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**Sectoral business surveys as an aid to short-term macroeconomic forecasting:
The services contribution**

by François Bouton* and Hélène Erkel-Rousse**

(provisional version, Comments welcome)

Affiliation: * Institut National de la Statistique et des Etudes Economiques (Insee), France.

** Institut National de la Statistique et des Etudes Economiques (Insee), France,
and TEAM-CNRS Paris I Panthéon-Sorbonne University, France.

Address: INSEE, Département de la Conjoncture, Division des Enquêtes de conjoncture, Timbre G120,
15 Bd Gabriel Péri, 92 245 Malakoff cedex, France.

Phone: 33 1 41 17 60 56.

Fax: 33 1 41 17 36 24.

e-mail addresses: francois.bouton@insee.fr and helene.erkel@insee.fr

Sectoral business surveys as an aid to short-term macroeconomic forecasting: the services contribution*

by François Bouton and H  l  ne Erkel-Rousse (Insee, France)

Abstract: On the basis of French data, we show that the short-term business survey in services delivers a specific piece of information with respect to the equivalent survey for industry, making it possible to improve short-term macro-economic analysis and forecasting of the GDP growth rate. This specific contribution may be due to a lower sensitivity of service sectors to international trade and inventory movements. We present and discuss GDP forecasts at a one or two-quarter horizon based on miscellaneous univariate as well as multivariate VAR models encompassing data relating to both industry and services. We then suggest that the short-term business survey in services can help one dating the turning points of economic activity. Finally, we show that static common factors are very robust with respect to the imperfect synchrony of their constituent balances. This result constitutes an ex post justification of the intensive use of this kind of synthetic indicators in the paper.

Keywords: Business cycles, service sectors, short-term macro-economic forecasting, sub-annual business survey data, balances of opinion, composite indicators of business climate, common factors, turning-point indicators, causality analysis, Granger causality.

JEL : C32, E32, E37.

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Introduction

Light and quick, sub-annual business surveys provide economists for timely pieces of information on business activity. Harmonised at the European level, they constitute an essential data source for short-term analysis and economic forecasting. In fact, balances of opinion, which summarise entrepreneurs' answers to these surveys, constitute invaluable indicators provided that they are carefully interpreted¹.

The French statistical institute Insee carries out a dozen of sub-annual business surveys, which cover most sectors of activity. These various surveys contain very similar questions and are based on the same kind of methodology. However, the industry survey benefits from wider media coverage. Moreover, while economists and researchers make considerable use of business survey results in industry, they more or less ignore those in the other sectors of activity².

This practice partly originates from the history of statistics. For a long time, the scarcity of figures relating to tertiary sectors led economists to develop their short-term diagnosis essentially on the basis of economic fluctuations in industry. The progressive enlargement of sectoral coverage in terms of short-term statistics has then begun to influence economists' practices. Nonetheless, the clear predominance of industrial fluctuations in economists' preoccupations has not yet disappeared. On the one hand, the availability of long-period time series relating to industry explains part of the specific interest aroused by this sector³. Above all, according to a widespread opinion, the major part of business cycle fluctuations are thought to originate from industry; consequently, overall business cycles are assumed to be satisfactorily analysed and forecast by focusing exclusively on industry data. Is this opinion still valid in the present context where service sectors represent a major part of economic activity in France, as is the case in most industrialised countries?

In this study, we aim to show that taking business survey data relating to miscellaneous sectors into account enables one to improve short-term macro-economic analysis and forecasting of French economic activity. More especially, we show that the contribution of the business survey in services (hereafter referred to as the Service survey) is particularly notable in this respect. The main data sources used in this paper are several sectoral sub-annual business surveys⁴ carried out by the French statistical institute Insee, as well as French quarterly national accounts.

¹ Most questions asked to sub-annual business surveys are qualitative questions with three modalities: a positive one ("increasing", "above normal" or "more than sufficient"), intermediate ("stable", "normal", "sufficient") or negative ("decreasing", "below normal" or "less than sufficient"). The balance of opinion relating to a question of this kind is defined as the difference between the proportion of entrepreneurs having given a positive answer and that of entrepreneurs having given a negative answer. In practice, balances of opinion constitute a good summary of entrepreneurs' answers even though they are not exhaustive statistics.

² Very few papers deal with short-term business cycles in non industrial sectors. As for services, see Fontaine [1992].

³ The Industry survey, which is the Insee oldest sub-annual business survey, was launched in the early sixties. Insee's last-born sub-annual business survey is that performed in services, which was carried out for the first time in January 1988. For further details, see Appendix 1.

⁴ Namely: the surveys performed in industry, services, wholesale trade, retail trade, and construction (consisting of the building industry plus public works). Note that, in this paper (following the Insee sectoral decomposition of sub-annual business surveys), industry does not include construction, which is treated separately. Similarly, services do not include wholesale and retail trade, which are surveyed using specific questionnaires.

In section I, we present simple graphs showing that all sectors, including services, are clearly subject to business cycles, a conclusion that runs counter to a formerly widespread preconception in this respect⁵. At first sight, business cycles in the different sectors considered (industry and services, but also wholesale and retail trade, and construction) seem to be closely linked with one another. However, short-term fluctuations are far from being perfectly identical from one sector to another, probably due to unequal sensitivity to international trade and stock (inventory) movements. Taking account of this sectoral heterogeneity might, to a larger extent, enable one to refine business cycle analysis. More especially, a simple correlation calculation suggests that service data might provide one with useful specific information with respect to business cycle analysis.

These intuitions are confirmed in section II, by a causality analysis that clearly establishes the significance of the extra information embodied in the Service survey with respect to that given by industry data in terms of *GDP* forecasting. Moreover, we show that some balances of opinion in services turn out to provide us with relatively advanced pieces of information on the business cycle.

In section III, we present several econometric models (two univariate calibration models as well as a *VAR* model) encompassing the growth rate of *GDP* and the main balances of opinion in both industry and services or, alternatively, a coincident composite indicator in each of the two sectors (services and industry) introduced in section I. The balances and the composite coincident indicator in services prove to be highly significant. The three models are then used to provide short-term forecasts of *GDP*.

In section IV, we also suggest that it might be useful to call upon the early piece of information contained in the Service survey to improve turning point dating. In particular, because the small number of observations prevents us from calculating a sophisticated turning-point indicator in services such as that introduced by Grégoir and Lengart [2000] using industry data, we suggest a possible leading indicator in services based on a very simple methodology.

Finally, in section V, we show that the common factor in services used in causality analyses, as well as in the *VAR* model used in section III, is very robust with respect to the imperfect synchrony of its constituent balances, although its underlying theoretical foundation does not take this characteristic feature of the balances into account. In other words, this apparent methodological weakness does not constitute a limitation of our work in practice.

I- Does the following of industry really enable one to capture most of the overall economic fluctuations of the French economic activity?

I-1 A simple correlation analysis

It is interesting to address the validity (as well as the limitations) of the common view according to which industrial fluctuations encompass most of the overall economic fluctuations of the French economic activity in the light of some figures derived from the French quarterly accounts. Manufacturing production accounts for around 40% of French market production. Meanwhile, services, retail and wholesale trade, and construction together make up around 60% of the total (within which 40% for services). The variability of industrial production is proportionally higher. In fact, strictly speaking it contributes to 50% of the variability of market

⁵ However, Fontaine [1992] had already found this result using French data relating to services (but from other sources).

production. Again, the share of the other sectors remains considerable (50%, within which 30% for services)⁶. However, if we take into account the correlation between fluctuations in non-industrial and industrial production, then the contribution of industry to the variability of market production becomes much higher. In fact, 89% of the variability of total production can be directly or indirectly captured through that of industrial production. These simple figures suggest that short-term analysis of economic activity might be relatively well captured through that of industry alone.

However, services can directly explain a large part of the residual variability of market production captured through industrial fluctuations (namely 8 points out of the remaining 11%)⁷. Moreover, this residual variability unexplained by industry may be higher in periods when economic activity in some non-industrial sectors undergoes very specific fluctuations. Besides, the total contribution of services to the variability of overall market production amounts to 82% (to be compared with the 89% for industry)⁸. Consequently, taking non-industrial sectors (and especially services) into account might enable one to qualify and improve diagnosis based on industry alone.

I-2 Industry is more sensitive to foreign shocks and inventory movements than other sectors

Contrarily to industry, services are characterised by a low degree of openness to international trade⁹. Consequently, they are less strongly exposed to foreign shocks. Inventory movements constitute another notable source of economic fluctuations in industry. On the other hand, inventories are quasi nonexistent in services. Therefore, the latter sectors are not subject to fluctuations specifically induced by inventory movements. Finally, production growth rate in services is more highly correlated to the growth rate of domestic demand excluding inventories (with a correlation of 0.80 between the first quarter of 1989 and the

⁶ Let P denote the growth rate of market production according to the French national accounts. It is easy to show that the variance of the growth rate of market production can be expressed as: $V(P) = \text{cov}(P, P_i) + \text{cov}(P, P_s) + \text{cov}(P, P_r)$, where V stands for variance, cov for covariance, and P_i, P_s and P_r for the direct contributions of industry, services and the rest of the economy (wholesale and retail trade, construction and agriculture) to the growth rate of market production, expressed in absolute terms ($P = P_i + P_s + P_r$). Figures given in the above paragraph correspond to, respectively: $\text{cov}(P, P_i)/V(P) = 50\%$ and $\text{cov}(P, P_s)/V(P) = 30\%$.

⁷ $V(P)$ (defined in the previous footnote) can also be formulated as follows:

$$V(P) = \left[1 + \left(\text{cov}(P_i, P_s) + \text{cov}(P_i, P_r) \right) / V(P_i) \right] \text{cov}(P, P_i) + \text{cov}(P, \tilde{P}_s) + \text{cov}(P, \tilde{P}_r)$$

where \tilde{P}_s and \tilde{P}_r represent the portions of P_s and P_r that are non-correlated with P_i .

The overall contribution of industry to the variability of market production expressed in relative terms is equal to: $\left[1 + \left(\text{cov}(P_i, P_s) + \text{cov}(P_i, P_r) \right) / V(P_i) \right] \text{cov}(P, P_i) / V(P) = 89\%$. The total contribution of services to the residual variability (*i.e.* to the remaining 11%) is obtained by adding the *direct* residual contribution of services $\text{cov}(P, \tilde{P}_s) / V(P)$ to its indirect contribution: $\text{cov}(P, \tilde{P}_s) \text{cov}(\tilde{P}_s, \tilde{P}_r) / V(\tilde{P}_s) V(P)$. The sum of these two terms equal 8%. All these figures are relating to the nineties.

⁸ These figures are essentially a sign of the high correlation between sectoral fluctuations.

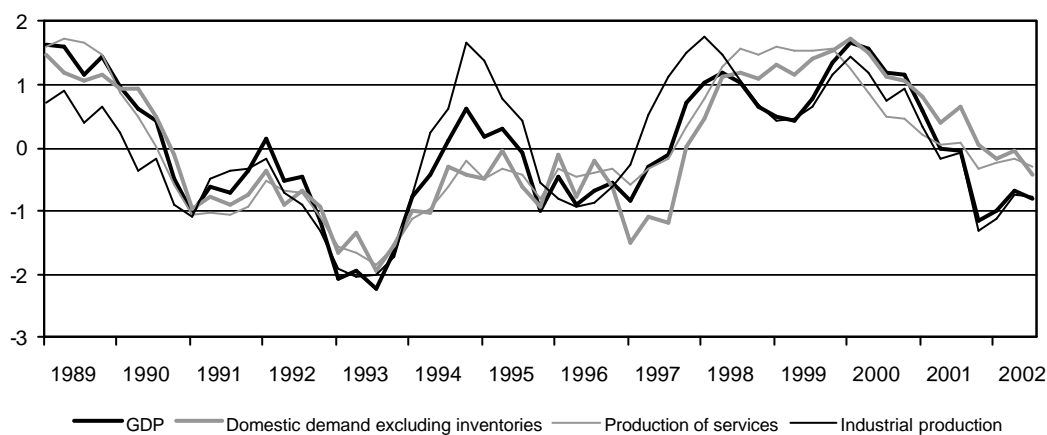
⁹ The degree of openness to trade, as is approximated by the ratio (import + export) / 2 production, has been stable, around 3%, since more than 20 years in services. Meanwhile, it has regularly increased in industry, in which sector it reached 43% in 2001 (source: French quarterly accounts).

third quarter of 2002) than manufactured production growth rate (whose correlation with the growth rate of domestic demand excluding inventories is 0.49 on the same period) - Cf. Graph I.

The examination of the main economic trends in the nineties shows a slowdown trend between the end of 1989 and the mid 1993, briefly interrupted in 1991, then a general accelerating trend during the seven following years, from 1994 to 2000, temporarily contradicted by the 1995 and 1998 inflections. These two major trends of the nineties were undergone with the same intensity by GDP and domestic demand excluding inventories. However, in the short run, the latter's growth rate experienced more moderate fluctuations than the GDP growth rate, especially in 1994 and 1999. Production in services went through very similar fluctuations, of much lesser short-term amplitude than manufactured production.

More pronounced short-term movements of the growth rates of GDP and, to a larger extent, of manufactured production in the nineties originate from inventory movement incidence and, above all, to higher sensitivity to foreign shocks. Now, the latter sensitivity was reinforced in the period due to increasing openness of the French economy. For instance, the better resistance of both production of services and domestic demand excluding inventories, during the late 1998 "blip", as well as the subsequent 2001 slowdown, seems to stem from a lesser exposure to the negative foreign demand shock and the absence of massive inventory reduction (as that observed in industry). More generally, foreign shocks caused most fluctuations undergone by the French economy in the second half of the nineties. The fact that production of services and domestic demand excluding inventories were affected later and less strongly than manufactured production during the 1997 acceleration and the subsequent late 1998 "blip" illustrates the progressive and softened propagation of shocks from more open sectors to less exposed ones.

GRAPH I: Production in services is strongly correlated with domestic demand excluding inventories
(French Quarterly Accounts, standardised yoy growth rates, in %)



Graph II presents the evolution of sectoral synthetic indicators derived from sub-annual business surveys in industry, services, wholesale and retail trade, and construction¹⁰. Unsurprisingly, the major cyclical movements of the French economy are perceived by a large majority of surveyed entrepreneurs, whatever the

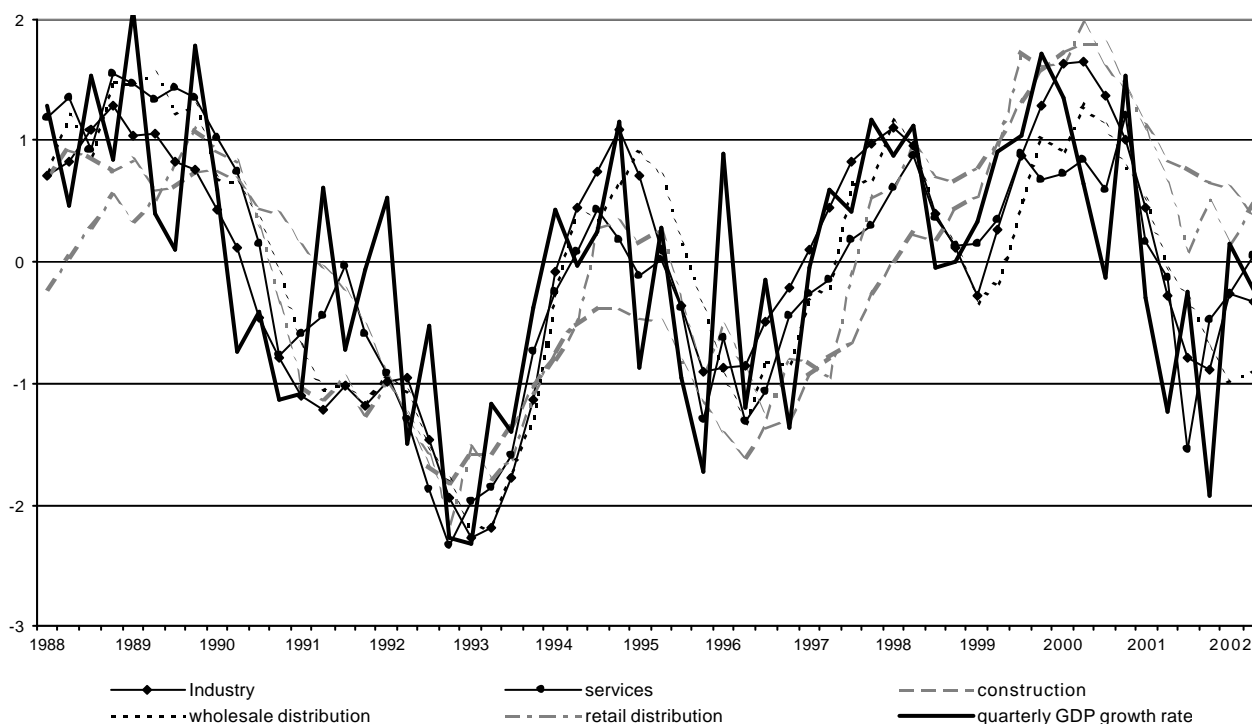
¹⁰ Cf. Box 1 for a precise definition of the synthetic indicators used. NB: Similar models have been used in different contexts by Geweke [1977], Sargent and Sims [1977], Geweke and Singleton [1981], Engle and Watson [1981, 1983], Watson and Kraft [1984] and, more recently, by Stock and Watson [1989, 1991, 1993], Quah and Sargent [1993] or Forni and Lippi [2001a].

sector of the economy. However, sectors' specific characteristics induce imperfectly homogeneous short-term fluctuations between sectors. Economic fluctuations may be of different magnitudes or, even, diverge from a sector to another during several quarters.

