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Auteurs : Erkel-Rousse Hélène et Minodier Christelle.

Organisme : INSEE.

Titre de la soumission : Do Business Tendency Surveys in Industry and Services Help in Forecasting GDP Growth? A Real-Time Analysis on French Data.

Résumé :

Les enquêtes de conjoncture dans l'industrie et dans les services de l'Insee sont utilisées pour la prévision à court terme du taux de croissance du PIB à deux trimestres depuis la démonstration par Bouton et Erkel-Rousse (2003) que l'enquête Services véhicule une information avancée sur le taux de croissance trimestriel du PIB complémentaire à celle apportée par l'enquête Industrie. Toutefois, à notre connaissance, il n'avait pas été établi jusqu'ici que cette information spécifique contenue dans l'enquête Services permettait d'établir des prévisions de croissance significativement meilleures que si l'on ne mobilisait que des indicateurs tirés de la seule enquête Industrie.

Dans ce papier, nous effectuons donc une analyse hors échantillon en temps réel qui consiste à estimer puis simuler plusieurs types de modèles de prévision du taux de croissance trimestriel du PIB. Ces modèles mobilisent des variables tirées soit de la seule enquête Industrie, soit des deux enquêtes de conjoncture, avec ou sans termes autorégressifs du PIB. Nous comparons les qualités prédictives des différents modèles, en prenant comme référence un simple modèle autorégressif du taux de croissance du PIB. Nous effectuons ces opérations sur quatre horizons de prévision au moyen de modèles VAR et sur les trimestres courants et les deux trimestres suivants au moyen de modèles d'étalonnages univariés de type multipériode. Nous comparons en outre les performances prédictives des deux types de modèles (VAR et multipériode), pour tester si l'un devrait être systématiquement préféré à l'autre ou non. Les résultats mettent en évidence la nette supériorité des modèles fondés sur les soldes d'opinion issus des enquêtes de conjoncture comparativement aux modèles autorégressifs. Ils mettent également en lumière l'apport de l'enquête Services, qui permet d'améliorer significativement la qualité des prévisions pour les mois coïncidant avec des publications d'enquêtes trimestrielles (janvier, avril, juillet et octobre), pour lesquels des séries de services suffisamment longues sont disponibles.

Mots clef : Enquêtes de conjoncture, Services, Prévision macroéconomique, Modèles multipériode et modèles VAR, Prévisions itérées et directes, Équivalence prédictive.

Codes JEL : C22, C32, E32, E37.

Do Business Tendency Surveys in Industry and Services Help in Forecasting GDP Growth?

A Real-Time Analysis on French Data

by Hélène ERKEL-ROUSSE and Christelle MINODIER*

Short abstract:

Business tendency surveys (BTS) carried out by the statistical institute INSEE are intensively used for the short-term forecasting of the French economic activity. In particular, the service BTS has been used together with the industry BTS for the short-term forecasting of GDP growth since Bouton and Erkel-Rousse (2003) showed that the former survey contained a specific piece of information on GDP growth with respect to the latter survey. However, it remained to be demonstrated that this specific piece of information permits one to significantly improve the quality of short-term GDP forecasts with respect to models involving variables from the industry survey exclusively. More generally, the predictive accuracy of models based on the two surveys with respect to simpler autoregressive (AR) models deserved to be assessed.

We, therefore, perform a real-time out-of-sample analysis which consists in estimating, then simulating miscellaneous kinds of models (VAR and univariate multistep models) aimed at the short-term forecasting of the quarterly GDP growth rate. Some BTS based models encompass industry and service data, others exclude service data. The predictive accuracy of these two kinds of models is compared to that of simple AR models; that of models including service data is also compared to that of models excluding them. Predictive accuracy tests (Harvey, Leybourne and Newbold, 1997, Clark-West, 2007) are performed up to four-quarter forecast horizons. To assess the robustness of the results, we carry out both recursive and rolling estimations as well as three tests (differing by the method used to estimate the variance of the test statistics' numerators) for each couple of competing forecasts. The results establish the usefulness of the two BTS, as well as the contribution of the service survey in the months (January, April, July, and October) when long enough service series are available.

Key Words: Business Tendency Surveys, Services, Macroeconomic forecasting, Multistep and VAR models, Iterated and direct forecasts, Forecast comparisons.

JEL Classification: C22, C32, E32, E37.

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* Institut National de la Statistique et des Études Économiques (INSEE). Corresponding author: Hélène Erkel-Rousse, INSEE - MK2, Département des Études Économiques d'Ensemble, Division Croissance et Politiques Macroéconomiques, Timbre G220, 15 Boulevard Gabriel Péri, PB 100, 92244 Malakoff cedex, France. E-mail address: helene.erkel@insee.fr. The views expressed herein are those of the authors and do not necessarily reflect those of the INSEE. We would like to thank Emmanuel Michaux as well as the participants to the OECD-European Commission and INSEE D3E workshops (November 2007 and January 2008) for helpful comments and suggestions. All remaining errors, however, are ours.

Résumé long :

Les enquêtes de conjoncture sont largement utilisées par les conjoncturistes pour prévoir l'activité économique. Depuis le début des années 2000, de nombreuses évaluations de leur pouvoir prédictif ont été effectuées sur diverses données d'enquêtes appartenant au système européen harmonisé des enquêtes de conjoncture. Les résultats obtenus ne sont pas unanimes. En outre, les évaluations concernant l'apport des enquêtes de conjoncture harmonisées dans les services (ci-après enquêtes Services) sont rares, du fait que ces enquêtes sont récentes. Gayer (2005) trouve que l'indicateur synthétique de confiance dans les services établi par la Commission européenne à partir des résultats des enquêtes Services harmonisées réalisées dans les États membres n'a pas d'apport significatif pour la prévision de croissance de la zone euro. Toutefois, ce résultat pourrait être lié à l'insuffisante longueur des séries de services au niveau européen. Il devrait être possible de tester cette hypothèse en réalisant une étude portant plus spécifiquement sur la France, dont l'enquête Services réalisée par l'Insee, créée en 1988, est la plus ancienne enquête de conjoncture harmonisée dans ce secteur.

Or, sur ces données françaises, Bouton et Erkel-Rousse (2003) ont montré que l'enquête Services de l'Insee véhiculait une information avancée sur le taux de croissance trimestriel du PIB complémentaire à celle apportée par l'enquête de conjoncture dans l'industrie (ci-après enquête Industrie) réalisée par l'institut. Toutefois, il n'avait jusqu'à présent pas été établi que cette information spécifique contenue dans l'enquête Services permettait d'établir des prévisions de croissance significativement meilleures que si l'on ne mobilisait que des indicateurs tirés de l'enquête Industrie.

C'est ce que nous nous proposons d'étudier, en estimant plusieurs modèles de prévision du taux de croissance trimestriel du PIB, mobilisant des variables tirées soit de la seule enquête Industrie, soit des deux enquêtes de conjoncture, avec ou sans termes autorégressifs du PIB. Nous comparons les qualités prédictives des différents modèles, en prenant comme référence un simple modèle autorégressif du taux de croissance du PIB. Nous effectuons ces opérations sur quatre horizons de prévision au moyen de modèles VAR et sur les trimestres courants et les deux trimestres suivants au moyen de modèles d'étalonnages univariés de type multipériode. Nous comparons en outre les performances prédictives des deux types de modèles (VAR et multipériode), pour tester si l'un devrait être systématiquement préféré à l'autre ou non. La littérature à cet égard n'est pas unanime, les résultats différant selon les applications. Ainsi Marcellino, Stock et Watson (2005) obtiennent un avantage en faveur des modèles univariés multipériode, tandis que Hansson, Jansson et Löf (2005) aboutissent à des résultats similaires avec les deux types de modèles.

