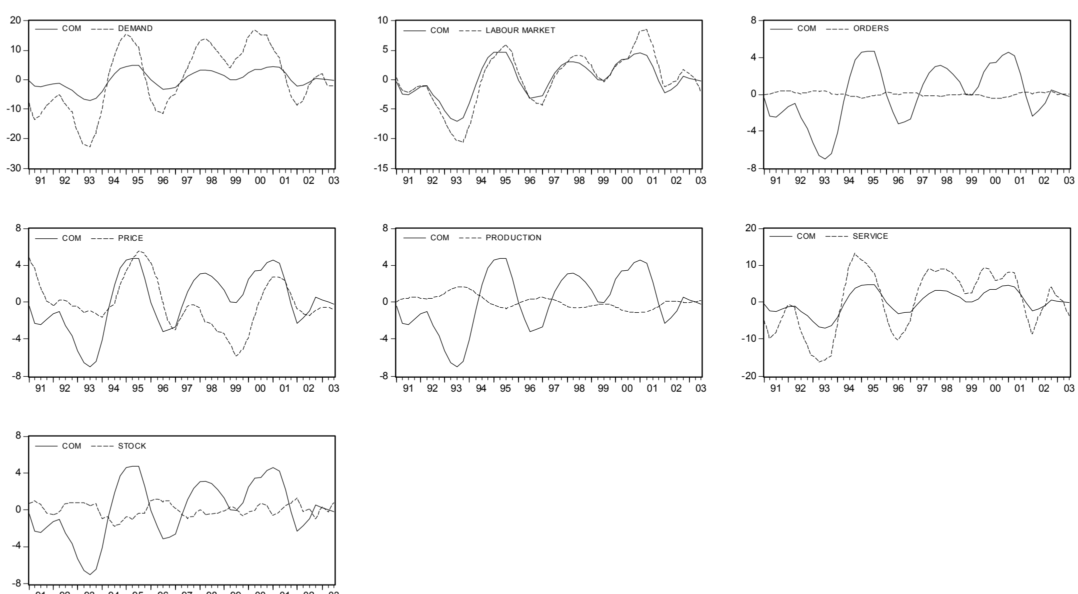
Table 2: Correlation Coefficients

	GROWTH	COM
Demand	0.94	0.87
Labor Market	0.94	0.82
Orders	-0.77	-0.70
Prices	0.26	-0.08
Production	-0.89	-0.88
Service Sector	0.94	0.80
Stocks	-0.50	-0.28

Notes: Correlation between the constructed indicator COM, the economic growth rate and the common components of each sector.

The results in Table 2 together with Figure 6 show that there is a significant correlation between orders, demand, production, services, labor market variables and the coincident indicator. Price and stocks display a non-significant correlation. Negative correlation coefficients do not necessarily indicate a negative relationship.The negative sign rather identifies variables that are leading or lagging by an average of two periods or more. Production can be seen as a leading indicator. Moreover, Figure 5 shows that demand, services, and labor market variables seem to be contemporaneous, and orders and stocks relatively constant throughout the sample period.

Figure 6: Coincident Indicator and Common Component of Each Sector



V. Conclusion

In this paper we propose a new way of constructing an indicator of economic activity for France with survey data. The advantage of using survey data is that they are available ahead of quantitative estimates. We use the generalized dynamic factor model approach of Forni and others (2000) to extract common components from a wide range of surveys. The results reveal that the constructed indicator predicts economic growth with a relatively high degree of accuracy. It implies that the opinion of economic agents has a high predictive power of economic performance in France.

Further work could include 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. Second, the approach used in this paper could also be applied to prices and other economic variables. And, finally, business surveys could also shed more light on the analysis of the behavior of economic agents. In computing latent factors, for example, common opinion of agents, one could shed light on whether or not agents are rational in their decision-making processes.

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 is: 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

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