Like the quarterly accounts, the French business surveys show that, in the last decades, services were subject to short-term fluctuations of lesser amplitude than industry, especially in the second half of the nineties. Retail trade seems to have experienced still lower fluctuations, especially during the late 1998 "blip" and the 2001 slowdown, due to sustained household consumption¹¹. Conversely, wholesale trade shows the same kind of fluctuations as industry.

As far as it is concerned, the French construction cycle was notably influenced by several specific factors in the late nineties. The activity in construction was fostered by the consequences of the December 1999 storms (until the middle of 2001, due to the spreading in time of the necessary reparations). It also benefited from several economic policy targeted measures, such as the Périssol Plan, whose effects were perceived in 1998 as well as in the three first quarters of 1999, or the drop in the VAT rate on maintenance and improvement works in September 1999. Moreover, activity in construction was supported by the local communities at the end of the nineties, just before local elections. Finally, the construction business cycle is strongly led by household demand and very little (as well as very indirectly) exposed to foreign shocks. The conjunction of these miscellaneous factors explains why this sector did not experience the late 1998 «blip» and better resisted to the 2001 slowdown than the rest of the French economy.

GRAPH II: Static common factors in the main sectors of the French economy



¹¹ In the nineties, the link between services and household consumption was not as crucial as for retail trade. In fact, economic fluctuations in services as a whole were closer to those in business services than to those in household services.

Box 1: Building synthetic indicators for the main sectors of the French economy

Since 1999, the French institute Insee has published a coincident indicator of the industrial climate for France on a monthly basis¹². This coincident indicator, also referred to as the “common factor” or, more simply, the “synthetic indicator”, was first introduced by Doz and Lengart [1996, 1999]. This indicator is based on a classical factor analysis methodology applied to the set of six balances of opinion in industry presented in Appendix I (see below). We have calculated sectoral synthetic indicators for industry, services, retail and wholesale trade, and construction, using the same methodology. Note, however, that our benchmark indicator for industry differs from the Insee official common factor by the length of the period considered and by its periodicity. In fact, for purposes of comparison with service data, we have calculated ours on a quarterly basis since 1988 instead of a monthly one since 1976 (*Cf.* appendix 1).

The common factor methodology is based on very classical principles. The objective is to summarise a set of I observed variables (here I balances of opinion) by a small number $J < I$ of latent variables called common factors. The underlying model supposes that each of the I observed variables results from the combination of both a small number of common factors $(F_{jt}^1)_{j=1,\dots,J}$ and an idiosyncratic component u_{it}^1 :

$$X_{it} = \sum_{j=1}^J I_{ij}^1 F_{jt}^1 + u_{it}^1$$

where X_{it} denotes the value taken by the i^{th} observed balance of opinion at time $t \in \{1, \dots, T\}$ (¹³). Idiosyncratic components are supposed to be independent from one another as well as from the J factors¹⁴. All variables are centred. The model is estimated by the maximum likelihood. The estimated common factors derived from this method are linear combinations of balances (X_{it}).

More precisely, in a first stage of the analysis, a test taking the time structure of data into account permits one to determine the number J of pertinent common factors for the set of balances considered. In the case of all sectors analysed in this paper, this test leads to $J = 1$. Consequently, one can summarise this set of balances within one sole composite indicator: the estimated (first and unique) common factor (hereafter noted F_t^1).

In a second stage, two estimation procedures may be considered: the dynamic procedure based on Kalman filtering is *a priori* preferable because it takes explicitly into account the time structure of the data; the other method, referred to as “static” and based on classical factor analysis, is less efficient, but simple to implement. However, at least on our data, the two methods led to extremely close results. Consequently, the second estimation method has been privileged¹⁵. The quarterly “static” common factor in industry derived from an estimation performed on from January 1988 to October 2002 is equal to (for a thorough definition of the balances of opinion used in the paper, see Appendix 1):

$$IND_t = 0.21 TP^{pa}_t + 0.11 TP^{exp}_t + 0.25 OVORD_t + 0.32 FOORD_t + 0.07 GEXP_t - 0.07 INVENT_t$$

where TP = trend of production, (exponents “*pa*” standing for “past” and “*exp*” for “expected”), $OVORD$ = overall orders, $FOORD$ = foreign orders, $GEXP$ = general expectations, $INVENT$ = inventories, all these balances of opinion being derived from the Insee business survey in industry.

Applying the same methodology to the set of six service balances (namely: past and expected turnover, past and expected operating profit, expected demand and past workforce size, noted respectively TO^{pa} , TO^{exp} , $OPRO^{pa}$, $OPRO^{exp}$, DEM^{exp} , WF^{pa}), leads to the determination of the following static common factor:

$$SER_t = 0.32 DEM^{exp}_t + 0.25 OPRO^{exp}_t + 0.24 TO^{exp}_t + 0.08 OPRO^{pa}_t + 0.08 TO^{pa}_t + 0.06 WF^{pa}_t$$

¹² Both Insee and the European Commission publish a similar kind of indicator for the Euro zone as well.

¹³ Index t corresponds to a couple year \times month (January, April, July or October). Balances are quarterly (see Appendix 1 for details on the way quarterly balances can be derived from two-monthly surveys in the case of retail trade and wholesale trade surveys).

¹⁴ This property differentiates the present methodology from principal component analysis.

¹⁵ For a thorough presentation of the estimation method and factor derivation, see Doz and Lengart [1996, 1999].

Box 1 - continued below.

The other static common factors presented in graph 2 have been calculated on the basis of the following balances of opinion, derived from business surveys carried out in the corresponding sectors of activity:

- **Wholesale trade:** $WHOD_t = 0.04FOSAL^{pa}_t + 0.10FOORD_t + 0.25FODEL_t + 0.07GEXP_t$

where $FOSAL$ = foreign sales (exponent “ pa ” standing for “past”), $FODEL$ = foreign deliveries, all these balances of opinion being derived from the Insee business survey in wholesale trade.

- **Retail trade:** $RETD_t = 0.09SAL^{pa}_t + 0.36OVORD_t + 0.08WF^{exp}_t + 0.52GEXP_t$

where SAL = sales, all these balances of opinion being derived from the Insee business survey in retail trade.

- **Construction:**

$$CONS_t = 0.10AC_{B,t}^{pa} + 0.09AC_{B,t}^{exp} + 0.16OVORD_{B,t} + 0.14WF_{B,t}^{pa} + 0.29WF_{B,t}^{exp} + 0.04GEXP_{B,t} \\ + 0.05AC_{PW,t}^{pa} + 0.17WF_{PW,t}^{exp}$$

where AC = activity, the balances of opinion referred to by a B subscript being derived from the Insee business survey in the building construction industry, while those referred to by a PW subscript are derived from the Insee - FNTP business survey in public works¹⁶.

All balances of opinion have been standardised before entering the calculus of the common factors. The latter are standardised too. They constitute summaries of the information contained in the corresponding surveys. As such, they can be considered as coincident indicators. Their common evolutions illustrate cyclical movements of large magnitude. Their disparities invite one to qualify the short-term economic diagnosis.

From an economic perspective, the degree of heterogeneity in sectoral fluctuations can be informative for short-term economic analysis. An unanimous drop in balances of opinion from all sectors lets one expect a more significant short-term slowdown than downward trends that are either concentrated in a few sectors or of very uneven magnitudes from one sector to another. In the late 1998, for instance, the relatively good resistance of common factors in services, retail trade and construction with respect to the clear decrease in those in industry and wholesale trade rightly suggested that the late 1998 «blip» would be a minor and short decrease. Conversely, the general drop in sectoral common factors during the year 2001 suggested a stronger slowdown - Cf. graph II. That is what actually happened in each case. Therefore, synthetic indicators derived from the different business surveys seem to be useful summaries of short-term sectoral business fluctuations. Those in industry and in services are the most highly correlated with the GDP growth rate (see Appendix 1). Consequently, they might be useful tools for GDP short-term forecasting. These pointers are confirmed by a causality analysis involving survey data and the GDP growth rate.

¹⁶ FNTP = the French professional federation in public works (Fédération Nationale des Travaux Publics).

II- Causality analyses.

One can easily test if a sub-annual business survey encompasses a significant surplus of information on the GDP growth rate with respect to a benchmark survey of the same kind (for instance the Industry survey).

Let Y represent the quarterly growth rate of GDP (in the appendices, we use the more explicit but longer “ GDP_t ” notation). Z denotes a $(1, K_C)$ vector of K_C “context” variables commonly used to predict Y . Most often, the context variables are derived from the same survey, especially the Industry survey. The determination of the context vector Z is very important, as it has a crucial influence on the causality analysis diagnosis. Finally, X stands for a $(1, K_A)$ vector of K_A additive variables. In general, the latter are relating to another sectoral survey than that from which the context variables are derived. A simple causality analysis performed within VAR models can show whether the additive variables encompassed in X provide a specific piece of information regarding the interest variable Y with respect to context data (summarised in the context vector Z) and, if this is the case, whether this specific piece of information is instantaneous or not - see Box 2 for a technical summary of the methodology.

As for the number of lags of each considered VAR model, the number of observations being rather low¹⁷, we have limited ourselves to a maximum of 4 lags. We have used the Hannan, Schwarz and Akaike information criteria, as well as both the sequential F -test of system reduction¹⁸ and additive F -tests checking for any $p - i$ lags versus i' lags (with $p - i < i' \leq p$). As these tests are not very robust when performed on a set of few observations, we have checked whether the causality tests would have given different results with VAR models including different numbers of lags. In practice, as VAR models with 4 lags are systematically rejected without any ambiguity whatever the set of variables taken into account, we have performed causality tests using equations (2) to (4) (Cf. Box 2) with alternatively $p = 1$ to 3 lags. We have also checked for multicollinearity, using both the Belsley, Kuh and Welsch (BKW) [1980] indicators and intercept-adjusted ones (see Appendix 2).

In a first stage, we have summarised the sectoral sub-annual business surveys by their synthetic indicators (as defined in Box 1). In other words, we have tested the contribution of each synthetic indicator in terms of information given on the GDP growth rate with respect to the synthetic indicator in industry (or, alternatively, in services), the former synthetic indicator representing the additive variable (X), the latter the context variable (Z). The results of this analysis are given in Appendix 2 (tables 1 and 2).

The first striking result concerns the Industry survey. The latter encompasses an invaluable piece of information on the past and future GDP growth rates. In fact, in the VAR model expressed in canonical form (table 1), the lagged values of the synthetic indicator in industry are always (overall) significant in the GDP equation, whatever the other sectoral synthetic indicator involved in the model. When the GDP equation is expressed in block-recursive form (table 2), the current value of the synthetic indicator is always significant:

¹⁷ At the moment when the causality analysis was performed, balances of opinion in services were available (on a definitive basis) from January 1988 to July 2002; therefore, the number of quarterly observations was close to sixty.

¹⁸ Each stage of the sequential system reduction F -test, namely each F -test: $H_0 : p - i$ lags versus $H_1 : p - i + 1$ lags, with $1 \leq p - i \leq p - 1$, is performed at the 1 % level, so that the overall level of the sequential test remains relatively low (about 3%). Consequently, the threshold of the overall testing process (number of lags + causality tests) never exceeds 4% to 10% (depending on the level chosen for the causality test).

the synthetic indicator in industry instantaneously causes the GDP growth rate, whatever the other sectoral synthetic indicator included in the model.

The second result stresses the specific contribution of the Service survey with respect to the Industry survey. In fact, the non instantaneous causality tests point out that the synthetic indicator in services contains a leading piece of information on the GDP growth rate which is not encompassed in the Industry survey. Moreover, the information included in the synthetic indicator in services on the GDP growth rate appears to be essentially leading. This is not surprising as balances relating to the near future are over-weighted with respect to balances relating to the recent past within the static common factor in services¹⁹. Consequently, business surveys in industry and in services convey short-term economic indications on GDP which are clearly complementary.

The third result concerns the other sectoral business surveys. The latter do not encompass any clearly identified additive information on macroeconomic growth (be it instantaneous or leading) with respect to that already contained in the Industry survey, or even the Service survey. In this respect, the synthetic indicator in construction might be an imperfect substitute of its counterpart in industry in the GDP equation in the canonical form also including the synthetic indicator in services. Nonetheless, the same equation in which the composite indicator in construction is replaced with that in industry proves to be preferable in terms of econometric adjustment. More generally, the model taking industry and services into account clearly outdoes the other models in this regard.

Therefore, the pointers of the previous section are confirmed by the causality analysis: the business surveys in industry and in services seem to encompass complementary pieces of information on the growth rate of GDP. These results do not shed doubt on the usefulness of the other sectoral surveys. In fact, the business surveys in wholesale trade, retail trade and construction enable one to derive early information on macroeconomic aggregates such as household consumption (retail trade survey), investment and imports (wholesale trade survey), as well as sectoral production and workforce size (every sectoral survey).

In a second stage, we have tried to identify which balances of opinion in services convey the specific leading information which is not perceived by the Industry survey. This causality analysis on VAR models including balances in industry and in services presents another advantage: the potentially different dynamics of balances relating to the recent past with respect to those concerning the near future can be taken into account in these models, which is not the case when the sectoral business surveys are summarised by their synthetic indicator (as defined in Box 1).

We thus define a benchmark VAR model including the GDP growth rate and the two balances of opinion in industry which, according to Reynaud and Scherrer [1996] constitute the best summary of the early information contained in the Industry survey. More precisely, Reynaud and Scherrer [1996] find that the balance relating to the past trend of production (TP^{pa}) is the best coincident indicator of IPI (Industrial Production Index) derived from the monthly business survey in industry, while that concerning expected trend of production (TP^{exp}) is its best leading indicator. We obtain the same result when limiting ourselves to the corresponding quarterly balances of opinion and replacing the monthly IPI with the quarterly growth rate of GDP. In particular, we find that adding any other industry balance (within the set of six defined in Box 1)

¹⁹ This is not the case for the synthetic indicator in industry - Cf. Box 1.

Box 2: Instantaneous and non-instantaneous Granger causality

All the considered variables being stationary, the $(K_C + K_A + 1, 1)$ vector $V_t = (Y_t, Z_t, X_t)'$ allows for an approximated VAR representation²⁰:

$$A(L)V_t + C = \mathbf{e}_t \quad (1)$$

where $A(L) = I + A_1L + \dots + A_pL^p$, p being the number of lags of the VAR model, L the lag operator, I the identity $(K_C + K_A + 1, K_C + K_A + 1)$ matrix, $(A_i)_{i=1, \dots, p}$ the set of $(K_C + K_A + 1, K_C + K_A + 1)$ matrices of coefficients of the VAR model and \mathbf{e}_t its vector of perturbations.

Let $\underline{X}_{t-1} \circ (X_{t-1}, X_{t-2}, \dots, X_{t-p})$ refer to the past of X_t up to its p^{th} lag. Similarly, we define: $\underline{Z}_{t-1} \circ (Z_{t-1}, Z_{t-2}, \dots, Z_{t-p})$ and $\underline{Y}_{t-1} \equiv (Y_{t-1}, Y_{t-2}, \dots, Y_{t-p})$.

• Causality *à la* Granger consists of several aspects:

- the fact that variable X 's past values help one to predict variable Y in the context $(\underline{Y}_{t-1}, \underline{Z}_{t-1})$ is referred to as *non-instantaneous causality*: it can be easily tested as the nullity of the vector \mathbf{g} of coefficients relating to \underline{X}_{t-1} in the equation of the VAR dealing with the dynamic of Y_t :

$$Y_t = \underline{Y}_{t-1}\mathbf{a} + \underline{Z}_{t-1}\mathbf{b} + \underline{X}_{t-1}\mathbf{g} + \mathbf{d} + \mathbf{e}_{1,t}^Y \quad (2)$$

and is hereafter noted: $\underline{X}_{t-1} \xrightarrow{Z} Y_t$ (or, more simply, $\underline{X}_{t-1} \textcircled{R} Y_t$ if the context vector is known without ambiguity).

- the fact that the present value of variable X helps one to predict variable Y in the context $(\underline{Y}_{t-1}, \underline{Z}_{t-1}, \underline{X}_{t-1})$ is referred to as *instantaneous causality* and can be tested as the nullity of the vector of K_S coefficients \mathbf{d} relating to X_t in equation (3) below:

$$Y_t = \underline{Y}_{t-1}\mathbf{a} + \underline{Z}_{t-1}\mathbf{b} + \underline{X}_{t-1}\mathbf{c} + X_t\mathbf{d} + \mathbf{f} + \mathbf{e}_{1,t}^Y \quad (3)$$

and is hereafter noted: $X_t \textcircled{R}_Z Y_t$ (or, more simply $X_t \textcircled{R} Y_t$). Note that the context vector can be slightly modified by including (part of) the current values of Z .

- It may also be interesting to test whether taking into account the past and present values of variable X enables one better to predict variable Y in the context $(\underline{Y}_{t-1}, \underline{Z}_{t-1})$ or $(\underline{Y}_{t-1}, \underline{Z}_{t-1}, Z_t^*)$, where Z_t^* represents a subset of vector Z_t . This hypothesis can be tested as the nullity of the vector of $K_C(p+1)$ coefficients Δ relating to $\underline{X}_t = (\underline{X}_{t-1}, X_t)$ in equation (4):

$$Y_t = \underline{Y}_{t-1}\mathbf{A} + \underline{Z}_{t-1}\mathbf{B} + \underline{X}_t\mathbf{D} + Z_t^*\mathbf{E} + \mathbf{G} + \mathbf{e}_{2,t}^Y \quad (4)$$

and is hereafter noted: $\underline{X}_t \textcircled{R}_{Z, Z^*} Y_t$ (or, if there is no ambiguity concerning the context vector, $\underline{X}_t \textcircled{R} Y_t$).