Notre analyse hors échantillon se rapproche le plus possible d'une analyse en temps réel (i.e. d'une analyse mobilisant, pour toute prévision réalisée à la date *t*, les informations disponibles jusqu'à cette date et pas au delà). Les prévisions du taux de croissance trimestriel du PIB sont effectuées au mois le mois plutôt qu'au trimestre le trimestre, afin de prendre en compte la dimension mensuelle des enquêtes de conjoncture.

Les résultats mettent en évidence la nette supériorité des modèles fondés sur les soldes d'opinion issus des deux enquêtes de conjoncture d'une part et de la seule enquête Industrie d'autre part, comparativement aux modèles autorégressifs. Ils mettent également en lumière l'apport de l'enquête Services par rapport à la seule enquête Industrie, l'enquête Services permettant d'améliorer significativement la qualité des prévisions pour les mois coïncidant avec des publications d'enquêtes trimestrielles (janvier, avril, juillet et octobre), particulièrement lors des premières prévisions de croissance du PIB au trimestre courant. L'apport de l'enquête Services est un peu moins net pour les autres mois, pour lesquels on ne dispose de données observées que depuis juin 2000, mois à partir duquel l’enquête Services a été mensualisée. Dès lors, une part notable de l’analyse a dû être effectuée sur des données mensuelles de services rétropolées à partir des données trimestrielles ou bien sur les dernières données trimestrielles de services disponibles, moins à jour que les données industrielles. Il en résulte très probablement un biais élevé en défaveur de l’enquête Services pour l’analyse de ces mois « non trimestriels ». Il conviendra donc de confirmer ces résultats exploratoires une fois que des séries mensuelles de services sensiblement plus longues seront disponibles.

Mots clef : Enquêtes de conjoncture, Services, Prévision macroéconomique, Modèles multipériode et modèles VAR, Prévisions itérées et directes, Équivalence prédictive.

1. Introduction

Sub-annual business tendency surveys (BTS) provide one with early pieces of information on economic activity. Within the European Union (EU), BTS are harmonised in the framework of the Joint Harmonised Programme of Business and Consumer Surveys[1]. As such, they constitute a unique set of comparable sources, which have become a focus of interest for central bankers, economic researchers, managers and other economic agents especially since the creation of the Euro zone. Their results are intensively used for short-term analysis and forecasting of economic activity in the Euro area considered as a whole, as well as in the EU Member States.

In this context, the use of BTS and, more generally, leading indicators, for short-term forecasting has become an important issue for European economists. Consequently, a number of recent articles have been published, aiming to precisely assess the contribution of harmonised BTS to the quality of forecasts of economic activity in Europe. However, the contribution of the BTS carried out in service sectors (hereafter referred to as the service surveys) is seldom studied, due to data scarcity. The few attempts in this respect up to now have led to mixed (if not negative) results. As Gayer (2005) suggests, this may be due to the short length of time series, most European service surveys having been created quite recently (cf. below, section 2, for a survey of literature).

The French statistical institute INSEE carries out ten sub-annual business surveys, which cover most sectors of activity. Created in January 1988 on a quarterly basis, its BTS in services is the oldest harmonised BTS in Europe in this sector. Even though time series derived from this survey are still a little short, especially those available on a monthly basis (available from June 2000 onwards), they constitute the longest available ones in Europe. From an in-sample analysis, Bouton and Erkel-Rousse (2003-2004) find that the service survey contains a specific piece of information on GDP growth with respect to the industry survey, which could be usefully taken into account in forecasting models. Four years later, it becomes possible to refine their conclusions and test Gayer (2005)'s assumption on the basis of a real-time out-of-sample analysis, at least on quarterly data. However, the results derived from monthly data will need to be refined when longer monthly series are available.

More precisely, our real-time out-of-sample analysis consists in estimating and, then, simulating miscellaneous kinds of models (VAR and univariate multistep calibration models) aimed at the short-term forecasting of the quarterly GDP growth rate using real-time data. Some models encompass industry and service data sometimes together with GDP growth lags, others exclude service data. The predictive accuracy of all these models is compared to that of simple autoregressive (AR) models; that of models including service data is also compared to that of models excluding them. The results prove the clear usefulness of the two BTS considered as a whole, as well as the sole industry survey, with respect to the AR models of GDP growth. They also lead to overall encouraging conclusions as concerns the contribution of the service survey to the short-term forecasting of GDP in addition to the industry survey, despite sometimes disappointing results obtained at this stage on the monthly data. However, the clearly positive results obtained with the quarterly data suggest that the monthly analysis suffers from serious

1 Cf. European Commission (2006).

methodological biases due to the excessively rough retropolation method used to alleviate the short length of monthly series in services.

The paper is organised as follows. Section 2 presents a brief review of the recent literature dealing with the assessment of BTS' contributions to short-term forecasting of economic activity. Section 3 provides details on the variables under analysis and the methodology used. Section 4 summarises and discusses the main findings. The conclusion recapitulates and suggests some tracks for further research.

2. The contribution of BTS to forecasting: A controversial issue

Survey indicators and, more generally, coincident and leading indicators are widely used to assess current economic developments or undertake short-term forecasts[2]. According to Emerson and Hendry (1998), the growing interest in using leading indicators to forecast a variety of economic time series seems to be "partly a reaction to […] forecasting failures by macro-econometric systems and partly due to developments in leading-indicator theory"[3]. More specifically, one can intuitively expect BTS to provide useful information for short-term forecasting due to their almost instantaneous availability (they are released much earlier than quantitative indicators, generally at the end of the month under analysis) and because they aim to measure economic agents' expectations, which play a crucial part in agents' decisions, the latter affecting the future developments of economic activity. From a more technical point of view, Pesaran (1987) points out that qualitative survey data are less subject to sampling and measurement errors than quantitative survey data dealing with the same economic variables. According to other authors, BTS are interesting tools for forecasting since they are never or little revised, unlike quantitative indicators (cf. Hansson, Jansson, and Löf, 2005, for instance)[4].

However, BTS data are not easy to use in forecasting. First, most of them are qualitative and their results need to be quantified before being introduced in forecasting models, which raises many methodological issues[5]. Besides, the use of BTS data in forecasting comes up against the same difficulties as that of leading indicators in general. The initial treatment of the underlying data (Weale, 1996) and the choice of indicators included in forecasting models (Stock and Watson, 1992) seem to be notable sources of uncertainty when using leading indicators for forecasting (see below). More especially, Emerson and Hendry (1998) suggest that the selection

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2 A coincident indicator refers to the present developments of a given variable of interest, while a leading indicator provides information on its near-term future. Numerous coincident and leading indicators are derived from BTS. Other coincident or leading indicators are based on quantitative statistics (such as the index of industrial production or monetary and financial statistics, for instance).

3 On leading indicators in general, see for instance Lahiri and Moore (1991). A more sceptical point of view is represented in Emerson and Hendry (1998) - see below.

4 This argument, however, does not completely hold if data revisions capture significant evolutions in agents' expectations or/and decisions. For instance, Ferrari (2005) shows that revisions in agents' expectations measured in the French BTS dealing with investment in industry carried out by INSEE encompass a piece of information that can be useful for the short-term forecasting of investment.