Equations (3) and (4) can be derived from (1) by premultiplying its left and right terms by a specific matrix transforming (1) into a block-recursive expression²¹. In each of these equations, the e term represents the perturbation.

²⁰ X, Y, Z, K_A and K_C have been defined above (Cf. two previous pages).

into a VAR model with 3 or 4 lags already including the GDP growth rate, TP^{pa} and TP^{exp} leads to a multicollinearity situation²². This means that we cannot make any reliable test of the optimal number of lags in a VAR model containing more industry balances than those two. Moreover, replacing either TP^{pa} or TP^{exp} with any another industry balance in the VAR model leads to a decrease in the quality of the fit, whatever the number of lags between 1 and 4. Therefore, TP^{pa} and TP^{exp} seem to be the best context variables for our causality analysis.

We must also decide how to proceed to check whether the past or the present values of any service balance add any valuable information with respect to the GDP growth rate in the context of TP^{pa} and TP^{exp} . As we have few observations at our disposal, we cannot add too many variables into the benchmark VAR model. Consequently, we limit ourselves to a one- or, at most, two-dimension vector X_t , representing one or two balances out of the list of five defined in Box 2 above.

Tables 3 and 4 in Appendix 2 summarise the main results of the causality analyses performed on the basis of these models. The GDP growth rate can be considered as weakly exogenous, whatever the VAR model.

Table 3 suggests that the three service balances relating to the near future, namely those relating to expected demand (DEM^{exp}), operating profit ($OPRO^{exp}$) and turnover (TO^{exp}), give specific advanced information on the GDP growth rate (hereafter referred to as GDP). $OPRO^{exp}$ appears to be somewhat particular as it also contains instantaneous information on GDP , even when the current values of the two industry balances taken into account are included in the model (Cf. table 4). This interesting characteristic feature of $OPRO^{exp}$ will be used in forecasting models defined in the following section. Moreover, the lagged values of DEM^{exp} and TO^{exp} add significant information on GDP in models with one lag, even when the current values of balances relating to the past and expected trends in industrial production (TP^{pa} and TP^{exp}) appear in the model. This property too will be used in our forecasting models (Cf. section III). Note that any service balance within the list of 6 defined in Box 2 instantaneously causes the GDP growth rate when the model includes the current value of TP^{pa} .

The service balances relating to the recent past, namely those referring to turnover (TO^{pa}) and operating profit ($OPRO^{pa}$), contain specific instantaneous information on GDP (especially in models with one lag). However, these balances (above all the second one) might also encompass some advanced information with respect to industry balances.

Symmetrically, the same econometric analysis confirms that information on GDP contained in the Service survey do not encompass the whole piece of information included in the Industry survey. In fact, TP^{exp} (resp. TP^{pa}) gives specific advanced (resp. instantaneous) information on macroeconomic growth.

To summarise, these causality analyses suggest that the Industry and Service surveys contain non only common but also complementary specific pieces of information on the GDP growth rate. Therefore, including industry and service balances together within macroeconomic models of GDP should enable one to improve GDP short-term forecasts. Moreover, it will be shown that the differentiated dynamic impacts of the diverse balances of opinion on the GDP growth rate can be exploited within univariate forecasting equations of GDP - Cf. section III below.

²¹ Cf., for instance, Capet and Gudin de Vallerin [1993] and subsequently Reynaud and Scherrer [1996].

²² The very few exceptions in this respect lead to a clear drop in the quality of the fit.

III- Business survey data in services and the short-term macroeconomic forecasting of *GDP*

III-1 The forecasting models used

Building calibration models enabling us to provide short-term *GDP* forecasts on the basis of balances of opinion relating to industry and services constitutes a logical follow-up of the previous results. An econometric analysis has enabled us to select three calibration models. Two of them are “traditional” univariate models in which the quarterly growth rate of *GDP* (noted *GDP*) is treated as endogenous and a certain number of balances of opinion in industry and in services as exogenous explanatory variables. The third model is a multivariate vector-autoregressive (VAR) model, in which all variables treated as endogenous. As for the estimation technique, we applied the ordinary least squares (OLS) method. Our estimation period was the longest possible (considering the length of the service series) at the time when the estimations were performed, namely: 1987 Q4 to 2002 Q2 (taking into account definitive survey data exclusively). The estimation results are presented in Appendix 3.

An advantage of VAR models in terms of *GDP* forecasting is that they lead to the determination of every variable simultaneously (owing to the endogenous status of the latter)²³. Their main weakness is to require long enough time series, owing to the relatively large number of coefficients to be estimated within such models. Here, the estimation period is rather short (corresponding to 60 quarterly observations or so). Including more than three variables in the VAR model would therefore have led to non-robust forecasting results²⁴. In the present case, we were able to circumvent this difficulty by summarising the information encompassed in each of the two business surveys considered through a single coincident synthetic indicator. Doing so, we could build a VAR model with only three variables: the *GDP* quarterly growth rate (*GDP*) and two synthetic indicators, one relating to industry (*IND*) and the other to services (*SER*). The main drawback of this approach is that it deprives us from the possibility of taking into account the differentiated dynamic impacts on *GDP* of the various balances constituent of each synthetic indicator. In this respect, it is noteworthy that the second causality analysis performed in section II confirms the intuition according to which the time structure of information given on the *GDP* growth rate differs from one balance of opinion to another, notably depending whether they refer to the recent past or to the near future.

Univariate calibration models enable one to differentiate the relative dynamic impact of the balances taken into account. The formulation of the two calibration models, presented in Appendix 3, has been inspired by the causality analysis results. It should be stressed that this possibility given by the univariate calibration models results in slightly better econometric adjustment than in the *GDP* block-recursive equation of the VAR model.

In conformity with intuition, the precision of forecasts based on these models decreases as their time-horizon becomes more distant. The precision of one-quarter horizon forecasts appears to be slightly more satisfactory (with a standard deviation of forecasting errors of about 0.3 of a point of the *GDP* growth rate) than that of

²³ On the contrary, using univariate calibration models in forecasting often requires extending the explanatory variables outside of these models. See Appendix 3 for details concerning the way we proceeded in this respect when using one of the two univariate models.

²⁴ In this respect, forecasting is more demanding than a simple causality analysis (for which we could push the econometric techniques a little further, up to VAR models with 4 variables). In fact, high robustness is a crucial property in terms of forecasting models. Several years of usage enable us to assert the robustness of the VAR model with 2 variables presented here. Significant modifications in successive *GDP* forecasts made on its basis are essentially due to the adding of new information, which is in accordance with what can be expected as regards a good forecasting model.

forecasts performed at a more distant two- or three-quarter horizon (the standard deviation of forecasting errors increases by 0.1, reaching 0.4). It can be stressed that the relatively large value of RMSE (root mean square errors) in these models stems from the combination of both a highly volatile explained variable (*GDP*) on the one hand and much smoother explanatory factors (the industry balances and, to a slightly lesser extent, the service balances - see below, section V) on the other hand.

III-2 How the forecasting models have captured the evolution of GDP since the late nineties

As an illustration, the series of successive *GDP* forecasts²⁵ performed on the basis of the VAR model presented in Appendix 3 shows the utility of this kind of model, as well as its limitations - *Cf.* table 6.

At the end of 1998, French economic growth experienced a short period of slowdown (the 1998-1999 blip). The estimation given by the VAR model establishes that surveys available at the second quarter of 1998 did indeed forecast a slowdown of activity. However, while the latter began to accelerate again from the first quarter of 1999, entrepreneurs' expectations in industry and in services remained depressed until Q2. Consequently, on the basis of business surveys available until April, the VAR model did not make it possible (at that time) to envisage any rebound. Business surveys published in July 1999 led to an upward revision in expected growth in 1999 Q2. Note that this result remains useful from a practical point of view, as the first growth estimation of the second quarter of 1999 was provided by the French quarterly accounts only six weeks later (in September).

Similarly, the maintenance of entrepreneurs' expectations at a high level in January 2001 led (at that time) to expectations of strong growth for the first quarter of 2001. Conversely, in April, the VAR model indicated an unambiguous downward turning point in French activity as of the first half-year of 2001. Moreover, the next survey results suggested an accentuation of the slowdown and, in October 2001, the VAR model indicated a drop in *GDP* at the end of the year: this forecast proved to be correct.

The quarterly data available in June 2002 (therefore corresponding to those of the April 2002 surveys) led to a forecast of a rebound in French economic activity as of the second quarter of 2002, due to a recovery in entrepreneurs' expectations in both industry and services - *Cf.* table 6 as well as graphs in Appendix 3. Taking into account the precision of estimates given over the past, the three models led to very similar *GDP* growth forecasts, as for the second and third quarters of 2002. However, entrepreneurs had been too optimistic. The latter's perceptions began to include the weakening of the recovery expected in Spring not sooner than in the July 2002 surveys. The forecasts derived from the VAR model after the publication of the July surveys then permitted one to very precisely anticipate the *GDP* growth rate of 0.5 which was released in September for the second quarter of 2002 (source: French quarterly accounts). Afterwards, the canonical form of the VAR model under-estimated the growth rate of 0.2 published in November by the quarterly accounts for the third quarter of 2002. Nonetheless, the block-recursive form of the VAR model including the

²⁵ As is explained in the legend of table 5 (Appendix 3), it is possible to significantly improve the *GDP* forecasts by taking into account the results derived from the latest monthly surveys performed between two quarterly surveys. Although this practice is common in short-term economic forecasting, the figures discussed in these paragraphs are based on quarterly survey results exclusively, notably due to the difficult *ext post* recreating of available monthly data for every quarter since 1999 Q2.

October 2002 survey results for the forecasting of the third quarter (contrarily to its canonical form²⁶) fully agreed with the quarterly accounts for this third quarter.

Moreover, as soon as the October 2002 surveys were published, the VAR model in canonical form announced the order of magnitude of the GDP growth rates that were released several months later for both the fourth quarter of 2002 and the first quarter of 2003 in the “First results” of the quarterly accounts, respectively in February 2003 for 2002 Q4 and then in May 2003 for 2003 Q1. However, the over-optimistic expectations expressed by entrepreneurs in the January 2003 Service survey (notably in terms of operating profit) then led to a misleading upward revision of the GDP forecasts for these two quarters, as well as to a unrealistic first estimation of the GDP growth rate for the second quarter of 2003. As the April 2003 Service survey shows, entrepreneurs then notably revised their expectations downwards. Similarly, the GDP forecasts relating to 2003 Q1 and 2003 Q2 came back to orders of magnitude compatible with the quarterly account figures that were published afterwards, in May (2003 Q1 “First results”) and, then, in August (2003 Q2 “First results”). The July surveys reiterated and refined the diagnosis of a negative growth rate for the second quarter of 2003. One month later, the 2003 Q2 “First results” of the quarterly accounts confirmed this estimation.

In sum, the models presented in this section clearly show that business surveys in both industry and services constitute very helpful information sources for short-term forecasting purposes, even though forecasts made using them suffer from a certain margin of imprecision.

IV- Dating turnings points of activity using the Service survey

Economists need to build indicators on the basis of which they can characterise the current economic situation with respect to the position in the business cycle. Is the economy in a phase of slowdown or acceleration; is it close to a turning point showing a transition towards another phase? The difficulty of this exercise is to succeed in detecting the signs of a durable turning point on the basis of recent evolutions that may not always be unanimous or very clear. Sub-annual business surveys prove to be invaluable tools in this regard, non only because they enable one to compare entrepreneurs’ appreciations on recent and future evolutions, but also because they lead to much smoother and regular series than quantitative indicators. This characteristic feature appreciably makes the latest observations of the series easier to interpret and limits the risk of incorrect diagnosis due to the presence of “noise” in series.

In this section, we aim to estimate whether the Service survey contains relevant specific information on turning points of economic activity. Our analysis constitutes a first evaluation, as it focuses on a short time period (the nineties) and is exclusively based on quarterly series, the only available series on a sufficiently long period as far as the Service survey is concerned²⁷.

²⁶ In fact, the canonical form of the VAR model produces forecasts at a one-quarter horizon on the basis of survey results until the previous quarter, i.e. in the present case, the second quarter of 2002, which corresponds to the July surveys - see Appendix 1 for a thorough explanation in this regard.

²⁷ In fact, having monthly industry series at one’s disposal is very useful for turning point dating. Working on quarterly series therefore constitutes a potentially strong limitation of the present analysis.

IV-1 Trying to isolate leading balances from those derived from the Industry and Service surveys

In a first stage, we determined 9 turning points in the 90's, defined on the basis of the inflection points of the moving average of order 3 of the synthetic indicator in industry. These nine extreme points very simply define benchmark cycles, which outstandingly coincide with those obtained if applying a low-pass filter following the Baxter-King methodology²⁸ to the industry synthetic indicator. In addition, the moving average of order 3 points out a low inflection point in April 2002, while the Baxter-King filter did not enable one to study such a recent period at the moment when the study was performed.

Then, we tried to isolate which balance of opinion in both industry and services would have better permitted one to distinguish these turning points in real time. In the nineties, industry balances were particularly smooth (smoother than service balances)²⁹. As for the latter, turning points can be more easily dated using smoothed series. Therefore, we have replaced the initial series with their moving averages of order 3. Indeed, this smoothing on three quarters is rather long for short-term economic analysis. In this respect, our analysis will have to be confirmed (or invalidated) using monthly service data as soon as long enough series are available.

According to table 8 in Appendix 5, the balance relating to the expected trend in industrial production (TP^{exp}) constitutes the most leading, as well as the most regular, indicator to forecast turning points within the set of balances considered. However, balances concerning past activity in services are seldom lagged with respect to the corresponding industry balances. This result invalidates a widespread prejudice according to which short-term fluctuations systematically affect services with some inertia. Service balances were even leading several times with respect to industrial balances in the first half of the nineties. Then they became somewhat lagged in the second half of the nineties, in a context when foreign shocks had a major influence on the French economy. The latter shocks hit first the most exposed activities (notably industry), then spread to less open sectors (services).

It is well known that temporary work reacts to the fluctuations of activity without delay. Actually, entrepreneurs' opinions in this specific service sector show a leading perception of turning points in 1992, 1993, 1995 and 1998. Nonetheless, this result does not hold on non smoothed series, which are more volatile at the neighbourhood of turning points (with several successive turnings), and therefore less easy to read.

IV-2 Building up a turning point indicator relating to services

In order to make the dating of turning points in industry easier, the French Statistical Institute Insee has developed an univariate indicator called the "turning point indicator" for France³⁰ on a monthly basis. Introduced by Grégoir and Lenglar [2000], this indicator is based on the same set of six balances in industry as the static common factor in that sector - *Cf.* above, Box 1. The principle underlying its calculation consists in extracting the most leading information contained in these balances and then deriving from it an estimation of the probability of a turning point in the near future. In a first stage, one estimates the innovations of the six balances derived from the Industry survey³¹. The larger the number of positive signs among the six

²⁸ *Cf.* Baxter and King [1999].

²⁹ This characteristic feature is confirmed by a spectral analysis of the two sets of balances - *Cf.* Appendix 4, table 7.

³⁰ Insee also publishes a similar kind of indicator for the Euro zone.

³¹ The authors define balance b 's innovation (or surprise) at the current quarter as the part of its short-term evolution which cannot be explained by its recent past. In practice, b 's innovation is derived from a model expressing that balance b is the sum of two terms: its

innovations, the higher the probability of economic acceleration (upward turning point). The lower this number, the higher the probability of economic deceleration (downward turning point)³². The number of plus and minus signs in the set of innovations is thus injected into a Markovian model, from which the probabilities of transition towards a new growth tendency (acceleration or deceleration) are derived. The turning-point indicator is defined as the difference between the estimated probability of an acceleration and that of a deceleration. It therefore takes its values within the [-1, +1] interval and can be easily interpreted. A turning-point indicator close to -1 (respectively +1) suggests a high probability of deceleration (respectively acceleration) of industrial activity in the near future. A turning-point indicator close to zero expresses a period of either uncertainty or an economic growth rate close to its long-term average.

Unfortunately, the turning-point indicator's calculation require a large number of observations³³. In particular, it has not been possible to calculate a leading indicator for services using this methodology. However, we have constructed an alternative leading indicator inspired by the logic of the Grégoir-Lenglart turning-point indicator, but whose main advantage is not to require long time series. This intuitive indicator does not benefit from strong theoretical foundations, contrarily to the Grégoir-Lenglart indicator. However, it gives convincing enough results to be of some help as concerns turning points dating as long as the number of available observations is too low to make the calculation of the Grégoir-Lenglart indicator possible.

As a first approximation, the signs of balances' first differences seem to be an acceptable approximation for those of their innovations. At least, they appear to be the best alternative with respect to the number of observations at our disposal³⁴. Each balance is associated with a dummy variable, whose value equals +1 (-1, 0) if its first difference is positive (negative, null). We then very simply obtain a summary of each Service survey's pseudo innovations by calculating the simple arithmetical average of these dummies. The "intuitive" turning point indicator results from the simple average of the summaries obtained in the two latest quarterly surveys. Taking account of two successive surveys enables us to obtain a more reliable indicator.

As for industry, the intuitive turning-point indicator calculated on a quarterly basis gives fairly satisfactory results on the whole. Indeed, it is highly correlated with the quarterly Gregoir-Lenglart turning-point indicator³⁵ (Cf. graph III below). Indeed, it gives less qualified diagnoses than the latter. For instance, owing to the rough estimation of innovations through balances' first differences, the intuitive indicator treats the late 1998 deceleration in the same way as more notable slowdowns such as those in 2001, 1996 or even 1993. In 1998, the benchmark indicator shed doubt on the robustness of the turning-point which emerged, by privileging an uncertainty diagnosis to that of clear deceleration. Nonetheless, the intuitive indicator would have provided one for valuable information if the benchmark indicator had not been available on this period. Moreover, the

long-term average; a cyclical component whose dynamics can be represented through an auto-regressive formulation. Balance *b*' innovation is proxied by the estimated residual of this auto-regressive formulation.