5 A huge literature is devoted to BTS quantification. Quick or more detailed surveys of this literature can be found in Nardo (2003), Mitchell, Smith and Weale (2004), D'Elia (2005) or Biau, Erkel-Rousse and Ferrari (2006), among many others.

of the components entering composite leading indicators (CLIs)[6] as well as the choice of their weighting schemes are subject to a certain degree of subjectivity and raise important methodological issues. They also stress that "historical leading indicators do not in practice systematically lead for long" for several reasons. "As there is no clear basis except extrapolation for CLIs invariably leading, they may suddenly fail to lead" in evolving economies where the causes of business cycles and the relationships between economic variables change over time. "Structural models would seek to account for such changes". In the case of simpler a-theoretical forecasting models linking a variable of interest to a small set of leading indicators, however, less formal analysis seems to (can?) occur. This latter aspect of the criticism towards the use of leading indicators in forecasting is not new and appears to be closely related to the historical Koopmans (1947) - Vining (1949) controversy[7].

These limitations of leading indicators when used in forecasting are well known and thoroughly documented in the literature. Nonetheless, the need for short-term forecasts and the shortcomings of competing techniques in this respect explain the broad use of leading indicators in forecasting as well as the dynamism of academic research and empirical work in the field. While most early empirical work deals with applications to the United States, the progresses of European integration, the creation of the European Monetary Union and the subsequent booming need for short-term indicators to gauge cyclical developments in the Euro area and the rest of the European Union has led to an increasing number of papers assessing the contribution of leading indicators derived from European sources, among which the harmonised BTS, to the forecasting of economic activity either in Euroland as a whole[8] or in some European Union's Member States[9], or both[10]. The results obtained in these papers concerning the contribution of

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6 CLIs result from the combination of several individual leading indicators, either using simple averaging methods (which raises the problem of the optimal weighting scheme to choose) or more complex methodologies, such as factor analysis techniques. The composite indicator resulting from a static factor analysis is a weighted average of its components, whose weights are endogenously determined. The relation between a composite indicator deriving from a dynamic factor analysis and its components is more complex. For theoretical foundations and various applications of the latter kinds of models, see Stone (1947), Sargent and Sims (1977), Stock and Watson (2002), Forni, Hallin, Lippi and Reichlin (2001), Camba-Mendes, Kapetanios, Smith, and Weale (2001), Grenouilleau (2004), among others. Doz and Lenglart (1996-1999) and Cornec and Deperraz (2006-2007) provide examples of applications of these kinds of techniques to the French data analysed in the present paper. We use their composite indicators in some of our models - cf. Below, section 3.

7 In his famous article "Measurement without Theory" (1947), Koopmans criticises Burns and Mitchell (1946) for simply "observing and summarizing the cyclical characteristics of a large number of economic series" without referring to any formal theoretical framework. Vining (1949) replies Koopmans' attack notably by arguing: that the state of econometric modelling is not advanced enough to allow one for carrying out accurate forecasts on their basis; that Koopmans' use of statistics focuses too narrowly on "the estimation of postulated relations" - Cf. also Simkins (1999).

8 Cf. for instance Fritsche and Marklein (2001), Marcellino (2002), Artís et al. (2003), Rua and Nunes (2003), Grenouilleau (2004), Barnejee, Marcellino, and Masten (2005), Gayer (2005), Claveria, Pons, and Ramos (2007).

9 Cf. Lindström (2000), Mourougane and Roma (2002), Heyer and Péléraux (2004), Dreger and Schumacher (2005), Hansson, Jansson, and Löf (2005), Lemmens, Croux, and Dekimpe (2005), among others.

BTS to forecasting are mixed, but some regularities can nonetheless be clearly observed in their conclusions.

First, the results depend notably on the data, especially on the out-of-sample period chosen and the country under analysis (Camba-Mendez et al., 2001). The initial treatment of the data (smoothing, trend removal, interpolation of missing values) plays an important role in Weale (1996) and Darné and Brunhes-Lesage (2007). Artís et al. (2003) also highlight the potential positive effects on forecasting accuracy of removing outliers from the data. Conversely, they consider that using models based on seasonally adjusted BTS data or, alternatively, raw BTS data and, then, apply a seasonal-adjustment method does not make much difference, most BTS data presenting low seasonal components. Besides, the miscellaneous quantification methods of BTS data tested by Claveria et al. (2007) do not alter the main conclusions concerning the contribution of BTS to forecasting.

The results also depend on the model used, but only to a certain extent. The selection of variables included in the model seems to play an important role (Stock and Watson, 1992, Darné and Brunhes-Lesage, 2007, among many others) and, therefore, requires special attention (Emerson and Hendry, 1994 and see below, sub-section 3.2). Conversely, simple linear models (either univariate or VAR models) usually perform as well as more complicated ones. For instance, Mourougane and Roma (2002) derive very limited improvements, if any, from the use of time-varying over constant parameter forecasting models. Similarly, Artís et al. (2003) and Claveria et al. (2007) find that non-linear models such as SETAR[11] or Markov-switching regime models do not outperform simpler linear models. Marcellino (2002), who compares linear with time-varying and non-linear univariate techniques, confirms these conclusions. The latter conclusions contradict the intuition of a possible improvement of forecasts by using methodologies that could better take into account the occurrences of structural breaks in the data than linear techniques. Though, the recent studies are carried out on periods that are undoubtedly affected by the major structural breaks experienced in Europe (single market, transition in Central and Eastern Europe, German reunification, European Monetary Union, European enlargement…). Moreover, the frequent observation of a significant deterioration of out-of-sample results with respect to in-sample results or of, at least, very weak links between the two kinds of analyses in papers where both are performed[12] might be due to the occurrence of structural breaks in the forecast period. Nonetheless, the best way to proceed in presence of structural breaks seems to combine numerous forecasts derived from simple models rather than to use complex models[13]. The less correlated the component forecasts, the more efficient their

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10 See Sédillot and Pain, 2003, whose application deals with Germany, France, Italy, the UK, the Euro area as a whole, and the US.

11 SETAR (for Self-Excited Threshold Auto-Regressive) models are simplified versions of Markov-Switching regime models as regard the distribution properties of their error-terms.

12 See Diebold and Rudebusch (1991), Stock and Watson (1992), Dreger and Schumacher (2005) among others, and Clements and Hendry (1998) and Ermeson and Hendry (1994) for methodological discussion in this respect.

13 For introductions to forecast combination methods and surveys of the large literature in this respect, see Diebold and Lopez (1996), Newbold and Harvey (2002), and Hendry and Clements (2002). For an example of the pooling of numerous forecasts, see Stock and Watson (2004).

pooling, so that the mean-square forecasting errors (MSFE) of the component forecasts tend to cancel each other out. For instance, by pooling the forecasts derived from the main German leading indicators, which rely on very different logics and kinds of data (some including BTS data), Dreger and Schumacher (2005) obtain combined forecasts that perform significantly better than their benchmark autoregressive model of industrial production growth rate, while each component forecast separately does not outperform the benchmark model. However, it cannot be proved that only non-encompassed devices should be retained in the combination of forecasts (Hendry and Clements, 2002).

The diagnoses are not so unanimous as concern the relative predictive performances of VAR models (which lead to dynamic iterated forecasts, also referred to as "indirect" forecasts in the literature) and simpler univariate multistep models, from which "direct" *h*-step forecasts can be derived[14]. Marcellino, Stock, and Watson (2005) present an application to a large set of monthly US macroeconomic time series where iterated step-by-step forecasts derived from VAR models are outperformed by "direct" *h*-step forecasts resulting from simpler univariate multistep models. However, they do not use BTS data. In an application on Swedish BTS data, Hansson et al. (2005) find that "direct" and "indirect" forecast set-ups have overall equivalent accuracy. Finally, Chevillon and Hendry (2005) show that, for forecast accuracy gains from multistep models, mis-specification and non-stationarity of the studied processes are necessary. They also show, however, that if models are well-specified, iterated step-by-step forecasts may not outperform "direct" *h*-step forecasts.

Similarly, the relative predictive performances of either CLIs or their individual components considered separately remain a controversial issue. A common argument in favour of using CLIs is that the averaging or filtering technique from which they are derived "entails getting rid of the individual series-specific "noise" and keeping those parts of the data that are common to the series under consideration" (cf. Hansson et al., 2005). Using CLIs may, therefore, permit one to improve the forecasting of economic activity, by thus removing any undesirable "noise" from the data used in the models. Conversely, CLIs may underperform the set of its components considered separately if the relations between the former and the latter variables evolve in time. In this case, forecast models based on CLIs may be excessively restricted with respect to those introducing their components separately, whose estimated parameters can better adapt to the evolutions in the relation between variables when the estimation period changes. That is without doubt why, depending on the data used, CLIs or, alternatively, individual components perform better.

In a majority of recent papers providing out-of-sample analyses, most tests of predictive equivalence lead to a positive conclusion as concerns the significance of the contribution of BTS

[14] Multistep models are regressions of a multistep-ahead value of the variable of interest (Y_{t+h}) on the current and past values of a certain number of explanatory variables (X_t, X_{t-1},..., X_{t_k}). From these models, direct static *h*-step forecasts of the variable of interest can be derived, by contrast with dynamic iterated forecasts at the *h* horizon derived from VAR models. Multistep models are more parsimonious than VAR models in the sense that they do not need forecasting every variable taken into account in the model to obtain a *h*-step forecast for the variable of interest. Their main drawback in practice is that it may be difficult to find indicators that are leading enough to show high correlations with the variable of interest brought *h*-step forward, especially when *h* grows.

based models to the forecasting of economic activity in the short run, namely up to around the two or three quarter horizon, at least -or, sometimes, at most- (Fritsche and Marklein, 2001, Mourougane and Roma, 2002, Sédillot and Pain, 2003, Gayer, 2005, Hansson et al., 2005, among others). Some authors, however, find that the generally observed decreases in MSFE when taking BTS data into account are seldom significant (Claveria et al., 2007) or that the contribution of leading indicators based on BTS data is lower than that of other (quantitative) indicators (Barnerjee, Marcellino, and Mastens, 2005). In any case, the contribution of BTS to forecasting is described as limited by most authors, due to the low accuracy of most forecasts obtained, even the best ones (see notably Hansson et al., 2005, for a discussion of the causes of high forecast errors at some periods of time). Note that, contrary to intuition, MSFEs do not always increase with the forecast horizon (Artís et al., 2003). Last, the effect of either recursive estimation or rolling estimation on the results is not clear, most papers employing either the one or the other technique exclusively[15].

Among the numerous papers dealing with the contribution of BTS to the short-term forecasting of GDP growth, very few address the issue of the contribution of service surveys, although services represent an increasing (and henceforth notable, if not majority) part of economic activity in most EU member states. Insufficient length of service series is the main reason for the scarcity of studies dealing with this issue. BTS in services are very recent in most European countries. As was mentioned above, the oldest one, carried out in France by INSEE, was created in 1988, but became monthly not sooner than in June 2000. Most other service surveys have been carried out since the mid 1990s or, even, the beginning of the 2000s only. The service survey entered the joint harmonised EU programme relatively recently, in 1996 (to be compared with the industry survey, which has been harmonised since 1962 - cf. European Commission, 2006). The late interest in business cycles in services stems from a long-lasting widespread scepticism among short-term analysts as concerns the usefulness of studying business cycles in services[16]. According to this widespread opinion, as the major part of business cycle fluctuations originate from industry, overall business cycles are assumed to be satisfactorily analysed and forecast by focusing on industry data exclusively. Bouton and Erkel-Rousse (2003) contradict this opinion by showing (using Granger causality tests within VAR and univariate calibration models) that the INSEE service survey provides a significant leading piece of information on GDP growth which is not encompassed in the corresponding industry survey and, therefore, might be useful for the short-term forecasting of GDP growth[17]. Martelli and Rocchetti (2006) study the properties of the Italian service survey in the same spirit. Cornec and Deperraz (2006-2007) introduce a new synthetic indicator in services for France derived from a dynamic factor analysis methodology generalising Doz and Lenglart (1996-1999) so that service data of different periodicities and beginning at various dates can be taken into account as soon as they are available. On the basis of an in-sample analysis, they show that this indicator might help forecasting GDP growth. Grenouilleau (2004) indicates that he completed the set of harmonised BTS data from the European Commission on which he based the estimation of his

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15 For a definition of recursive and rolling estimation, see below, sub-section 3.2.3.

16 In France, Fontaine (1992) constitutes a notable exception in this respect.

17 In this respect see also Heyer and Péléraux (2004) who include a composite indicator derived from the INSEE service survey into their leading indicator for the French GDP quarterly growth rate.

forecasting model of GDP growth with “some selected country-wise survey results […] when they provide additional information, for example […] INSEE service survey or the Bank of France credit survey”, adding that “some balances in service surveys conducted in France […] exhibit outstanding cross-correlation with euro area GDP” (page 14).

To our knowledge, however, the only out-of-sample assessments of the contribution of service surveys to GDP forecasting performed up to now are due to Gayer (2005) and Darné and Brunhes-Lesage (2007). Somewhat disappointingly, Gayer (2005) finds that the European Commission’s confidence indicator in services has no useful informative content for the short-term forecasting of Euroland’s GDP growth, contrary to most other Commission’s confidence indicators. The author points out that “the weaker performance of the service index in the out-of-sample scenario seems to be owed to the shorter estimation sample; the first forecast calculations are based on estimation samples of only three to four years”. In fact, at the Euroland level, the service confidence indicator is available from April 1995 onwards only. Darné and Brunhes-Lesage (2007) have longer service series at their disposal, those from the French service BTS carried out by the Bank of France, which begin in 1989 on a two-monthly basis, and are monthly from June 2002 onwards[18]. The authors retropolate the service series on a monthly basis from 1989. They, then, transform them into quarterly series, using diverse competing techniques. Next, they compare the predictive accuracy of several quarterly models of GDP growth based on broken-up or aggregate industry survey data on the one hand and overall industry and service survey data on the other hand. The results crucially depend on: the methods used to interpolate missing values in the initial service series; the forecasting method used; the way the service data are taken into account (either as individual series or as a restricted set of common factors derived from a static factor analysis of the individual series). In a majority of cases, the models including aggregate industry and service data fail to be significantly more informative than those involving aggregate industry data only. Nonetheless, when the missing values are completed using averaging methods, the contribution of individual service series appear to be significant at least as concerns the first forecast of GDP growth.