³² The balance relating to the level of inventories appears in the calculus with a negative sign, so that a positive innovation is a sign of acceleration whatever the balance within the set of six.

³³ The reasoning behind the turning-point indicator requires the presence of a sufficient number of balances in the model for the number of positive and negative signs within the vector of innovations to be significant. That is why limiting the number of balances in order to be able to apply the Grégoir-Lenglart methodology is not a good solution.

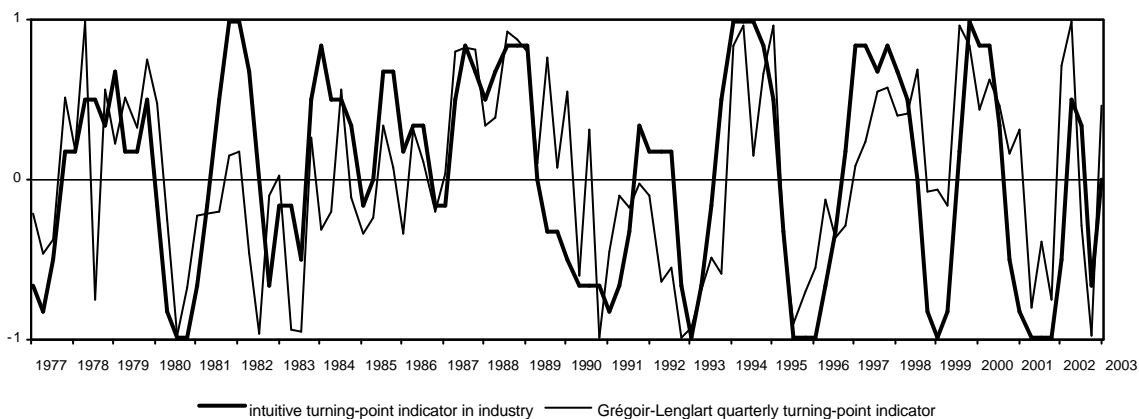
³⁴ The intuition is that balance *b*'s innovation at time *t* is automatically included in its current evolution (its first difference), if not all of it. The first difference therefore appears to be the roughest possible estimation of the innovation.

³⁵ We consider the quarterly Grégoir-Lenglart indicator, calculated by retaining one point out of four (those relating to the January, April, July and October surveys).

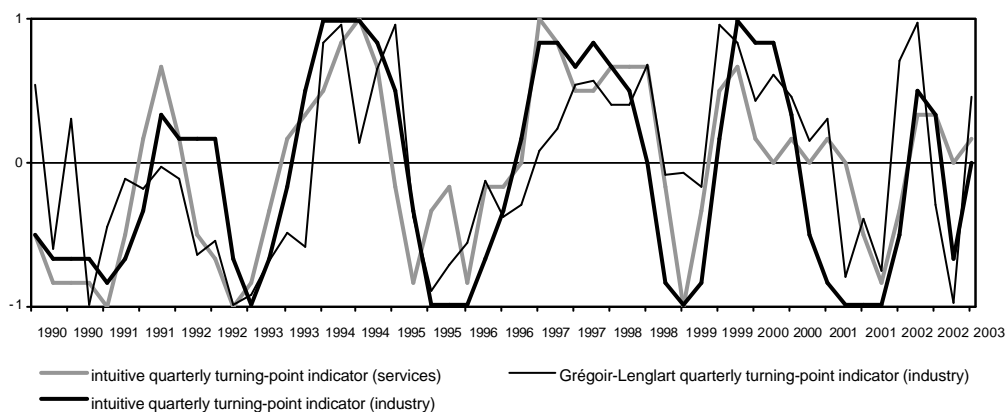
intuitive indicator calculated on a monthly basis taking account of the three monthly Industry survey instead of the two quarter ones proves to be much closer to the Grégoir-Lenglart monthly indicator.

As for services, the intuitive indicator in services is presented in graph IV below³⁶. This indicator sometimes appears to be slightly leading with respect to its equivalents in industry, but also, at least occasionally, to the Grégoir-Lenglart quarterly turning-point indicator. Consequently, despite its drawbacks (which are the same as its equivalent in industry), this very simple turning-point indicator in services may give a useful leading piece of information on business cycles, until the Service survey series become long enough to allow the calculation of a turning-point indicator of the Grégoir-Lenglart type in this sector. Moreover, due to the low number of observations required in its calculus, it is already possible to build an intuitive indicator in services on a monthly basis (since June 2000). The good performance of the equivalent indicator in industry suggests to favour this monthly approach.

GRAPH III: the intuitive turning-point indicator compared with the Grégoir-Lenglart indicator (industry)



GRAPH IV: the intuitive turning-point indicator in services compared with the two previous turning point-indicators in industry



³⁶ The set of balances in services considered is unchanged with respect to the previous sections.

V- Analysing the static common factor in services

V-1 Two questions on the static common factor's methodology

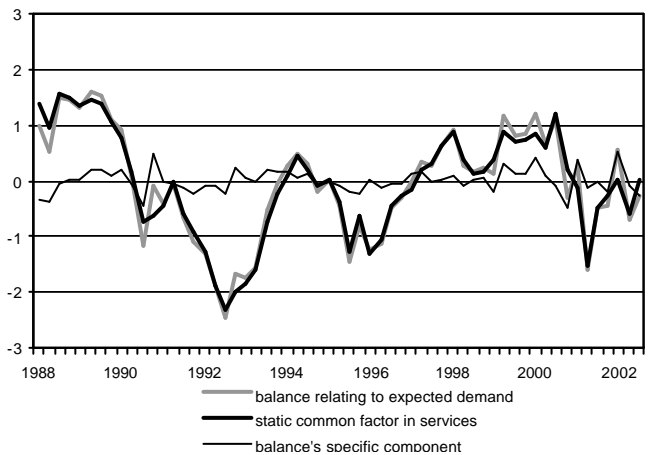
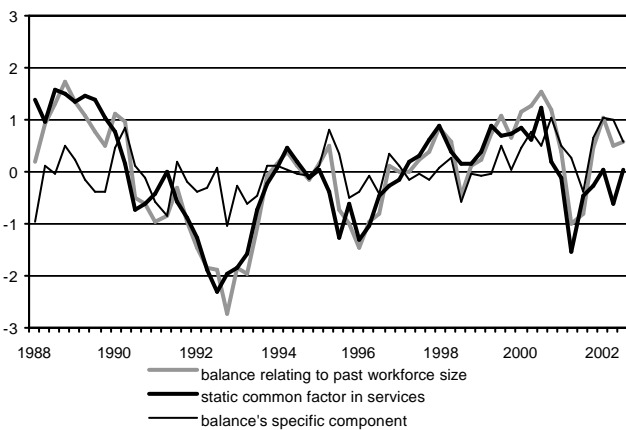
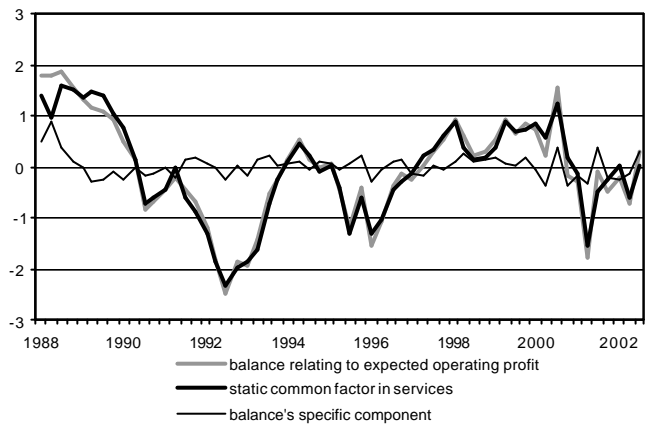
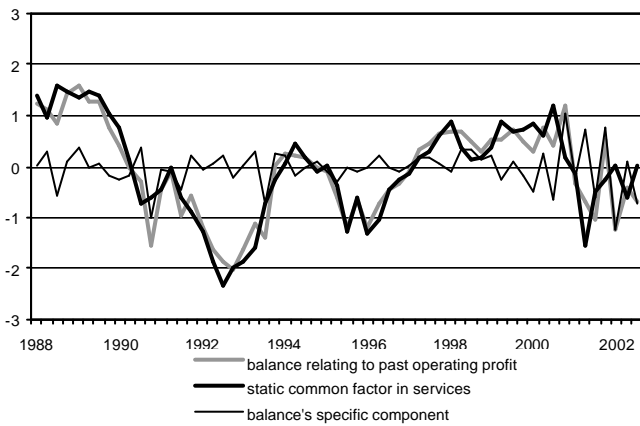
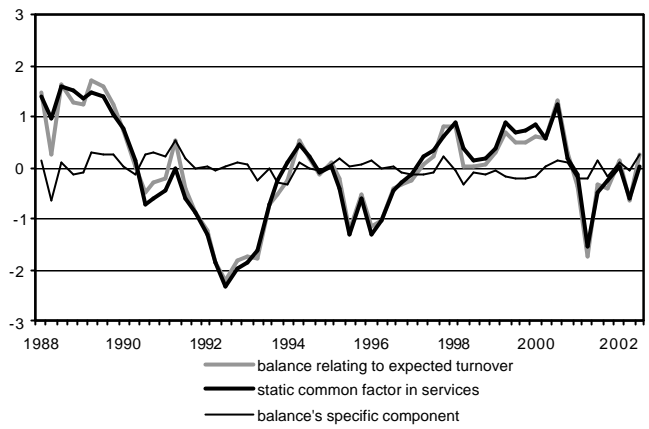
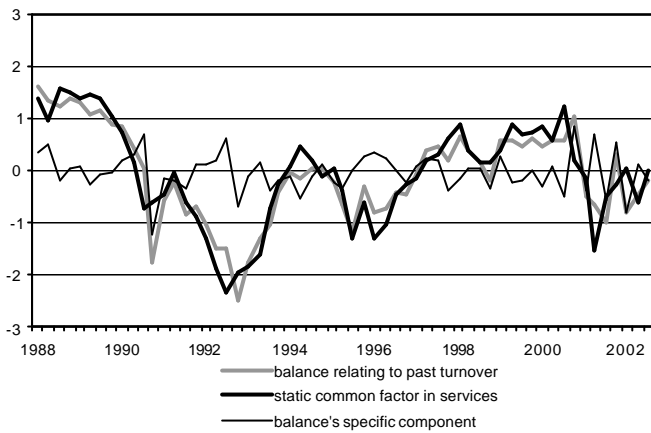
Before ending this study, it is worthy to discuss the ability of the synthetic indicators defined in Box 1 to make an optimal use of their constituents' differentiated dynamics. This methodological question has been briefly raised in sections II (causality analyses) and III (forecasting models).

For a given quarter, the static common factor relating to a given sector summarises the main tendencies given by the *current* corresponding business survey (*Cf.* Box 1). In so doing, the static common factor mixes balances of opinion that in principle relate to slightly different periods (namely those referring to the recent past and to the near future within the same survey). In other terms, the methodology leading to the determination of the static factor does not exploit the asynchronous nature of balances of opinion.

In this respect, it is noteworthy that the static common factor in services is highly correlated with the balances relating to the near future, a little less so with those dealing with the recent past. Moreover, the specific components of the three balances relating to the past often appear to be negative in the neighbourhood of a favourable turning point (acceleration) of the economy, and *vice versa*. This puzzling result probably originates from the fact that the balances referring to past activity in services lag slightly behind the static common factor (the latter being closer to balances referring to the near future) (*Cf.* graphs V). This configuration raises some interrogations as to the methodology underlying the static common factor in services. In particular, the question may be raised whether one could make better use of the shift between the balances relating to the recent past and those relating to the near future. We have considered several ways of doing so and compared the results obtained with respect to the static common factor in services.

Moreover, as was mentioned in section III, balances of opinion relating to services appear to be a little less smooth than those relating to industry. Some difficulties in terms of graphical business cycle analysis may originate from this characteristic feature of service data. A way of dealing with this problem is to extract the "noise" components from the balances of opinion in service sectors in order to obtain a clearer view of both the position in the cycle and the occurrence of turning points. As the results of Baxter-King filtering applied to service data would show, this kind of approach permits one to clarify the analysis of business cycles in services from a historical point of view. However, using filtering methods of this kind leads to the loss of one or several observations at the end of the series, which constitutes a serious drawback for short-term economic analysis. It therefore seems preferable to tackle the issue in another way. Building composite indicators of entrepreneurs' opinions in service sectors may be a possible response. In fact, the static common factor in services (calculated as a weighted average of a set of balances of opinion in services) is smoother than the balances themselves, which suggests that the noise components of the latter are not perfectly synchronous. Nonetheless, the static common factor in services remains less smooth than the equivalent synthetic indicator in industry. This characteristic feature seems a priori damaging in terms of readability. Do we have to aim for a smoother alternative composite indicator? We have tried to give an answer to this question as well. To do so, we have considered several possible alternative common factors.

GRAPHS V: The static common factor in services and the corresponding specific components



V-2 The “shifted” common factor

Our first attempt consists in shifting past balances by one quarter with respect to expected balances and then calculating a static common factor on the basis of the set of three shifted past balances and three unchanged expected balances. In other terms, at year Y and quarter Q , this "shifted common factor" is based on the set of three past balances relating to the survey published in year Y and quarter $Q+1$ (for $Q = 1, 2$ or 3) or in year $Y+1$ and quarter 1 (for $Q = 4$) and to the three expected balances relating to the survey published in year Y and quarter Q (³⁷, ³⁸).

The shifted common factor estimated over the same period as the static factor (April 1988 - July 2002) is equal to:

$$SHSER_t = 0.34 DEM^{exp}_t + 0.22 OPRO^{exp}_t + 0.15 TO^{exp}_t + 0.13 OPRO^{pa}_{t+1} + 0.13 TO^{pa}_{t+1} + 0.06 WF^{pa}_{t+1}$$

It explains a larger part of the variance in past balances (especially TO^{pa} and $OPRO^{pa}$) than the static common factor (things remaining unchanged in the case of expected balances). These results express the fact that the shifting of past balances with respect to expected balances has enabled us to rephrase the set of six balances and to achieve better coincidence in service sectors. However, the shifted common factor remains very close to the static common factor, as Graph VI below illustrates.

Since past balances have been shifted by one quarter, the shifted common factor might be expected to be slightly leading with respect to the static common factor. Actually, both common factors prove to be practically synchronous, owing to the fact that expected balances are over-weighted with respect to past balances in the static factor.

V-3 A dynamic common factor encompassing both the static and the shifted common factors

A more rigorous (and less restrictive) way of dealing with the imperfect synchrony of past and expected balances would be to consider a slightly more general underlying model:

$$X_{it} = \mathbf{I}_i^0 F_t + \mathbf{I}_i^1 F_{t-1} + u_{it}^1$$

and estimate the common factor F_t in this model using a Kalman filter technique. In fact, this model expresses that the past and expected balances may be slightly differently affected by the common factor in terms of dynamics³⁹. Now, this estimated common factor proves to be very close to both the static common factor and the shifted common factor (as well as from the common factor estimated using a Kalman filter on the basis of the original model, presented in Box 1) - Cf. graph VI.

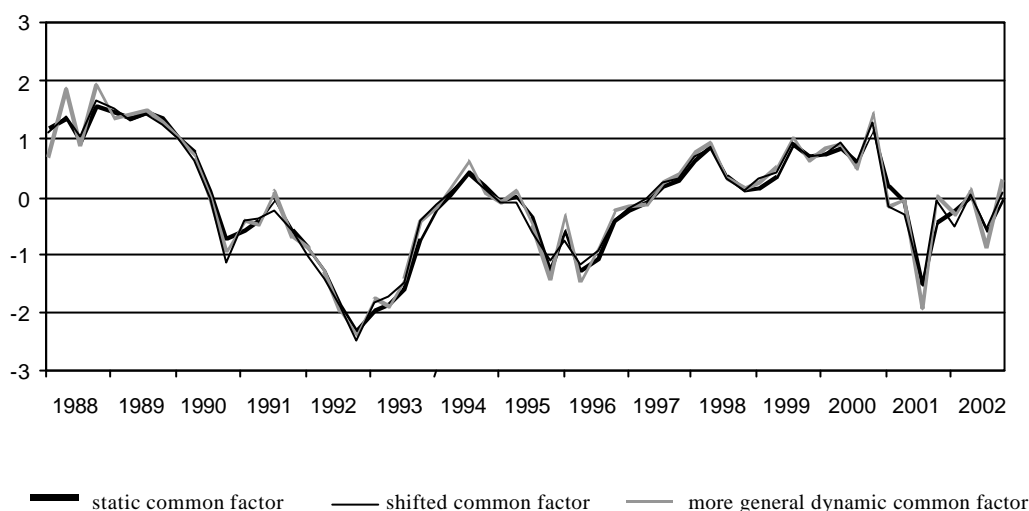
³⁷ The main advantage of this very simple method is that it can be easily understood and used in operational contexts. Nonetheless, more sophisticated methods, using spectral analysis, have been suggested in the literature to address this issue - Cf. Forni, Hallin, Lippi and Reichlin [2001b,c].

³⁸ In order not to lose one point at the end of the series, the still unknown three past balances relating to the next quarterly business survey are estimated using auxiliary regression models linking past balances to expected ones. Over the past decade, the last point of the shifted common factor estimated in this way turns out to be quite close to its actual value, observed one quarter later.

³⁹ Owing to the small number of observations in services, it has not been possible to estimate a common factor on the basis of a model with a larger number of lags, using the Kalman technique.

In sum, as all common factors studied up to now almost always lead to identical diagnoses, it seems best to take the one that is simplest to implement, namely the static common factor.

GRAPH VI: The static common factor compared with the shifted common factor and the more general dynamic common factor



V-4 The “iterative” common factor

Unsurprisingly, the common factors in services that we have considered up to now are slightly smoother than the individual balances from which they derive. Nonetheless, we might expect an ideal composite indicator to be smoother still. In fact, it is not always easy to infer the position in the cycle in the light of these indicators (see 1996 for instance). In this third stage, we therefore explore an iterative approach enabling us to obtain a smoother coincident composite indicator in services. The method used *a priori* presents two other advantages: it suggests a simple way of dealing with the imperfect synchrony of variables; and it enables one to endogenously determine the degree of lead or lag of each balance within the considered set of six.

Inspired by a simple methodology referred to in Fayolle [1987], the approach consists in progressively rephrasing the *I* balances of opinion relating to the recent past to those referring to the near future by proceeding as follows.

In a first stage, we calculate the static common factor SER_t (also noted in this sub-section F_t^1). In a second stage, we regress the static common factor with respect to the first lag, current value and first lead of each balance:

$$F_t^1 = \sum_{t=-1}^{+1} \mathbf{a}_{it}^1 X_{it+t} + v_{it}^1 \quad \forall i,$$

which enables us to derive a set of $(\hat{\mathbf{a}}_{it}^1)$ estimates of (\mathbf{a}_{it}^1) . We then estimate the model:

$$X_{it}^1 = \mathbf{I}_i^2 F_t^2 + u_{it}^2$$

where $X_{it}^1 = \sum_{t=-1}^{+1} \hat{a}_{it}^1 X_{it+t}$ represents the value taken by the i^{th} “partially rephased” balance of opinion and F_t^2 that taken by the static common factor of the set of "partially rephased" variables at time $t \in \{1, \dots, T\}$. This process is then iterated. More precisely, the common factor F_t^k having been estimated at a previous stage, we calculate the *OLS* estimators (\hat{a}_{it}^k) of the coefficients (a_{it}^k) in the model:

$$F_t^k = \sum_{t=-1}^{+1} \hat{a}_{it}^k X_{it+t} + v_{it}^k \quad " i$$

The common factor F_t^{k+1} then results from the estimation of the model:

$$X_{it}^k = \mathbf{I}_i^{k+1} F_t^{k+1} + u_{it}^{k+1}, \quad \text{with } X_{it}^k = \sum_{t=-1}^{+1} \hat{a}_{it}^k X_{it+t}.$$

The iteration goes on until the common factor resulting from the current iteration is no longer modified with respect to that derived from the previous iteration⁴⁰. Let F_t^{K+1} be the “iterative” common factor resulting from the convergence process. F_t^{K+1} should be smoother than the common factors studied up to now, in that it is derived from a set of smoothed balances. Moreover, in principle, the corresponding *I* transformed balances of opinion (X_{it}^K) are more synchronous than the initial (X_{it}) variables, owing to the asymmetric values of the (\hat{a}_{it}^K) weights. In this respect -- and this is the other major interest of the method (in addition to the smoothing aspect) -- one can intuitively expect the coefficient relating to the first lag \hat{a}_{i-1}^K of variable i to be higher (respectively lower) than that of its first lead \hat{a}_{i+1}^K if variable i is a leading (respectively lagged) indicator with respect to the set of the remaining $I-1$ variables. The difference $\hat{a}_{i+1}^K - \hat{a}_{i-1}^K$ can therefore be considered as an indicator of the degree of lead or lag of variable i with respect to the other $I-1$ in the business cycle.

Strictly applying this procedure implies that the most recent quarter corresponds to a missing value in the iterative common factor (owing to regressions with respect to the first leads of balances of opinion within the iterative estimation process). To limit this problem we have extended the balances by one point using a VAR model, before proceeding to the estimation of the iterative common factor. Simulating this method for the past illustrates that the predictive evolution of an iterative common factor whose last observation is partially derived from a VAR model is almost always of the correct sign.

The main characteristic features of the iterative common factor can be described as follows:

1) The iterative common factor can be expressed with respect to rephased balances as follows:

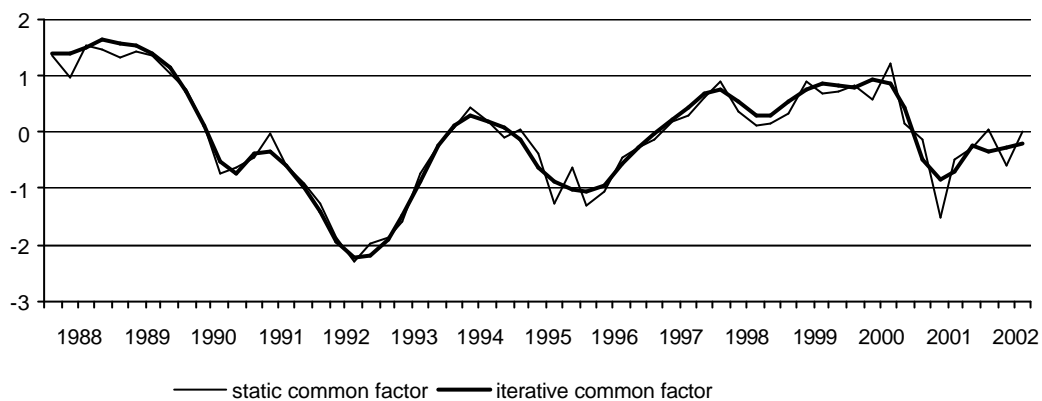
$$ITSER_t = 0.25 DEM^{exp*}_t + 0.22 OPRO^{exp*}_t + 0.19 TO^{exp*}_t + 0.18 OPRO^{pa*}_t + 0.13 TO^{pa*}_t + 0.04 WF^{pa*}_t$$

Therefore, the iterative common factor differs from the static common factor by the weights of the six balances on which they are based. The rephasing of balances by the iterative method leads to a readjustment of the relative shares of past and expected balances in the constitution of the iterative common factor.

⁴⁰ More precisely the iterative process stops at stage: $K+1 = \text{Min}_k (k+1) \left/ \sum_{t=1}^T |F_t^{k+1} - F_t^k|^2 < 10^{-6} \right.$

2) As was expected, the iterative common factor in services is smoother than the preceding indicators, which enables us to have a better perception of turning points – Cf. graph VII. More precisely, the iterative common factor seems to give a perfectly coherent view of the fluctuations of economic activity in the last decade. The static common factor gave the same overall picture of economic activity in services, but may occasionally provide less clear (if not excessive) messages at the neighbourhood of turning points, owing to increased noise in the service survey results in such periods.

GRAPH VII: The iterative common factor compared to the static common factor



However, smoothness is not an advantage in all contexts. In particular, in that of *GDP* forecasting, the static common factor proves to be more suitable than the iterative common factor, owing to the fact that it is better at rendering the notable short-term fluctuations of the *GDP* growth rate. In other words, the imperfectly smooth characteristic feature of the static common factor might not be fortuitous.

3) The iterative common factor is superior to a simple moving average of the static common factor, not so much in terms of overall smoothness but because the estimated $\hat{\mathbf{a}}$ weights provide us with interesting results in terms of the relative lagging or leading characteristic of the 6 balances from which it derives. In accordance with intuition, if variables i and i' relate respectively to the recent past and the near future of the same aggregate (turnover or operating profit), then:

$$\hat{\mathbf{a}}_{i,+1}^K - \hat{\mathbf{a}}_{i,-1}^K > \hat{\mathbf{a}}_{i',+1}^K - \hat{\mathbf{a}}_{i',-1}^K.$$

In other words, a balance referring to the near future is more shifted towards the past (less shifted towards the future) than the corresponding balance referring to the recent past – Cf. table 9 (Appendix 5).

The balances relating to demand and expected operating profit appear to be the most leading indicators out of the set of six balances (with a $\hat{\mathbf{a}}_{i,+1}^K - \hat{\mathbf{a}}_{i,-1}^K$ reaching a minimum). Conversely, the balance relating to expected turnover does not seem to be shifted towards the past, which suggests that it might not be as leading as those relating to expected demand or to expected operating profit. At the opposite extreme, the most lagged balance out of the set of six seems to be past workforce size and past turnover (with a $\hat{\mathbf{a}}_{i,+1}^K - \hat{\mathbf{a}}_{i,-1}^K$ reaching a maximum).

In sum, the three approaches explored in this last section enable us to conclude that the static common factor is so robust with respect to the imperfect synchrony of its constituent balances that the *a priori* theoretical weakness of its underlying methodology in this respect cannot be considered as a significant problem. Moreover, the imperfectly smooth characteristic feature of the static common factor in services might not be due to pure noise. These results are clearly in favour of the static common factor usage.

Conclusion

Business survey results, as well as French quarterly accounts, show that the big sectors of the French economy are subject to economic fluctuations that are similar, but not identical, from one sector to another. A certain structural heterogeneity between sectors leads to limited, but significant, punctual divergences or short-term phase differences between sectors, notably due to the occurrence of specific shocks or to sectors' uneven degrees of exposure to international shocks. In this paper, we show that early sectoral information can profitably be used by economists to improve their diagnosis at a one-or-two-quarter horizon, especially as concerns short-term GDP forecasting. In this respect, the Industry and Service surveys performed by the French statistical institute Insee prove to be useful complementary sources of early information on the quarterly growth rate of GDP.

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Appendix 1: Definition and construction of the main variables used

- Variables derived from the French Quarterly Accounts:

- *GDP* represents the quarterly growth rate of GDP;
- *YGDP* the year-over-year growth rate of GDP.

- The balances of opinion⁴¹ derived from sub-annual business surveys in industry and in service sectors:

The oldest French short-term business survey is that relating to industry, which started in 1962. The most recent one, the French business survey in services, began only in January 1988. It is nevertheless the oldest service survey within the European harmonised system of business surveys.

The French service survey almost entirely covers three sectors of the NES16 (*i.e.* the French comprehensive economic nomenclature at its 16 level), namely: business services (computer and related activities, advertising, temporary work, etc.), household services and real estate activities. These three activities amount to, respectively 66%, 21% and 13% of total turnover in services covered by the survey. The present coverage of the latter survey includes neither transports, nor financial or insurance services. In the paper, the “services” terminology refers to the sectors covered by the Service survey performed by Insee.

The latter was quarterly from its creation to April 2000. It became monthly in June 2000. Consequently, relatively long series are available only on a quarterly basis for balances of opinion derived from this survey. For homogeneity purpose, we have considered balances of opinion in industry derived from quarterly surveys (*i.e.* those relating to January, April, July and October) as well.

The main balances of opinion derived from the quarterly service surveys⁴² are: those relating to the recent and expected evolutions of turnover and operating profit (hereafter referred to as, respectively, TO^{pa} , TO^{exp} , $OPRO^{pa}$, $OPRO^{exp}$), as well as those concerning expected demand (DEM^{exp}) and, to a lesser extent, past workforce size (WF^{pa}). We compare these balances of opinion with those dealing with recent and expected production (TP^{pa} , TP^{exp}), overall and foreign orders ($OVORD$ and $FOORD$), inventories ($INVEN$) and general expectations ($GEXP$) in the corresponding business survey in industry⁴³. These balances are seasonally-adjusted. All of them can be considered as stationary processes, as well as the GDP growth rate⁴⁴. The main seasonally-adjusted series of the service survey are highly correlated with the quarterly growth rate of GDP⁴⁵, although appreciably smoother.

⁴¹ The concept of balance of opinion is defined in the introduction of the paper (see footnote 1).

⁴² Namely, those performed in January, April, July and October.

⁴³ This set of 6 industry balances is that used by Doz and Lenglart [1996, 1999] and subsequently Grégoir and Lenglart [2000] to build their coincident and advanced composite indicators.

⁴⁴ According to the sequential Dickey Fuller test à la Jobert [1992], as well as the Schmidt-Phillips and Phillips-Perron tests, the GDP growth rate is I(0). Similarly, the industry balances defined below prove to be I(0) without ambiguity. The stationarity of some service balances, although less clearly established owing to their smaller number of observations, are still acceptable at least by one test at a usual threshold.

⁴⁵ Correlation coefficients with the quarterly growth rate of GDP (1987 Q4 - 2002 Q2):

Services - $OPRO^{exp}$: 0.75, $OPRO^{pa}$: 0.74, DEM^{exp} : 0.73, TO^{pa} : 0.72, TO^{exp} : 0.68, WF^{pa} : 0.65.

Industry - TP^{pa} : 0.74, TP^{exp} and $GEXP$: 0.71, $OVORD$: 0.70, $FOORD$: 0.68, $INVEN$: -0.66.

- The synthetic indicators (static common factors):

These indicators have been defined in box 2. The common factor in services has been calculated on a quarterly basis from January 1988 to July 2002. For homogeneity purpose, the common factor in industry has been calculated on the same estimation period, also on a quarterly basis (keeping balances relating to surveys performed in January, April, July and October). Thus, the synthetic indicator in industry considered here is not identical to the official synthetic indicator in industry published by Insee on a monthly basis (and estimated on a period starting in 1976). However, the correlation between the quarterly common factor and the official synthetic indicator (quarterlised by keeping one point out of 3) is very high. The weights of the balances of opinion in these two synthetic indicators are very similar, to the exception of that relating to the balance of opinion concerning foreign orders, which is twice as high in the common factor considered here with respect to that in the official synthetic indicator. This result is not surprising as the latter indicator is estimated on a period during which, on average, the French economy was less open to the rest of the world.

The survey in public works being quarterly, the common factor in construction has been calculated on the basis of quarterly balances relating to public works and building industry, keeping one point out of 3 monthly ones (those relating to January, April, July and October) in the case of balances derived from the building industry survey).

The business survey in wholesale trade is carried out every two months (in January, March, May, July, September and November). The business survey in retail trade was also performed on the same two-monthly basis until it became monthly at the end of 1990. The common factors in these sectors have been estimated on two-monthly series. In a second stage, they have been quarterlised for purpose of comparison with respect to the other synthetic indicators as well as to the quarterly growth rate of GDP. Taking into account the way questions are formulated in the surveys in wholesale and retail trade (with reference to the two last months for questions relating to the recent past and to the two next months for questions relating to the near future⁴⁶), the method chosen to derive quarterly balances and synthetic indicators is the following one:

- Quarterly balances corresponding to January have been calculated as the weighted averages of the corresponding balances relating to the surveys performed in: November of the previous year (with a weight of 1/3) and January of the current year (with a weight of 2/3);
- Quarterly balances corresponding to April have been calculated as the weighted averages of the corresponding balances relating to the surveys performed in: March (with a weight of 2/3) and May (with a weight of 1/3);

⁴⁶ Most questions asked to the surveys in industry, services, and construction refer to a period of three months (the three last months for the questions relating to the recent past, and the three months to come for the questions relating to the near future). The quarterly balances calculated on the basis of two-monthly survey results must be based on a similar logic. For instance, a balance calculated on a quarterly basis for January on past activity in wholesale trade must cover October, November and December (i.e. the fourth quarter of the previous year). The weighted average chosen includes the piece of information relating to November and December (collected at the January survey) as well as October (collected at the November survey), the weights of 2/3 and 1/3 being consistent with the number of months in the fourth quarter taken into account by each two-monthly survey. The survey counting for 1/3 enables us to take into account the month which misses in the interrogations of the survey counting for 2/3 (even though imperfectly, this month constituting a half interrogation period of this survey). NB: The balances concerning entrepreneurs' expectations thus calculated on a quarterly basis (for instance for January) do not exactly refer to the first quarter of the current year (January to March), but to the period December to February. This drawback is counterbalanced by the advantage of deriving balances on a quarterly basis that refer to the same interrogation period whatever the kind of question asked (dealing with the recent past or the near future).

- Quarterly balances corresponding to July have been calculated as the weighted averages of the corresponding balances relating to the surveys performed in: May (with a weight of 1/3) and July (with a weight of 2/3);

- Quarterly balances corresponding to October have been calculated as the weighted averages of the corresponding balances relating to the surveys performed in: September (with a weight of 2/3) and November (with a weight of 1/3);

All sectoral synthetic indicators have been standardised on the estimation period chosen for the causality analyses. This period covers the quarterly surveys from January 1988 to July 2002⁴⁷.

• Linking balances of opinion with results of French quarterly accounts:

In the paper, when a survey result is compared with a macro-economic aggregate from the quarterly accounts, it is treated as relating to the quarter preceding that of the survey's publication. For instance, the April 2002 survey results are treated as relating to the first quarter of 2002 (2002 Q1). The reason for this convention is that:

- questions dealing with past evolutions (from which past balances are derived) relate to the three last months, *i.e.* to the previous quarter,

- the *GDP* figure relating to the first (respectively second, third and fourth) quarter is published in the French quarterly accounts a few weeks after the publication of the quarterly business surveys carried out in April (respectively July or October of the current year and January of the following year). Therefore, data published within a short time interval of a few weeks are gathered together as relating to the same quarter.

On the estimation period chosen for the causality analyses and the estimation of forecasting models (1987 Q4 to 2002 Q2), the correlation matrix of the synthetic indicators thus dated in quarterly terms and the quarterly and year-over-year growth rates of *GDP* is equal to:

	<i>YGDP</i>	<i>GDP</i>	<i>Industry</i>	<i>Services</i>	<i>Wholesale trade</i>	<i>Retail trade</i>	<i>Construction</i>
<i>YGDP</i>	1.00	0.75	0.87	0.87	0.90	0.79	0.74
<i>GDP</i>		1.00	0.73	0.75	0.66	0.56	0.54
<i>Industry</i>			1.00	0.86	0.93	0.81	0.69
<i>Services</i>				1.00	0.88	0.76	0.75
<i>Wholesale trade</i>					1.00	0.79	0.71
<i>Retail trade</i>						1.00	0.88
<i>Construction</i>							1.00

The synthetic indicators in services and in industry are the most correlated to *GDP*.