18 This survey is not harmonised at the European level.

3. Data and Methodology

3.1 Data

The variable of interest of our study is the quarterly growth rate of GDP derived from the French quarterly accounts (cf. Labarthe, undated). The causality analyses performed by Bouton and Erkel-Rousse (2003-2004) not only show that the INSEE industry and service surveys contain partly complementary specific pieces of information on GDP growth. They also show that the BTS carried out by INSEE in other sectors of activity (retail trade, wholesale trade, construction, public works) do not add any significant piece of information on GDP growth *in addition to* that encompassed in the industry survey[19]. That is why our empirical work is based on the INSEE BTS in industry and services exclusively. Table 1 (next page) gives a brief presentation of the two surveys' main characteristic features[20]. Of the ten business surveys currently managed by INSEE, the industry survey is the one that has remained most stable over time, especially during the period under analysis in the present paper (1988 to 2007, due to the availability of service data on this period exclusively). More especially, all series are either monthly or quarterly on the whole period 1988-2007. Conversely, the much younger service survey has experienced several major changes since 1988. Consequently, the time series derived from the service survey differ both in periodicity and length: some are quarterly during the whole period 1988-2007, others are quarterly before June 2000 and monthly afterwards, and some begin in June 2000, or even later. It is noteworthy that the later stabilisation of the service survey due to its younger age may induce a bias against the service survey in our results[21]. This is all the more the case that we retropolated those series that became monthly in June 2000 from 1988 on a monthly basis, as we wanted both to follow the usual practice of short-term analysts and to give a first experimental assessment of the predictive performance of the monthly data from the service survey[22]. However, any conclusion derived from the monthly service data in the present paper must be considered with caution and needs to be confirmed when longer "true" monthly series are available. Note, however, that the results derived from pure quarterly data that we also present can serve as benchmarks with respect to the less reliable results derived from monthly data.

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19 Conversely, these surveys give useful pieces of information on sectoral variables, such as production and employment growth at sector level.

20 In addition to the information given in table 1, note that the INSEE survey data are revised once, at the moment when the survey immediately following the first release is published, to take late responses into account. However, the revisions, are most often rather limited.

21 This risk has been taken into account in the testing methodology as far as possible - cf. below, end of sub-section 3.3.

22 Following the usual practice of INSEE short-term analysts, we used the procedure EXPAND of the SAS software, option method = join, which approximately comes down to linear interpolation between two successive quarterly observations (Cornec and Deperraz, 2007, do the same). Doing so, we put ourselves in a position to assess the predictive contribution of the series data that are used in practice for short-term forecasting. The question whether a better interpolation method might be used would deserve some attention and is left for future research.

Table 1 The INSEE BTS in industry and services: Overall characteristic features

Characteristic features	Industry survey	Service survey
Creation	1951, harmonised at the European level since 1984	January 1988, harmonised at the European level since 1996
Periodicity	Monthly (except August), with a more thorough "quarterly" questionnaire in January, April, July and October.	Quarterly from January 1998 to April 2000, then monthly (except August) since June 2000 for some questions
Sample	4,000 enterprises of more than 20 employees surveyed, among which all enterprises of 500 or more employees, as well as all enterprises with annual turnover exceeding €150 million, irrespective of size.	4,500 enterprises surveyed, among which all enterprises with annual turnover exceeding €45 million, irrespective of size.
Sector coverage	Equipment goods, consumption goods, intermediary goods, automobile and food industries, oil refineries[23]	Business services (computer and related activities, advertising, temporary work, etc.), household services and real estate activities[24]
Release	Around the 25th of the month under analysis	
Main evolutions since their creations (besides change in periodicity - in this respect, see above)	1979: the four-monthly section of the survey becomes quarterly 1991: harmonisation of the scope of coverage (exclusion of enterprises with fewer than 20 employees); the survey's quarterly waves are conducted in January, April, July & October. 1997: simplified questions on total and export demand; new questions on competitiveness 2004: slight modifications of a few questions for harmonisation purpose [25]	1998: enlargement of the sector coverage to telecommunications, arts, entertainment, and recreation activities 2004: the question relating to expected demand becomes monthly 2006: extension of the sector coverage of the survey to landing transports

Sources: INSEE Méthodes (2007) for the industry survey, available on the INSEE website; BTS Unit, INSEE, for the service survey. A future volume on the service survey in the *INSEE méthodes* series is under preparation.

23 Specific BTS are performed in construction and public works. Note that the industry survey data taken into account in this paper refer to manufacturing (food industries and oil refineries excluded).

24 The coverage of the service survey includes neither financial nor insurance services. Transports have been included in the survey's coverage since February 2006 (the results are not published yet).

25 If we focus on the variables used in this paper, the only change concerns the questions on past and expected "tendency" of production, which have become questions on the "evolution" of production since 2004.

The questions of the two surveys are both backward-looking (regarding the situation in the past three months) and forward-looking (regarding the outlook for the next three months). Most of them are qualitative questions relating to a particular variable of interest (for instance production, demand, or turnover) requiring a response among three possible ones: positive ("increasing", "above normal" or "more than sufficient"), intermediate ("stable", "normal", sufficient") or negative ("decreasing, "below normal" or "less than sufficient").

The main monthly questions relating to activity that are asked at the monthly industry survey deal with: past and expected production, overall and foreign orders, general expectations, and inventories. The resulting monthly balances of opinion[26] are referred to as, respectively, $PROI^{pa}, PROI^{ex}, OORI, FORI, GENI^{ex}$ and INV_i. The synthetic indicator introduced by Doz and Lenglart (1996-1999) results from a dynamic factor analysis on the set of these six balances. The authors stress that this dynamic factor does not significantly differ from a common factor derived from a static factor analysis of the same set of variables. Therefore, as it is simpler to implement, the static factor is published each month by INSEE. Let $FACI^m$ denote the corresponding standardised factor. The two quarterly questions of the industry survey relating to past and expected demand are also widely used by short-term analysts for the forecasting of industrial production growth (cf. also Hild, 2007). Let DEM_i^{pa} and $DEMI^{ex}$ denote the corresponding quarterly balances of opinion (see Figure 1, below).

The main questions derived from the service survey for which relatively long series are available on a quarterly basis are those relating to expected demand, plus the recent and expected evolutions of turnover and operating profit. Let the corresponding balances of opinion be referred to as: $TOVS^{pa}, TOVS^{ex}, OPPS^{pa}, OPPS^{ex}$, and $DEMS^{ex}$. The first two series have been monthly since June 2000; the last three ones have remained quarterly[27]. Let $FACS^m$ denote the synthetic indicator in services introduced by Cornec and Deperraz (2006-2007) and published each month by INSEE since September 2004, after standardisation. $FACS^m$ derives from a dynamic factor analysis involving the five above defined service balances, to the addition of that concerning general expectations[28]. As was already mentioned in section 2, Cornec and Deperraz (2006-2007) have extended the Doz and Lenglart (1996-1999) framework in order to cope with service series with different lengths and periodicities.