47 At the moment when this part of the study was performed, July 2002 corresponded to the last available quarterly observation for which definitive results were known for all the considered surveys.

Appendix 2: The results of the causality analyses.

- **Causality analyses performed on the basis of VAR models with 3 variables: the quarterly growth rate of GDP (*GDP*) and two sectoral synthetic indicators (static common factors):**

Table 1 (page 34) summarises the main results of non-instantaneous causality analyses carried out on the basis of these models, expressed in canonical form.

Table 2 (page 35) summarises the results of instantaneous and overall causality analyses carried out in the same models, expressed in block-recursive form. .

- **Causality analyses performed on the basis of VAR models with 4 variables: *GDP*, the balances of opinion relating to past and expected production in industry (TP^{pa} and TP^{exp}) and a balance of opinion in services among those defined in Appendix 1:**

Table 3 (page 36) summarises the main results of non-instantaneous causality analyses carried out on the basis of these models, expressed in canonical form.

Table 4 (page 37) summarises the results of instantaneous and overall causality analyses carried out in the same models, expressed in block-recursive form.

Table 1: Results of non-instantaneous causality tests (VAR models with 3 variables)

(Figures in parentheses = P-values)

Context variable Z = common factor in...	Industry	Industry	Industry	Industry	Services	Services	Services
Additive variable X = common factor in...	Services	Wholes. trade	Retail trade	Construc.	Wholes. trade	Retail trade	Construc
Number of lags in the VAR (P-value 2 lags / 1 lag:)	2 (0.004)	2 or 1 (0.046)	2 or 1 (0.022)	1 (0.009)	2 or 1 (0.048)	1 (0.081)	2 (0.007)
VAR models with 2 lags: GDP equation (canonical form)							
Causality $Z_{t-1} \text{®} GDP_t$	(0.010)	(0.005)	(0.012)	(0.025)	(0.001)	(0.005)	(0.002)
Causality $X_{t-1} \text{®} GDP_t$	(0.003)	(0.432)	(0.269)	(0.106)	(0.161)	(0.420)	(0.003)
R^2 :	0.564	0.469	0.479	0.498	0.514	0.495	0.545
Adjusted R^2 :	0.512	0.405	0.416	0.437	0.455	0.434	0.490
RMSE:	0.351	0.387	0.384	0.377	0.371	0.378	0.358
Collinearity: NO	13 - 12	17 - 17	12 - 12	18 - 18	11 - 10	13 - 13	15 - 16
Durbin Watson:	2.08	2.11	2.08	2.10	2.14	2.17	2.08
Univariate Portmanteau:	4.73	8.25	8.81	6.42	5.04	6.68	5.31
Multivariate Portmanteau:	36.65	49.79	48.52	45.94	41.24	56.04	55.15
VAR models with 1 lag: GDP equation (canonical form)							
Causality $Z_{t-1} \text{®} GDP_t$	-	(0.012)	(0.003)	(0.003)	(0.000)	(0.000)	-
Causality $X_{t-1} \text{®} GDP_t$	-	(0.433)	(0.601)	(0.580)	(0.367)	(0.640)	-
R^2 :	-	0.372	0.368	0.368	0.442	0.436	-
Adjusted R^2 :	-	0.337	0.332	0.333	0.411	0.405	-
RMSE:	-	0.411	0.412	0.412	0.387	0.389	-
Collinearity: NO	-	6 - 6	5 - 4	4 - 3	5 - 5	5 - 4	-
Durbin Watson:	-	1.86	1.86	1.83	1.76	1.72	-
Univariate Portmanteau:	-	12.69	14.95	13.71	6.53	7.75	-
Multivariate Portmanteau:	-	88.29	100.52	152.50	59.47	57.82	-

Legend (tables 1 and 2):

- . Tests performed in VAR models with 3 variables: GDP, the context variable Z and the additional variable X, the two last variables being sectoral synthetic indicators (defined in box 2).
- . P-value < $\alpha \hat{U}$ the null hypothesis (non significant last lag, null coefficient, non causality) is rejected at the α significance level.
- . The number of lags of the VAR is determined on the basis of system reduction tests, completed with 3 information criteria (Schwarz, Hannan, Akaike), within VAR models with 1 to 4 lags. We do not present the results of VAR models with 1 lag when the tests exclude this configuration (risk of bias). However, we present the results of VAR models with 2 lags systematically (in the case of models with 1 lag, the risk is that of low power of tests).
- . Collinearity: maximal condition index (1st index: Cf. Belsley-Kuh and Welsch (1980), 2nd index: intercept adjusted models). For more details, see additional legends under tables 2 and 3.
- . Software used: PC-GIVE (PC-FIML) for multivariate analyses and Portmanteau tests, SAS (PROC REG) for univariate analyses.

Significant coefficient, or non-instantaneous causality clearly accepted. P-value < 0.010
 Ambiguous result of the test, depending on the level of the test. 0.010 ≤ P-value ≤ 0.100

Non-significant coefficient, or non-instantaneous causality rejected at usual levels. P-value > 0.100

(same conventions in tables 2, 3 and 4).

Table 2: Results of other causality tests performed on the VAR models with 3 variables

(Figures in parentheses = P-values)

Context variable Z: Variable additive X:	IND SER	IND WHOLE	IND RETAIL	IND CONST	SER WHOLE	SER RETAIL	SER CONST
Number of lags of the GDP equation (P-value 2 lags / 1 lag:)	1 (0,878)	1 (0,893)	1 (0,685)	1 (0,942)	1 (0,360)	1 (0,091)	1 (0,942)
<i>GDP equations with 2 lags (block-recursive form)</i>							
Instantaneous causality $Z_t \otimes GDP_t$	(0.001)	(0.000)	(0.001)	(0.000)	(0.071)	(0.054)	(0.005)
Instantaneous causality $X_t \otimes GDP_t$	(0.319)	(0.923)	(0.628)	(0.699)	(0.157)	(0.205)	(0.487)
Overall causality $\underline{Z}_t \otimes GDP_t$	(0.005)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Overall causality $\underline{X}_t \otimes GDP_t$	(0.008)	(0.625)	(0.831)	(0.740)	(0.307)	(0.425)	(0.732)
R^2 :	0.704	0.646	0.629	0.632	0.628	0.594	0.625
Adjusted R^2 :	0.655	0.575	0.567	0.571	0.592	0.555	0.562
RMSE:	0.295	0.327	0.330	0.329	0.322	0.336	0.332
Collinearity: SOMETIMES	22 - 22	26 - 27	21 - 22	35 - 36	9 - 9	12 - 13	34 - 36
Durbin Watson:	1.94	2.03	2.02	1.99	2.05	2.05	2.00
Univariate Portmanteau:	7.53	10.04	10.54	8.73	6.40	8.06	9.25
Multivariate Portmanteau:	6.40	8.41	8.88	7.29	5.58	6.65	7.77
<i>GDP equations with 1 lag (block-recursive form)</i>							
Instantaneous causality $Z_t \otimes GDP_t$	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.061)	(0.003)
Instantaneous causality $X_t \otimes GDP_t$	(0.320)	(0.932)	(0.947)	(0.684)	(0.051)	(0.156)	(0.129)
Overall causality $\underline{Z}_t \otimes GDP_t$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Overall causality $\underline{X}_t \otimes GDP_t$	(0.001)	(0.259)	(0.904)	(0.343)	(0.032)	(0.296)	(0.153)
R^2 :	0.708	0.633	0.615	0.629	0.628	0.594	0.604
Adjusted R^2 :	0.680	0.597	0.578	0.593	0.592	0.555	0.556
RMSE:	0.285	0.320	0.328	0.322	0.322	0.336	0.332
Collinearity: NO	10 - 10	15 - 15	11 - 11	16 - 17	9 - 9	12 - 13	14 - 14
Durbin Watson:	2.03	2.04	1.97	1.98	2.05	2.05	2.00
Univariate Portmanteau:	8.76	10.71	10.04	8.66	5.63	6.94	13.17
Multivariate Portmanteau:	7.45	8.93	8.61	7.33	4.89	5.50	10.64

Legend:

The causality tests have been carried out on GDP equations with 1 or 2 lags. In fact, if the tests of the number of lags performed in the GDP equation alone always lead to the diagnosis of 1 lag, those carried out in VAR models often suggest an ambiguity between 1 or 2 lags (in 3 cases out of 7), if not a diagnosis of 2 lags (in 2 other cases). A priori, in case of an ambiguous diagnosis on the number of lags of the VAR model, privileging the results of tests performed in models with 2 lags is a way of protecting oneself against the risk of bias, to the expense of potentially little powerful tests (and vice versa if one privileges the results of tests performed on equations with 1 lag). However, the potential or established presence of collinearity in some models with 2 lags may cast doubt on the robustness of the causality tests made within their scope (NB: maximal condition indices superior to 25 - 20 (resp. 30 - 25) = ambiguous (resp. positive) diagnosis of collinearity. In any case, the causality analyses lead to results that do not depend on the choice of the number of lags.

Table 3: Results of non-instantaneous causality tests on VAR models with 4 variables: GDP , TP^{pa} , TP^{exp} and a balance of opinion relating to services (X)

(Figures in parentheses = P-values)

Balance in services $X =$	TO^{pa}	$OPRO^{pa}$	TO^{exp}	$OPRO^{exp}$	DEM^{exp}
Number of lags of the VAR	2 or 3	2	1, 2 or 3	2	2 or 3
(P-value 2 lags / 1 lag)	(0.001)	(0.000)	(0.029)	(0.001)	(0.002)
(P-value 3 lags / 1 lag)	(0.001)	(0.001)	(0.004)	(0.002)	(0.000)
(P-value 3 lags / 2 lags)	(0.049)	(0.171)	(0.011)	(0.065)	(0.016)
Number of lags of the GDP equation	2 or 3	1 or 2	1	1	1
(P-value 2 lags / 1 lag)	(0.042)	(0.043)	(0.384)	(0.374)	(0.268)
(P-value 3 lags / 1 lag)	(0.008)	-	(0.162)	-	(0.290)
(P-value 3 lags / 2 lags)	(0.035)	-	(0.114)	-	(0.240)
Models with 1 lag (canonical form)					
Causality $TP_{t-1}^{pa} \text{ @ } GDP_t$	-	(0.026)	(0.029)	(0.029)	(0.015)
Causality $TP_{t-1}^{exp} \text{ @ } GDP_t$	-	(0.000)	(0.000)	(0.001)	(0.000)
Causality $X_{t-1} \text{ @ } GDP_t$	-	(0.041)	(0.005)	(0.003)	(0.001)
R^2 - adjusted R^2 :	-	0.52 - 0.49	0.56 - 0.52	0.57 - 0.53	0.28 - 0.55
RMSE:	-	0.361	0.348	0.344	0.340
Collinearity: NO	-	7 - 6	7 - 6	7 - 6	6 - 6
Models with 2 lags (canonical form)					
Causality $TP_{t-1}^{pa} \text{ @ } GDP_t$	(0.242)	(0.123)	(0.521)	(0.331)	(0.398)
Causality $TP_{t-1}^{exp} \text{ @ } GDP_t$	(0.000)	(0.000)	(0.004)	(0.006)	(0.007)
Causality $X_{t-1} \text{ @ } GDP_t$	(0.015)	(0.009)	(0.048)	(0.010)	(0.008)
R^2 - adjusted R^2 :	0.61 - 0.54	0.62 - 0.55	0.59 - 0.52	0.62 - 0.55	0.62 - 0.56
RMSE:	0.339	0.336	0.347	0.336	0.335
Collinearity: NO	15 - 13	15 - 13	15 - 13	15 - 13	14 - 12
Models with 3 lags (canonical form)					
Causality $TP_{t-1}^{pa} \text{ @ } GDP_t$	(0.944)	-	(0.933)	-	(0.918)
Causality $TP_{t-1}^{exp} \text{ @ } GDP_t$	(0.000)	-	(0.003)	-	(0.003)
Causality $X_{t-1} \text{ @ } GDP_t$	(0.403)	-	(0.272)	-	(0.198)
R^2 - adjusted R^2 :	0.62 - 0.65	-	0.66 - 0.56	-	0.66 - 0.57
RMSE:	0.339	-	0.335	-	0.332
Collinearity: AMBIGUOUS	28 - 25	-	24 - 21	-	25 - 23

Legend:

VAR models with 2 lags are systematically accepted at the 1% significance level. Therefore, the results of models with 3 lags are presented for information only, especially as these models show ambiguous collinearity diagnoses. In practice, a maximal condition index superior to 25 (F^1 indicator, defined by Belsley, Kuh and Welsch) or an intercept-adjusted indicator superior to 20 (F^2 indicator, same as the previous indicator, but calculated on centred explanatory variables in an intercept-excluded model) suggests a potential situation of collinearity. The estimated coefficients of the model may be imprecise, as well as the tests performed on their basis (which may be little reliable).

Non-instantaneous causality is accepted for any low P-value (inferior to 1%), ambiguous for P-values between 1 and 10 % and rejected for P-values superior to 10%. See comments on table 1 for more details on P-values.

Table 4: Results of the causality tests performed on VAR models with 4 variables: GDP, TP^{pa} , TP^{exp} plus a balance in services (X) - GDP equation (block-recursive form)

Legend:

The results below are relating to equations with 1 or 2 lags. The case of 1 lag is presented as tests of the number of lags within the GDP equation lead to this diagnosis (see below). The case of 2 lags is consistent with the results of tests of the number of lags performed in the VAR models (at the significance level of 1%) (see table 3).

The ambiguity between 2 and 3 lags observed for some VAR models at significance levels superior to 1 % also led us to carry out causality analyses within equations with 3 lags. However, we have only summarised the results obtained in this box, due to the presence of collinearity in these models (the Belsley, Kuh and Welsch maximal condition index amounts to an order of magnitude of 30, except in models including the current value of balance X (and not those of the other balances): in these cases, the collinearity diagnosis is ambiguous). In fact, in this context, causality tests are not reliable. Consequently, the following summary is presented for information only.

- in the model including the current values of every balance, collinearity is maximal. No test perceives any overall causality for any variable. Nonetheless, some instantaneous causality tests lead to a positive diagnosis for TP^{pa} , TO^{exp} and DEM^{exp} , but their results cannot be considered to be robust.

- In the models including the current value of X only, the instantaneous causality of X is systematically accepted, as well as the overall causality of X when $X = TO^{exp}$ and DEM^{exp} .

- In the other models, instantaneous and overall causalities of X are ambiguous (P-values between 0.014 and 0.092 for instantaneous causality, and between 0.011 and 0.126 for overall causality). Exceptions: the overall causality of TO^{exp} or DEM^{exp} in models excluding the current value of TP^{pa} is clearly accepted.

However, the causality analyses performed within models with 2 lags (or even one lag) seem much more reliable .