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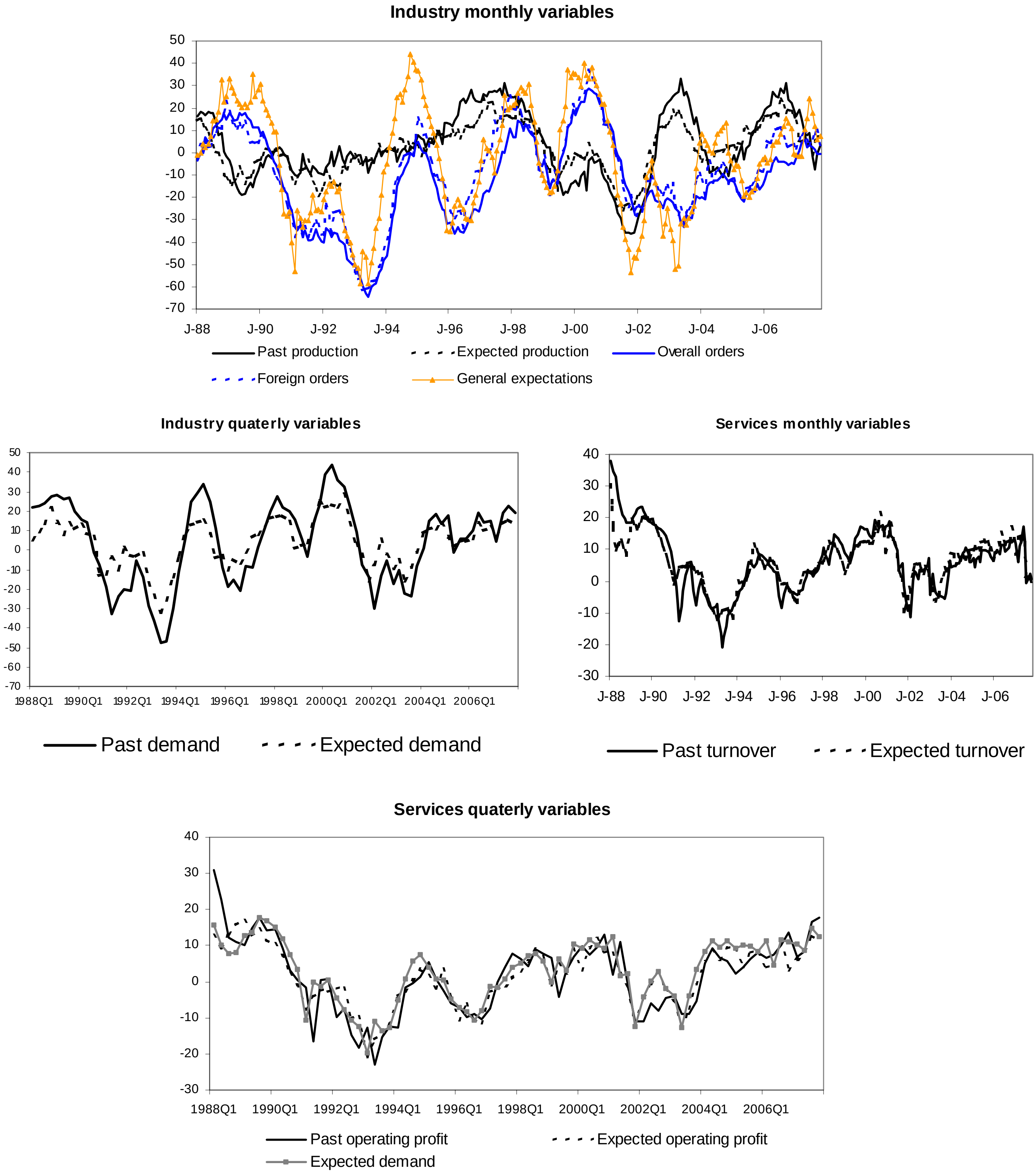
26 For a given qualitative question requiring a response between three modalities (positive, intermediate or negative), a balance of opinion, also called net balance, is defined as the difference between the (generally weighted) share of firms that have specified a positive response and the share of firms that have specified a negative one. For theoretical foundations of the balances of opinion, see Theil (1952) and, among many subsequent papers, Fansten (1976).

27 The question relating to expected demand has become monthly in September 2004, but the resulting monthly series are not published yet.

28 The corresponding question has been asked since June 2000 only, that is why we do not mention it above.

Figures 1 The balances of opinion under analysis



Sources: INSEE industry and service surveys.

In addition to all these variables, for symmetry purpose, we also consider a dynamic factor in industry $FACI^{m'}$ calculated *à la* Cornec and Deperraz (2006-2007), including all the mentioned balances in industry, among which the two quarterly balances relating to demand. We also introduce two static common factors in industry $FACI^{q}$ and in services $FACS^{q}$ derived from a static common factor analysis performed on the quarterly values of the whole set of balances mentioned, for industry on the one hand and services on the other[29]. All the introduced balances are seasonally-adjusted[30]. Every series under analysis can be considered as a stationary process[31].

It is noteworthy that the composite indicators considered in the paper are not conceived to be CLIs. The large sets of balances on which they are based (most balances derived from each survey as concerns activity, including those relating to the past three months) give them the ex ante status of summaries of the underlying surveys rather than that of CLIs. However, some forecast models used by INSEE short-term analysts are based on the official synthetic indicators in industry and services (in addition to other models based on balances of opinion considered separately) and prove to perform relatively well. Nonetheless, a possible extent to the present study might indeed consist in trying to introduce additive composite indicators derived from a restricted set of balances containing the most leading ones as concerns GDP growth. The drawback of this approach, however, would be to limit the number of factor components to a lower number, so that the calculation of a common factor would lose part of its interest. All in all, even though one might envisage to introduce other composite indicators specifically elaborated as CLIs in addition to those considered in this study, we have chosen to privilege, as a first approach, kinds of composite indicators which are usually introduced in forecast models by French short-term analysts. The main point at this stage is to allow the comparison of the forecast performances of several individual and composite indicators, which, as suggests the literature, may perform differently - cf. above, section 2.

More fundamentally, we chose to restrict ourselves to balances of opinion and composite indicators based on balances, while many other quantification methods of the individual responses to the surveys might have been envisaged. There are three reasons for this choice. First, balances of opinion are the officially published data in the INSEE BTS and, more widely, the joint harmonised EU programme of business and consumer surveys. Second, Claveria et al. (2007) do not find notable differences between results derived from balances or, alternatively, other quantification methods. Last, there is no unambiguous evidence on INSEE data that balances should perform less well than other quantification methods[32]. Nonetheless, three recent applications on French data introducing non standard quantification methods (Hild, 2003 and 2007, and Biau, Biau and Rouvière, 2006) suggest that this issue might deserve future research.

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29 Bouton and Erkel-Rousse (2003-2004) used a static quarterly common factor in services too.

30 Note that the synthetic indicators in industry and services are calculated on the basis of seasonally-adjusted balances.

31 The GDP growth rate can be considered as stationary without ambiguity. The stationarity of balances is accepted at least by the KPSS test at a usual threshold.

32 Such as that introduced by Mitchell, Smith and Weale (2004, 2005), for instance - cf. Biau, Erkel-Rousse and Ferrari (2006-2007).

3.2 Four sets of models of two different kinds

We aim to elaborate forecasting models of the quarterly GDP growth rate that enable us to up-date our forecasts every month, using the last available data in the most rigorous possible way. To do so, we use a methodology suggested by Dubois and Michaux (2006) and privileged since then by INSEE short-term analysts on macro data[33], which requires introducing the following notations. If x is a monthly series derived from either the industry or the service survey, let x_{m1} (x_{m2}, x_{m3} respectively) denote the quarterly series whose value at any quarter *q* is equal to that in the first (resp. second, third) month of quarter *q*. Let, in addition, x_{m4} denote the quarterly series whose value at quarter *q* is equal to that at the first month of the following quarter *q*+1. Quarterly series can also be transformed in the same way, but their sub-series x_{m2} and x_{m3} contain missing values only. The interest of considering sub-series x_{m1} to x_{m4} is that: one does not have to transform the monthly data into quarterly data using averaging or extrapolation econometric techniques[34]; one, thus, fully uses the piece of information given in the monthly surveys[35].

For instance, suppose that, at the end of January of year *y* ([36]), one wishes to forecast the quarterly growth rate of GDP (*g*) in the recent past (last quarter of the previous year *y*-1) at a one-step horizon, and at the current quarter at a two-step horizon. As concerns the forecasting of the previous quarter, for any possible regressor x, one should intuitively gain by using a model linking *g* to sub-series x_{m4}, which encompasses the most timely information on that quarter (possibly together with less recent observed values of other sub-series). As concerns the forecasting of the current quarter, conversely, one should intuitively gain by using a model linking *g* to sub-series x_{m1}, which encompasses the most timely information on the current quarter (also possibly together with less recent observed values of other sub-series). In other terms, in order to use the most recent monthly piece of information from the two surveys, one should intuitively gain by using different models depending both on the position of the current month in the quarter and the forecast horizon *h*. Figures 2, next page, illustrate the way subseries relating to *m*1 to *m*4 evolve with respect to one another, on the example of the published common factors in industry and in services. The subseries relating to quarter *m*4 are slightly more leading than those relating to *m*1.