(Figures in parentheses = P-values)

Balance in services X =	TO^{pa}	$OPRO^{pa}$	TO^{exp}	$OPRO^{exp}$	DEM^{exp}
Test of the number of lags in the GDP equation including all balances' current values					
Number of lags of the GDP equation	1	1	1	1	1
(P-value 2 lags / 1 lag)	(0.370)	(0.201)	(0.882)	(0.567)	(0.862)
(P-value 3 lags / 1 lag)	(0.612)	-	(0.536)	-	(0.500)
(P-value 3 lags / 2 lags)	(0.809)	-	(0.227)	-	(0.213)

(Figures in parentheses = P-values)

Balance in services $X =$	TO^{pa}	$OPRO^{pa}$	TO^{exp}	$OPRO^{exp}$	DEM^{exp}
Model with 1 lag including all balances' current values					
Instantaneous causality $TP^{pa}_t \text{ ® } GDP_t$	(0.028)	(0.021)	(0.001)	(0.001)	(0.004)
Overall causality $\underline{TP}^{pa}_t \text{ ® } GDP_t$	(0.003)	(0.008)	(0.000)	(0.001)	(0.001)
Instantaneous causality $TP^{exp}_t \text{ ® } GDP_t$	(0.403)	(0.417)	(0.149)	(0.976)	(0.430)
Overall causality $\underline{TP}^{exp}_t \text{ ® } GDP_t$	(0.195)	(0.018)	(0.596)	(0.650)	(0.054)
Instantaneous causality $X_t \text{ ® } GDP_t$	(0.007)	(0.027)	(0.126)	(0.016)	(0.155)
Overall causality $\underline{X}_t \text{ ® } GDP_t$	(0.005)	(0.006)	(0.001)	(0.001)	(0.002)
R^2 - adjusted R^2 :	0.73 - 0.69	0.72 - 0.69	0.74 - 0.71	0.75 - 0.71	0.73 - 0.70
RMSE:	0.282	0.282	0.273	0.271	0.272
Collinearity: NO	13 - 12	12 - 12	12 - 11	12 - 11	12 - 11
Model with 1 lag including the current value of X only					
Advanced causality $TP^{pa}_{t-1} \text{ ® } GDP_t$	(0.088)	(0.020)	(0.016)	(0.010)	(0.011)
Advanced causality $TP^{exp}_{t-1} \text{ ® } GDP_t$	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Instantaneous causality $X_t \text{ ® } GDP_t$	(0.000)	(0.000)	(0.010)	(0.000)	(0.005)
Advanced causality $X_{t-1} \text{ ® } GDP_t$	(0.132)	(0.935)	(0.077)	(0.210)	(0.032)
Overall causality $\underline{X}_t \text{ ® } GDP_t$ (P-value)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
R^2 - adjusted R^2 :	0.67 0.64	0.66 0.63	0.61 - 0.57	0.67 0.64	0.64 0.60
RMSE:	0.303	0.306	0.330	0.303	0.308
Collinearity: NO	8 - 7	7 - 7	7 - 6	7 - 6	7 - 6
Model with 1 lag including X and TP^{pa} 's current values					
Instantaneous causality $TP^{pa}_t \text{ ® } GDP_t$	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)
Advanced causality $TP^{pa}_{t-1} \text{ ® } GDP_t$	(0.004)	(0.001)	(0.000)	(0.000)	(0.000)
Overall causality $\underline{TP}^{pa}_t \text{ ® } GDP_t$	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)
Advanced causality $TP^{exp}_{t-1} \text{ ® } GDP_t$	(0.107)	(0.096)	(0.450)	(0.351)	(0.439)
Instantaneous causality $X_t \text{ ® } GDP_t$	(0.005)	(0.021)	(0.032)	(0.005)	(0.036)
Advanced causality $X_{t-1} \text{ ® } GDP_t$	(0.747)	(0.376)	(0.020)	(0.117)	(0.030)
Overall causality $\underline{X}_t \text{ ® } GDP_t$	(0.003)	(0.004)	(0.000)	(0.000)	(0.001)
R^2 - adjusted R^2 :	0.72 - 0.69	0.72 - 0.69	0.74 - 0.71	0.75 - 0.72	0.73 - 0.70
RMSE:	0.281	0.282	0.271	0.268	0.276
Collinearity: NO	12 - 10	10 - 10	10 - 8	10 - 9	9 - 8
Model with 1 lag including X and TP^{exp} 's current values					
Advanced causality $TP^{pa}_{t-1} \text{ ® } GDP_t$	(0.121)	(0.038)	(0.036)	(0.024)	(0.021)
Instantaneous causality $TP^{exp}_t \text{ ® } GDP_t$	(0.035)	(0.032)	(0.002)	(0.076)	(0.006)
Advanced causality $TP^{exp}_{t-1} \text{ ® } GDP_t$	(0.026)	(0.021)	(0.107)	(0.073)	(0.171)
Overall causality $\underline{TP}^{exp}_t \text{ ® } GDP_t$	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Instantaneous causality $X_t \text{ ® } GDP_t$	(0.000)	(0.001)	(0.384)	(0.031)	(0.295)
Advanced causality $X_{t-1} \text{ ® } GDP_t$	(0.277)	(0.874)	(0.009)	(0.090)	(0.005)
Overall causality $\underline{X}_t \text{ ® } GDP_t$	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)
R^2 - adjusted R^2 :	0.70 - 0.66	0.69 - 0.66	0.68 - 0.64	0.69 - 0.65	0.69 - 0.65
RMSE:	0.293	0.295	0.304	0.297	0.298
Collinearity: NO	9 - 8	9 - 8	10 - 8	10 - 9	9 - 8

(Figures in parentheses = P-values)

Balance in services X_t :	TO^{pa}	$OPRO^{pa}$	TO^{exp}	$OPRO^{exp}$	DEM^{exp}
Model with 2 lags including all balances' current values					
Instantaneous causality $TP^{pa}_t \text{ @ } GDP_t$	(0.106)	(0.111)	(0.002)	(0.003)	(0.011)
Overall causality $\underline{TP}^{pa}_t \text{ @ } GDP_t$	(0.193)	(0.089)	(0.011)	(0.010)	(0.048)
Instantaneous causality $TP^{exp}_t \text{ @ } GDP_t$	(0.280)	(0.251)	(0.498)	(0.912)	(0.472)
Overall causality $\underline{TP}^{exp}_t \text{ @ } GDP_t$	(0.205)	(0.152)	(0.619)	(0.435)	(0.559)
Instantaneous causality $X_t \text{ @ } GDP_t$	(0.092)	(0.145)	(0.166)	(0.031)	(0.145)
Overall causality $\underline{X}_t \text{ @ } GDP_t$	(0.025)	(0.013)	(0.028)	(0.005)	(0.041)
R^2 - adjusted R^2	0.75 - 0.68	0.75 - 0.69	0.74 - 0.68	0.76 - 0.71	0.74 - 0.68
RMSE:	0.283	0.278	0.283	0.272	0.286
Collinearity: AMBIGUOUS	27 - 24	27 - 26	22 - 19	21 - 20	23 - 21
Model with 2 lags including X 's current value only					
Test of 1 lag versus 2 in this model	(0.127)	(0.051)	(0.562)	(0.493)	(0.603)
Advanced causality $TP^{pa}_{t-1} \text{ @ } GDP_t$	(0.195)	(0.007)	(0.449)	(0.213)	(0.506)
Advanced causality $TP^{exp}_{t-1} \text{ @ } GDP_t$	(0.001)	(0.001)	(0.012)	(0.007)	(0.042)
Instantaneous causality $X_t \text{ @ } GDP_t$	(0.000)	(0.000)	(0.011)	(0.001)	(0.020)
Overall causality $\underline{X}_t \text{ @ } GDP_t$	(0.000)	(0.000)	(0.006)	(0.000)	(0.002)
R^2 - adjusted R^2	0.71 - 0.66	0.72 - 0.67	0.64 - 0.57	0.70 - 0.65	0.66 - 0.60
RMSE:	0.294	0.290	0.328	0.298	0.319
Collinearity: NO	16 - 14	15 - 14	16 - 14	16 - 14	15 - 13
Model with 2 lags including X and TP^{pa} 's current values					
Test of 1 lag versus 2 in this model	(0.412)	(0.243)	(0.891)	(0.557)	(0.826)
Instantaneous causality $TP^{pa}_t \text{ @ } GDP_t$	(0.037)	(0.039)	(0.000)	(0.001)	(0.001)
Overall causality $\underline{TP}^{pa}_t \text{ @ } GDP_t$	(0.053)	(0.023)	(0.001)	(0.003)	(0.004)
Advanced causality $TP^{exp}_{t-1} \text{ @ } GDP_t$	(0.180)	(0.137)	(0.515)	(0.253)	(0.459)
Instantaneous causality $X_t \text{ @ } GDP_t$	(0.052)	(0.091)	(0.037)	(0.009)	(0.039)
Overall causality $\underline{X}_t \text{ @ } GDP_t$	(0.015)	(0.008)	(0.012)	(0.002)	(0.018)
R^2 - adjusted R^2	0.74 - 0.68	0.75 - 0.69	0.74 - 0.69	0.76 - 0.71	0.74 - 0.68
RMSE:	0.283	0.279	0.282	0.269	0.284
Collinearity: AMBIGUOUS / NO	26 - 23	26 - 25	20 - 17	20 - 19	20 - 19
Model with 2 lags including X and TP^{exp} 's current values					
Test of 1 lag versus 2 in this model	(0.241)	(0.102)	(0.871)	(0.734)	(0.851)
Advanced causality $TP^{pa}_{t-1} \text{ @ } GDP_t$	(0.354)	(0.138)	(0.544)	(0.269)	(0.500)
Instantaneous causality $TP^{exp}_t \text{ @ } GDP_t$	(0.091)	(0.084)	(0.022)	(0.200)	(0.019)
Overall causality $\underline{TP}^{exp}_t \text{ @ } GDP_t$	(0.001)	(0.001)	(0.003)	(0.010)	(0.008)
Instantaneous causality $X_t \text{ @ } GDP_t$	(0.006)	(0.006)	(0.360)	(0.036)	(0.313)
Overall causality $\underline{X}_t \text{ @ } GDP_t$	(0.001)	(0.001)	(0.049)	(0.005)	(0.014)
R^2 - adjusted R^2	0.73 - 0.67	0.74 - 0.68	0.68 - 0.61	0.71 - 0.65	0.70 - 0.63
RMSE:	0.288	0.283	0.313	0.296	0.304
Collinearity: NO	17 - 15	17 - 15	17 - 14	16 - 14	16 - 14

**Appendix 3: Forecasting models of the growth rate of GDP
with respect to business survey data in industry and in services.**

We present two univariate calibration models and a vector auto-regressive model (VAR). The variables used are defined in Appendix 1. Δx denotes the first difference of variable x . All models are estimated on quarterly data from the fourth quarter of 1987 to the second quarter of 2002.

1) The three forecasting models of the GDP growth rate:

a) The first calibration model:

GDP	= 0.54		$-0.27 GDP_{-1}$		$+0.02 \Delta TP^{ia}$		$+0.01 TP^{exp}_{-1}$		$+0.01 \Delta TO^{ia}$		$+0.02 TO^{exp}_{-1}$		$+0.03 OPRO^{exp}$	
<i>T-Stat</i>	(8.9)		(-2.6)		(3.5)		(2.5)		(2.0)		(2.4)		(3.9)	
<i>P-value</i>	(0.000)		(0.011)		(0.001)		(0.014)		(0.049)		(0.021)		(0.000)	
$R^2 =$	0.78				$R^2_{adj.} =$	0.76		$RMSE =$	0.246		$F-Stat =$	30.4	$DW =$	1.99

Maximal condition index (Belsley, Kuh and Welsch): 5.3

b) The second calibration model:

GDP	= 0.53		$-0.27 GDP_{-1}$		$+0.02 \Delta TP^{ia}$		$+0.01 TP^{exp}_{-1}$		$+0.02 TO^{exp}_{-1}$		$+0.03 OPRO^{exp}$			
<i>T-Stat</i>	(8.6)		(-2.6)		(5.3)		(2.4)		(2.3)		(3.8)			
<i>P-value</i>	(0.000)		(0.012)		(0.000)		(0.018)		(0.027)		(0.000)			
$R^2 =$	0.76				$R^2_{adj.} =$	0.74		$RMSE =$	0.254		$F-Stat =$	33.7	$DW =$	2.11

Maximal condition index (Belsley, Kuh and Welsch): 5.3

c) The VAR model:

A vector auto-regressive model (VAR) treats every variables as endogenous. This type of model contains one equation per variable. Its use in forecasting leads to the joint determination of all these variables. The chosen model here contains three variables: the quarterly growth rate of GDP (GDP), the synthetic indicator in industry (IND) and the synthetic indicator in services (SER) defined in box 2 (static common factors). The number of lags of the VAR is 2 (⁴⁸). The usual specification tests are clearly accepted⁴⁹. The estimation of the model leads to the following results:

⁴⁸ This result derives from information criteria (Schwarz, Hannan, Akaike) as well as system reduction tests (sequential tests completed by the other possible tests F tests, for instance of 4 lags versus 2). Software used: PC-GIVE (PC- FIML).

⁴⁹ I.e. the Portmanteau tests, ARCH test, the White heteroskedasticity tests, and the normality test performed by PC-FIML.

• **The VAR model in canonical form:**

1-1) Equation relating to the GDP growth rate:

$$GDP = 0.84 - 0.43 GDP_{-1} - 0.13 GDP_{-2} + 0.59 IND_{-1} - 0.44 IND_{-2} + 0.43 SER_{-1} - 0.05 SER_{-2}$$

T-Stat	(5.3)	(-2.5)	(-0.8)	(3.1)	(-2.7)	(3.2)	(-0.4)
P-value	(0.000)	(0.016)	(0.420)	(0.003)	(0.009)	(0.002)	(0.721)

$R^2 = 0.56$ $R_{adj.}^2 = 0.51$ $RMSE = 0.351$ $DW = 2.08$ Maximal condition index (Belsley, Kuh and Welsch): 13.2

1-2) Equation relating to the synthetic indicator in services:

$$SER = 0.15 - 0.16 GDP_{-1} - 0.17 GDP_{-2} + 0.86 IND_{-1} - 0.65 IND_{-2} + 0.54 SER_{-1} + 0.25 SER_{-2}$$

T-Stat	(0.8)	(-0.8)	(-0.9)	(3.8)	(-3.3)	(3.4)	(1.6)
P-value	(0.445)	(0.428)	(0.400)	(0.000)	(0.002)	(0.002)	(0.120)

$R^2 = 0.83$ $R_{adj.}^2 = 0.81$ $RMSE = 0.425$ $DW = 1.91$ Maximal condition index (Belsley, Kuh and Welsch): 13.2

1-3) Equation relating to the synthetic indicator in industry:

$$IND = 0.02 + 0.01 GDP_{-1} - 0.06 GDP_{-2} + 1.50 IND_{-1} - 0.67 IND_{-2} + 0.13 SER_{-1} - 0.07 SER_{-2}$$

T-Stat	(0.2)	(0.1)	(-0.5)	(10.1)	(-5.3)	(1.3)	(-0.7)
P-value	(0.856)	(0.946)	(0.640)	(0.000)	(0.000)	(0.205)	(0.514)

$R^2 = 0.93$ $R_{adj.}^2 = 0.93$ $RMSE = 0.277$ $DW = 2.07$ Maximal condition index (Belsley, Kuh and Welsch): 13.2

• **The VAR model in block-recursive form:**

2-1') Equation relating to the GDP growth rate:

$$GDP = 0.81 - 0.41 GDP_{-1} - 0.08 GDP_{-2} + 0.61 IND - 0.42 IND_{-1} + 0.04 IND_{-2} + 0.12 SER + 0.28 SER_{-1} - 0.04 SER_{-2}$$

T-Stat	(6.0)	(-2.9)	(-0.6)	(3.4)	(-1.5)	(0.3)	(1.0)	(2.3)	(-0.3)
P-value	(0.000)	(0.006)	(0.583)	(0.001)	(0.137)	(0.802)	(0.319)	(0.027)	(0.763)

$R^2 = 0.70$ $R_{adj.}^2 = 0.66$ $RMSE = 0.295$ $DW = 1.94$ Maximal condition index (Belsley, Kuh and Welsch): 21.8

Model made up of equations 2-1, 2-2 and 2-3 (canonical form) is strictly identical to that consisting of equations 2-1', 2-2 and 2-3 (block-recursive form). The canonical form enables one to produce a one-or-two-quarter forecast for the current GDP growth rate before the publication of the corresponding business survey, without need for extending the synthetic indicators. *Ex post*, (*i.e.* after the publication of this survey), the block-recursive form permits one to study how the previous forecasts are modified as a result of the availability of new information. Of course, the two forms of the VAR model lead to the same forecasting results, provided that the information set used is identical in both cases.

2) An ex post analysis of the forecasting results derived from the three models:

Table 5: **The results of forecasts realised on the basis of the available piece of information at the moment when the Insee “Note of conjuncture” (short-term forecasts of the French activity), published in December 2002, was prepared, depending on the model used**⁵⁰

(%)

	Actual GDP	First univariate model		Second univariate model		VAR model			
		Fitted GDP	Estimation residual	Fitted GDP	Estimation residual	Canonical form		Block-recursive form	
						Fitted GDP	Estimation residual	Fitted GDP	Estimation residual
2000 Q1	1.17	0.90	0.27	0.88	0.29	0.75	0.42	0.91	0.27
2000 Q2	0.83	0.83	0.01	0.84	-0.00	0.83	0.00	0.87	-0.03
2000 Q3	0.46	0.73	-0.27	0.68	-0.22	0.91	-0.45	0.86	-0.40
2000 Q4	1.26	1.24	0.02	1.22	0.04	0.82	0.44	0.94	0.32
2001 Q1	0.38	0.58	-0.21	0.46	-0.08	0.72	-0.34	0.50	-0.12
2001 Q2	-0.07	0.14	-0.20	0.26	-0.33	0.34	-0.41	0.22	-0.29
2001 Q3	0.40	0.09	0.31	0.07	0.33	0.39	0.02	0.25	0.16
2001 Q4	-0.40	-0.24	-0.16	-0.28	-0.11	-0.31	-0.09	-0.05	-0.35
2002 Q1	0.59	1.03	-0.43	0.93	-0.33	0.65	-0.06	1.01	-0.41
2002 Q2	0.41	0.33	0.09	0.49	-0.07	0.78	-0.37	0.41	0.00
2002 Q3	0.21	0.26	-0.05	0.17	0.05	0.53	-0.32	0.21	0.01
2002 Q4		0.33		0.43		0.09		0.39	
2003 Q1						0.25		0.42	

Legend:

Shaded areas: forecasts realised on the basis of the available piece of information at the moment when the Insee “Note of conjuncture” (short-term forecasts of the French activity), published in December 2002, was prepared.

Other figures: known figures at that time

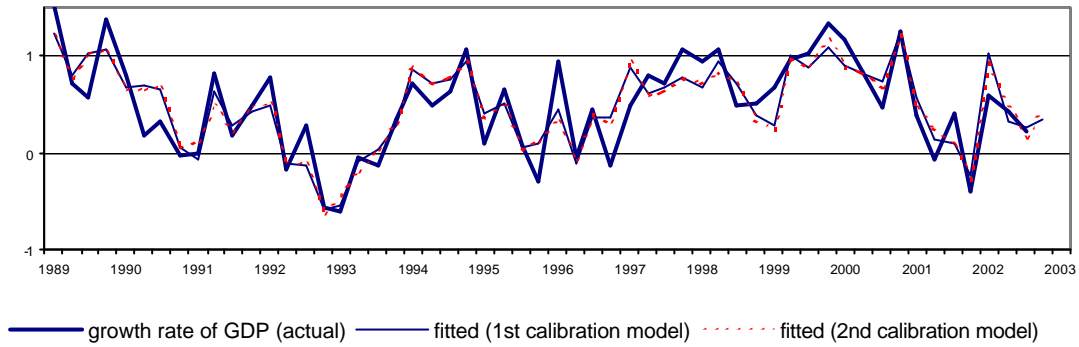
NB: In this table, the forecasts made on the basis of the canonical form of the model include the results of the last available quarterly surveys (i.e. until October 2002 for the forecast of the last quarter of 2002). The other models take into account monthly survey results published in November 2002 for the forecast of the last quarter of 2002. These results are considered as an approximation of the future quarterly survey results of January 2003 (unknown at that time). Experience shows that taking account of the results relating to the most recent monthly business surveys and treating them as an approximation of the next- to-come quarterly survey results on average enables one to significantly improve forecasts of the growth rate of GDP at a two-quarter horizon. Thus, the forecasts derived from the univariate calibration models and the block-recursive form of the VAR model appear to be more reliable than those resulting from the canonical form of the VAR model. NB: the forecasts derived from the latter form suggests a later recovery in industry and services than those made of the basis of the other models. This is due not only to the fact that the November business surveys are not taken into account in the canonical form, but also (and above all) because the latter does not include current survey results (contrarily to the other kinds of models). This methodological difference is of consequence in the context of the end of 2002, while the French business surveys have perceived the first signs of stabilization of activity not sooner than in July 2002, and a possible recovery in the short term since October only.