33 Cf. for instance Cornec and Deperraz (2006-2007).

34 For illustrations of these techniques, see Darné and Bruhnes-Lesage (2007) or Bouton and Erkel-Rousse (2003-2004), for instance.

35 Doing so, we hope to better capture the fluctuations of GDP growth than if we used quarterly data derived from averaging the monthly data, for instance.

36 At that time, the last available observation of the quarterly accounts refers to the third quarter of the previous year and the surveys relating to January of year *y* have just been published.

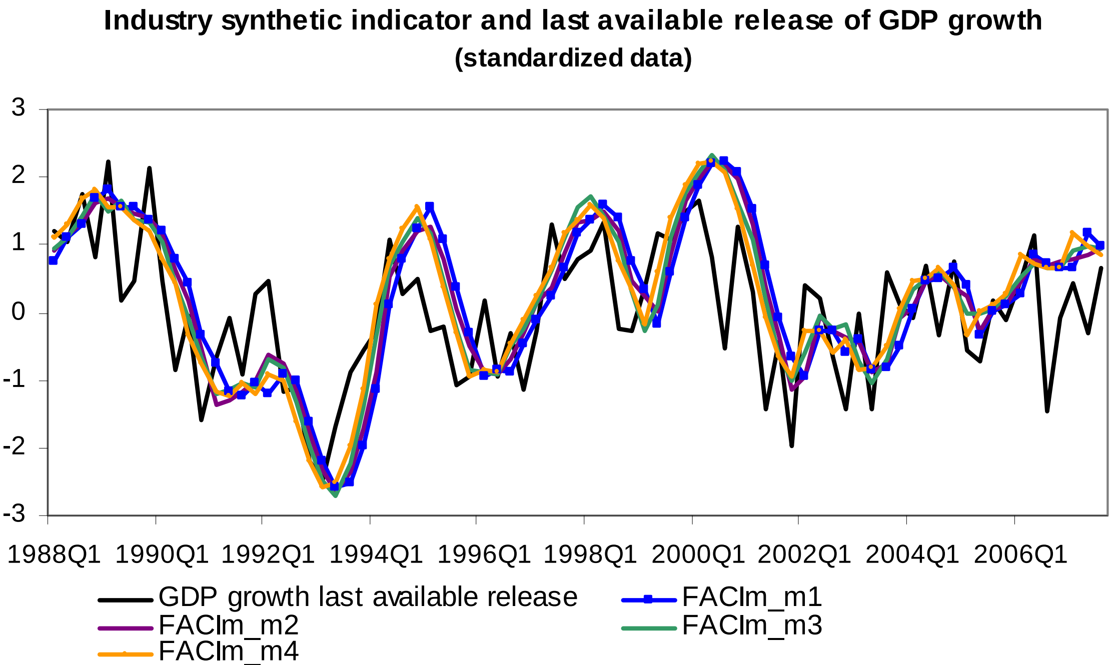
More precisely, we shall define four sets of models: three for the forecasting of the current and following quarters in, respectively: January, April, July, and October (months *m*1, for “first month” in the current quarter), February, May, August, and November (months *m*2), March, June, September, and December (months *m*3), plus one for the forecasting of the previous and following quarters in January, April, July, and October (months “*m*4”, to differentiate from forecast models relating to months *m*1). Note that, due to the absence of survey in August, we do not calculate forecasts at the end of this month[37].

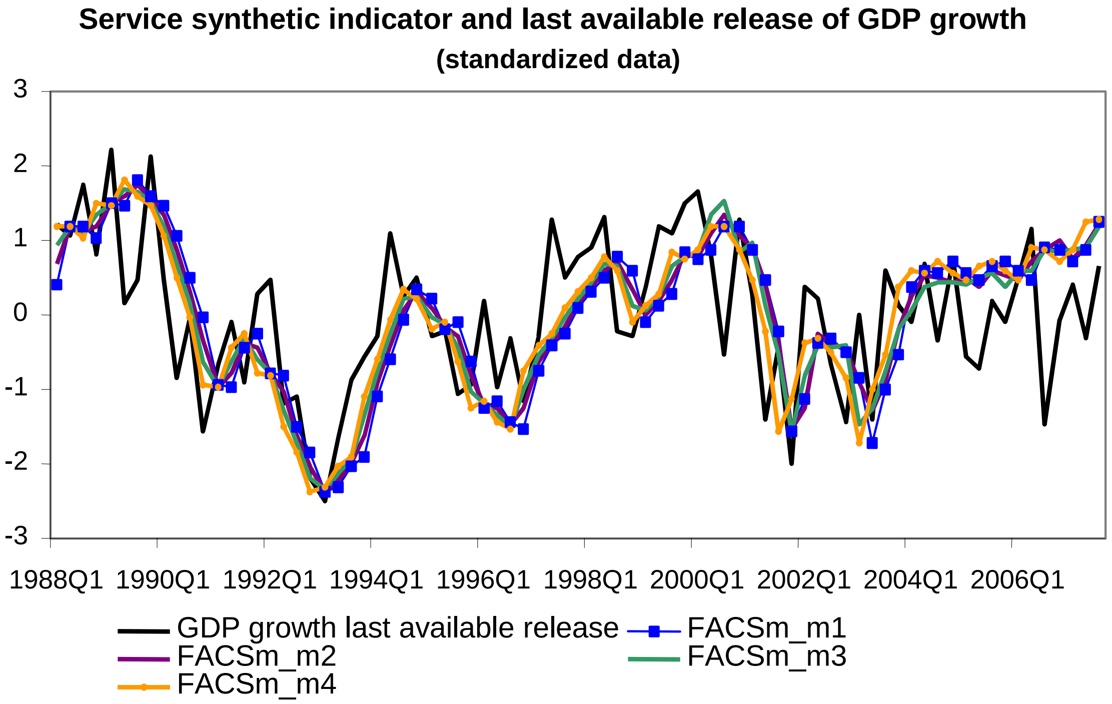
As concerns the kinds of models used, the literature suggests that simple linear models perform at least as well as more complex models (see above, section 2). Consequently, we restrict ourselves to linear models. Conversely, there is no unanimous diagnosis as for the relative predictive performances of multivariate VAR models (leading to “indirect” iterated forecasts) on the one hand, and univariate multistep models (leading to “direct” *h*-step forecasts) on the other hand. Therefore, we test both kinds of models. Moreover, the issue of whether it is more appropriate to use either composite indicators or their components separately in forecasting models is still unresolved in the literature. Therefore, we test both VAR models with common factors or, alternatively, individual balances of opinion. We utilize the multistep univariate models to calculate GDP growth forecasts for the current, next and next-to-next quarters, which corresponds to either forecasts at the one, two, and three quarter horizons, or to forecasts at the two, three, and four-quarter horizons, depending on the month when the forecast exercise is performed. Besides, we calculate forecasts up to the four-quarter horizon from the VAR models. Performing forecasts at longer quarter horizons does not seem to be of much interest, most assessments of the BTS contributions to forecasting suggesting that this kind of surveys is essentially useful in the very short run. See table 2, next-to-next page, for an overall view of the agenda of quarterly accounts releases in France together with that of our successive forecasts, using either VAR or univariate multistep models of GDP growth.