Reminder: The GDP forecasts of the Insee “Note of Conjuncture” published in December 2002 were respectively +0.3 for the fourth quarter of 2002 and +0.4 for the first quarter of 2003. They took into account not only the forecasting results derived from the previous models, but also the further stages of the forecasting exercise that permit the Insee to build a coherent overall diagnosis in macro-economic terms. Nonetheless, the combination of forecasts performed using the simple models considered above already provided one with a first estimation which proved to be very close to the diagnosis published in December in the Insee “Note de Conjuncture”. Moreover, the first results of the French quarterly accounts for the fourth quarter of 2002 (+0.2) published in February 2003 (i.e. 3 months after the moment when the above forecasts were made) and for the first quarter of 2003 (+0.3) published in May 2003 belong to the intervals of values given by this combination of early forecasts.

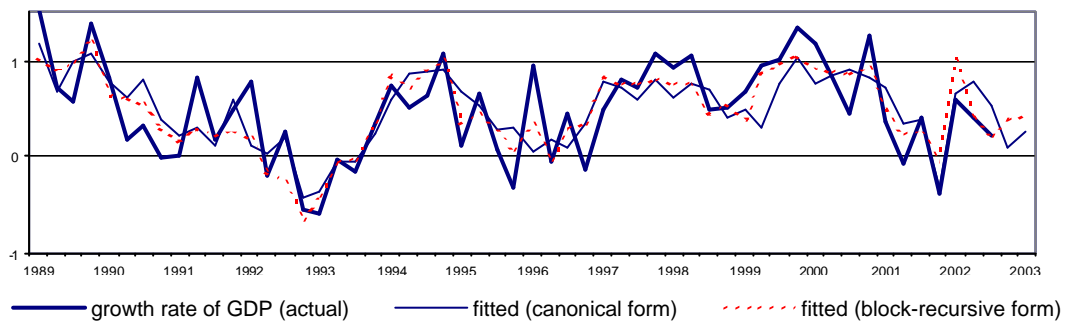
⁵⁰ To make GDP growth forecasts on the basis of the two univariate models, we had to extend the explanatory variables on the fourth quarter of 2002 beforehand, outside of these models. For instance, Balances relating to industry were extended within a VAR model with 3 variables (the quarterly growth rate of manufactured production, TP^{pa} , TP^{exp}) and 3 lags.

Graphs corresponding to Table 5:

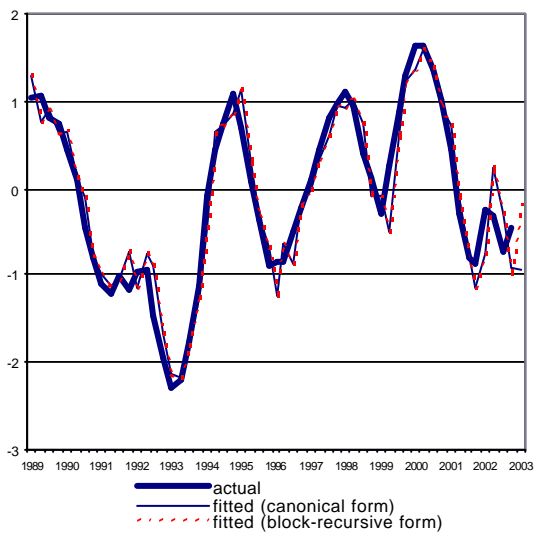
Actual and fitted GDP growth rates using the univariate calibration models



Actual and fitted GDP growth rates - VAR model (%)



Synthetic indicator in industry



Synthetic indicator in services

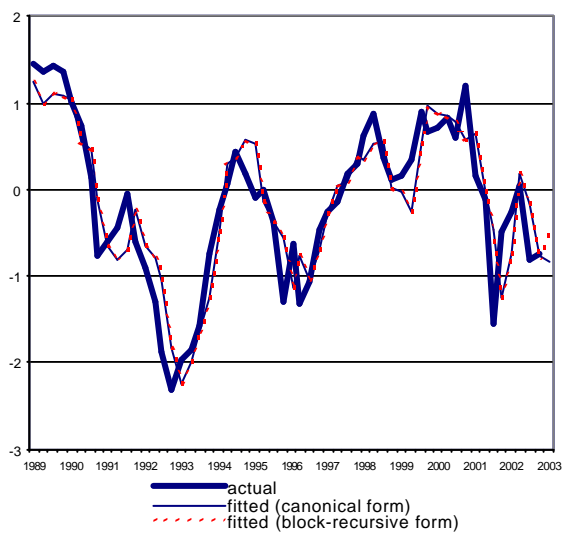


Table 6: Evolution in GDP growth forecasts depending on the information available

Forecasts performed on the basis of the VAR model without use of monthly results

Quarter	7-month horizon forecasts	4-month horizon forecasts	1-month horizon forecasts	National Accounts initial results at the time	National Accounts last available results ⁵¹
1999 Q2		0.4	1.3	0.6	1.0
1999 Q3	0.2	0.9	1.0	1.0	1.1
1999 Q4	0.9	1.0	1.0	0.9	1.3
2000 Q1	0.9	0.9	0.9	0.7	1.2
2000 Q2	0.9	0.8	0.8	0.7	0.8
2000 Q3	0.8	0.8	0.7	0.7	0.5
2000 Q4	0.7	0.6	0.8	0.9	1.3
2001 Q1	0.5	0.9	0.6	0.5	0.5
2001 Q2	0.7	0.3	0.1	0.3	-0.0
2001 Q3	0.4	0.2	-0.0	0.5	0.4
2001 Q4	0.2	-0.5	-0.1	-0.1	-0.3
2002 Q1	0.0	0.5	1.0	0.4	0.6
2002 Q2	0.1	0.8	0.5	0.5	0.6
2002 Q3	0.8	0.5	0.2	0.2	0.3
2002 Q4	0.5	0.1	0.6	0.2	-0.1
2003 Q1	0.3	0.8	0.1	0.3	0.2
2003 Q2	0.6	-0.5	-0.4	-0.3	-0.3

Forecasts are made on the basis of the VAR (7 and 4 month horizon: canonical form; 1 month horizon: block-recursive form).

To understand table 6:

Year N Quarter Q	7-month horizon forecasts:		4-month horizon forecasts:		1-month horizon forecasts:	
	Quarterly national accounts available until:	Business surveys available until:	Quarterly national accounts available until:	Business surveys available until:	Quarterly national accounts available until:	Business surveys available until:
N Q1	N-1 Q3	N-1 Q3 (October)	N-1 Q4	N-1 Q4 (January)	N-1 Q4	N Q1 (April)
N Q2	N-1 Q4	N-1 Q4 (January)	N Q1	N Q1 (April)	N-1 Q1	N Q2 (July)
N Q3	N Q1	N Q1 (April)	N Q2	N Q2 (July)	N Q2	N Q3 (October)
N Q4	N Q2	N Q2 (July)	N Q3	N Q3 (October)	N Q3	N Q4 (January)

⁵¹ "Detailed results" until 2003 Q2, published in September 2003.

Appendix 4: Service sectors are submitted to significant business cycles

Spectral analysis allows one to decompose the variance of a time series into different frequencies, and consequently to evaluate the share of its variance contained in any frequency band. Examining the spectral density or variance decomposition makes it possible to distinguish the series that exhibit real cycles from a white noise. In fact, the spectral density of the former is characterised by density peaks, whereas that of the latter is perfectly smooth.

Table 7 below presents the results of the variance decomposition for some balances of opinion derived from the business survey in service sectors. For the purpose of comparison, the variance decomposition of the balance relating to past production in industry (TP^{pa}) is also presented, as well as that of a simulated white noise (to be compared with the *theoretical* decomposition of a white noise). The result of the Kappa F-test⁵² is given for each of these series: a test statistic higher than the 5% threshold of 5.70 indicates that the series cannot be considered as a white noise.

TABLE 7: The variance decomposition of the main balances of opinion

(Distribution of variance by frequency bands - in %)

Frequency bands	Whole Services		Past turnover by service sector				Industry	White Noise	
	Past turnover TO^{pa}	Expected turnover TO^{exp}	Real estate activities	Business services	Household services	Temporary work	Past production TP^{pa}	Simulated	Theoretical
Trend T (> 24 quarters)	69	68	86	65	51	47	50	5	8
Short-term cycle C (6 - 24 quarters)	24	27	7	27	29	37	48	27	28
Noise N (< 6 quarters)	7	5	7	8	20	16	2	68	64
Kappa F-Test	9.05	8.72	18.36	9.18	10.57	6.44	7.58	2.92	1.00

NB: For an explanation concerning our choice of frequency bands for T , C and N , see Box 3 below.

The Kappa F-test fortunately concludes that the simulated white noise does not significantly differ from a theoretical white noise, although it generates density peaks of almost three times (2.92) the average. The Kappa F-test also suggests that no balance of opinion can be considered to be a white noise.

It is noteworthy that the variances of balances of opinion are not mainly concentrated in the frequency band corresponding to 6-24 quarters that can be interpreted as their short-term cycle C_t (⁵³), especially those relating to service sectors. In fact, the variances of balances of opinion in services are more concentrated in the low-frequency band (corresponding to periods exceeding 24 quarters, *i.e.* interpretable as the trend T_t). However, this result appears to be essentially due to the particular period (1988-2002) for which results from the business survey on service sectors were available at the moment when the study was performed⁵⁴.

⁵² The Kappa F -test is supposed to detect a sinusoidal component within a white noise. More precisely, the Kappa F -test statistic is the ratio of the largest coefficient of the variance decomposition to its average coefficient. It therefore enables one to detect density peaks within a series. A test statistic close to unity may identify a white noise.

⁵³ For definitions and explanations in this respect, see Box 3, at the end of this appendix.

⁵⁴ In fact, the portion of variance of past production in industry lying in the low-frequency band decreases significantly when calculated over a longer period. Similarly, time series relating to service sectors derived from other sources (employment sources and quarterly national accounts), which are available for a much longer period (since 1970), show a lower portion of variance in the low-frequency band when analysed over this long period.

The share of high frequencies (periods of less than 6 months, corresponding to the noise N_t) is low in industry, slightly higher in services as a whole, and still higher for balances of opinion relating to particular service sectors. This result is consistent with the smoother characteristic feature of balances of opinion in industry. Unsurprisingly, the share of high frequencies appears to be negatively correlated with the number of answers on the basis of which balances of opinion have been calculated.

Box 3: Definitions and conventions

Let X_t denote a time series (balance of opinion) derived from either the Industry or the Service survey. X_t can be viewed as the sum of three components:

$$X_t = T_t + C_t + N_t$$

where T_t represents the trend of X_t , C_t its short-term cycle, and N_t its noise component.

In spectral analysis, the short-term cycle of a time series C_t is defined as the aggregate of its components corresponding to intermediate frequencies (let us say between w_1 and w_2 , $w_1 < w_2$), while the noise N_t encompasses its components of higher frequencies (superior to w_2), and the trend T_t those of lower frequencies (inferior to w_1).

Following several NBER studies, Baxter and King [1999] recommend defining the short-term cycle C_t as a process “6 - 32”, i.e. whose periodicity is included between 6 and 32 quarters (in other terms, whose frequency is included between $w_1 = 2p / 32 = p / 16$ and $w_2 = 2p / 6 = p / 3$). The trend T_t then corresponds to periodicities exceeding 32 quarters, while periods under 6 quarters are related to the noise N_t . However, studying business cycles supposes that one has at least two complete cycles at one’s disposal. As this is not the case when applying a low-pass filter of 32 quarters to time series of only 60 quarters⁵⁵, we have defined the short-term cycle C_t as a process “6 - 24” (therefore, the trend T_t corresponds to periodicities exceeding 24 quarters, i.e. to a frequency inferior to $w_1 = 2p / 24 = p / 12$).

⁵⁵ Remember that balances of opinion derived from the Service survey performed by the French statistical institute Insee are time series whose length amounts to 60 quarters or so.

Appendix 5: Looking for leading indicators in services.

Table 8: Turning points of different quarterly indicators

High point (<i>IND</i>)		Jul.92		Apr.95		Jul.98		Oct.00	
Low point (<i>IND</i>)	Jan.92		Jul.93		Jul.96		Jul.99		Apr.02
Indicators in total industry									
Synthetic indicator (<i>IND</i>)	0	0	0	0	0	0	0	0	0
Past production (TP^{pa})	-1	+1	0	0	0	0	0	-1	0
Overall orders	0	-1	+1	0	0	0	0	0	0 ^a
Expected production (TP^{exp})	-3	-1	0	-1	-2	0	-1	-2/ 0	-1 ^a
Indicators in total services									
Synthetic indicator (<i>SER</i>)	-2	-2	-1	-1	0	+1	0	-2/+1	0 ^a
Past turnover (TO^{pa})	-1	-2	0	0	0/+2	0	-1	-2/+2	-1/+1
Expected turnover (TO^{exp})	-2	-3	-1	0	0	0	-1	-2/+1	0 ^a
Past operating profit ($OPRO^{pa}$)	-2	-2	0	-1	0	+1	0	-3/+2	-1/+1
Expected operating profit ($OPRO^{exp}$)	-2	-2	0	-1	0	+1	0	-2/+1	-2/ 0 ^a
Expected demand (DEM^{exp})	-2	-3	-1	-1	0	0	0	-1/+1	0 ^a
Indicators in industrial intermediary goods									
Synthetic indicator	-1	-1	0	0	0	-1	0	-1	-1
Past production	-1	0	0	0	0	-1	0	-1	0
Expected production	-2	-1	0	0	-1	-1	-1	0	-1 ^a
Indicators in temporary work									
Past turnover	-2	-2	-2	-2/ 0	+2	-3/+1	0	-1/+2	0
Expected turnover	-3	-2	-1	-2	0	-1	-1	-4/+2	-1

Legend:

Balances and synthetic indicators have first been smoothed, using a symmetrical moving average of order 3. The quarterly synthetic indicator in industry (*IND*, defined in Box 2) is our benchmark indicator for our analysis of the degree of lead or lag of the series considered above with respect to the observed turning points of activity in industry and in services in the nineties. + *i* (respectively - *i*) = *i* lags (respectively *i* leads) in quarterly terms relatively to the benchmark. 0 = in phase with the benchmark.

Some series have experienced several successive turning points at the neighbourhood of a turning point of the benchmark. In such a case, we have indicated the lag and lead of the first and last successive turning points (example: -1/ +1 expresses that the series experienced a turning point one quarter earlier than the benchmark. Then, after having been contradicted the quarter after, this turning point was confirmed one quarter later. Notice the notable number of successive turning points in 2000, notably in services, suggesting increasing uncertainty.

^a The corresponding smoothed balances of opinion experienced a downward turning point after the last perceptible upward turning point of the benchmark, in April 2002. It is too early to say whether this downward turning point is reliable or corresponds to a temporary irregular movement. The cyclical characteristic feature of the April 2002 turning point itself could not be confirmed by a filtering using the Baxter and King (1999) methodology.

Table 9: The transition from the initial service balances to the rephased balances

Variable	$\hat{a}_{i,-1}^K$	$\hat{a}_{i,0}^K$	$\hat{a}_{i,+1}^K$	$\hat{a}_{i,+1}^K - \hat{a}_{i,-1}^K$
Expected demand DEM^{exp}	0.37	0.43	0.27	-0.10
Expected operating profit $OPRO^{exp}$	0.34	0.42	0.29	-0.05
Expected turnover TO^{exp}	0.27	0.43	0.38	0.11
Past operating profit $OPRO^{pa}$	0.19	0.49	0.37	0.18
Past workforce size WF^{pa}	0.17	0.36	0.47	0.30
Past turnover TO^{pa}	0.10	0.47	0.46	0.36

Legend:

- The above weights derive from the last estimation stage of the iterative common factor (Cf. sub-section V-4). They have been determined endogenously.
- Each rephased balance has been derived from the corresponding initial balance by applying the following formula:

$$X_{it}^K = \sum_{t=-1}^{+1} \hat{a}_{it}^K X_{it+t} \quad (\text{Cf. sub-section V-4}).$$

For instance, the rephased balance relating to expected demand is defined by:

$$DEM_t^{exp*} = 0.37 DEM_{t-1}^{exp} + 0.43 DEM_t^{exp} + 0.27 DEM_{t+1}^{exp}$$

- The balances constituting the iterative common factor have been ranked by decreasing degree of lead according to the $\hat{a}_{i,+1}^K - \hat{a}_{i,-1}^K$ criteria, the balances relating to expected demand and operating profit appearing to be the best leading indicators, while those relating to past workforce size and past turnover seem to be lagged with respect to the other balances taken into account.