As is stressed in the literature, the variable selection stage seems to be of high importance for the results and, therefore, requires some special care. The methods used in this respect in the paper depend on the models, whose main characteristic features differ notably. This point is addressed in the following two sub-sections.

[37] Although there is no additive information from the BTS in August, one might nonetheless wish to perform forecasts at the end of this month due to the release of a new piece of information (that of the first release of the quarterly accounts for the second quarter of the current year). As our aim, however, is to assess the contribution of the BTS, not that of the past values from the national accounts, to GDP growth forecasting, we chose not to consider forecast up-dates due to non BTS sources.

Figures 2 Subseries derived from the published synthetic indicators and GDP growth





Sources: French quarterly accounts and industry and service surveys. Authors' calculations.

Table 2 Agenda of INSEE quarterly account releases and consequent *h*-step forecasts

Current quarter[a]	End of current	Month in the current	Last released[b]	*h*-step forecasts[c]			
				h = 1	*h* = 2	*h* = 3	*h* = 4
(y-1)q4	January	m4	(y-1)q3 DR	(y-1)q4	yq1	yq2	yq3
yq1	January	m1	(y-1)q3 DR	(y-1)q4	yq1	yq2	yq3
yq1	February	m2	(y-1)q4 FR	yq1	yq2	yq3	yq4
yq1	March	m3	(y-1)q4 FR	yq1	yq2	yq3	yq4
yq1	April	m4	(y-1)q4 DR	yq1	yq2	yq3	yq4
yq2	April	m1	(y-1)q4 DR	yq1	yq2	yq3	yq4
yq2	May	m2	yq1 FR	yq2	yq3	yq4	(y+1)q1
yq2	June	m3	yq1 DR	yq2	yq3	yq4	(y+1)q1
yq2	July	m4	yq1 DR	yq2	yq3	yq4	(y+1)q1
yq3	July	m1	yq1 DR	yq2	yq3	yq4	(y+1)q1
yq3	August	m2	yq2 FR	yq3	yq4	(y+1)q1	(y+1)q2
yq3	September	m3	yq2 DR	yq3	yq4	(y+1)q1	(y+1)q2
yq3	October	m4	yq2 DR	yq3	yq4	(y+1)q1	(y+1)q2
yq4	October	m1	yq2 DR	yq3	yq4	(y+1)q1	(y+1)q2
yq4	November	m2	yq3 FR	yq4	(y+1)q1	(y+1)q2	(y+1)q3
yq4	December	m3	yq3 FR	yq4	(y+1)q1	(y+1)q2	(y+1)q3
yq4	January	m4	yq3 DR	yq4	(y+1)q1	(y+1)q2	(y+1)q3
(y+1)q1	January	m1	yq3 DR	yq4	(y+1)q1	(y+1)q2	(y+1)q3
(y+1)q1	February	m2	yq4 FR	(y+1)q1	(y+1)q2	(y+1)q3	(y+1)q4
(y+1)q1	March	m3	yq4 DR	(y+1)q1	(y+1)q2	(y+1)q3	(y+1)q4

a) *yqn* = n^{th} quarter of year *y*, *n* = 1 to 4, with the convention defined above for *m*4.

b) FR = First Results, DR = Detailed Results. Note that, in this respect, the release agenda of the French quarterly accounts has evolved over time. The description given in table 2 corresponds to its current agenda.

c) Grey tint: forecasts of the current, next, and next-to-next quarters. The concepts of forecasts of the current, next and next-to-next quarters (used in our multistep models) coincide with those of one, two and three-step forecasts used in our VAR models, except in month *m*1, when they correspond to, respectively, two, three, and four-step forecasts.

3.2.1 Variable selection in the case of univariate multistep models

The set of pre-selected variables for this kind of models consists of "*mi*" subseries (*i* = 1 to 4) relating the five service balances introduced in sub-section 3.1 above, as well as (most of the time[38]) five industry balances (three monthly and two quarterly ones): past and expected production, overall orders, and past and expected demand. We, most often, do not take all the

38 See below, the case of forecast models of the next-to-next quarter.

balances included in the industry common factors into account for several reasons. First, the other balances (general expectations, foreign orders, and inventories) are those that most seldom appear in calibration models of GDP growth based on either manual or automated selection procedures. Second, our assessment of the contribution of the service survey to GDP growth forecasting would have been biased against the service survey if the number of industry balances had exceeded the number of service balances, especially the monthly ones, which are, in addition, observed on the whole period in the case of industry, while those relating to services are retropolated from the quarterly data from January 1988 to May 2000. By restricting the number of monthly industry variables to the subset of five chosen ones, we, therefore, tend to create the conditions for a balanced enough although not excessively restricted analysis. We estimate models of GDP growth on subsets of industry variables on the one hand and both industry and service variables on the other. Each subset is taken from a more comprehensive set (either relating to industry or to industry plus services) containing the "*m*1" to "*m*4" subseries relating to the levels of the five industry or ten industry-plus-service balances, as well as the first and second monthly lags of their first differences, which makes a total of either 60 or 120 possible regressors. We carry out the variable selection process on the period 1989Q1 to 2006Q4, for which all series are complete on full years. The GDP growth series is that published at the "2007Q3 First Release" of the French quarterly accounts.

For each month *m*1 to *m*4, step *h*, and sector coverage (industry or industry+ services), we estimate two forecasts models. As concerns the forecasting of the current and next quarters, we consider a model based on mixing *savoir faire* and automated selection (hereafter referred to as the "manual" model), together with a model determined from a purely automated selection procedure (hereafter referred to as the "automatic" model). As concerns the forecasting of the next-to-next quarter, two models are selected from automated selection on slightly different sets of variables (see below). Whenever it is used, the automated selection procedure applied is that proposed by Hoover and Perez (1999), as refined by Krolzig and Hendry (2001). The detailed procedure is explained in Dubois and Michaux (2006b) and programmed in the GROCER package of the Scilab software developed first by Éric Dubois alone, then with Emmanuel Michaux[39]. Let us just mention that this iterative procedure combines several stages and arborescences involving descending elimination processes, along which non significant variables and models which do not satisfy a certain number of specification tests are progressively eliminated, as well as stages at which the models that have passed the previous elimination process are compared, using Fisher tests in encompassing models and AIC, BIC or HQ criteria[40].

[39] See Dubois and Michaux (2006a) for a presentation of GROCER, which is freely downlable from Dubois's home page. See also Hendry and Krolzig (2005).

[40] The specification tests are: the Lagrange multiplier of residual autocorrelation of order 5 (Godfrey, 1978), the Doornik and Hansen (1994) normality test, the quadratic heteroskedasticity test between regressors (Nicholls and Pagan, 1983), the Chow test of predictive failure on, respectively, 50% and 90% of the estimation period. This set of tests constitutes those recommanded by Krolzig and Hendry (2001). In the GROCER package, the coefficients' significance tests are performed at 5% and the specification tests at 1% at the first stage of the selection process (again following Krolzig and Hendry, 2001), and the Fischer tests of model selection (at the fourth stage of the process) are carried out at the 5% threshold - for more details, see Dubois and Michaux (2006a,b).

The selection of the industry variables, however, is mainly manual, the automated selection of a high number of variables being rather delicate (due to risks of collinearity, notably). Therefore, by nature, the selection process is not easy to describe (and still less easy to reproduce, which constitutes its main drawback). Nonetheless, here are the main characteristics of the selection of industry variables. The latter selection is based on the INSEE experience in GDP forecasting, which gives us clear insights on which balances perform well in GDP growth forecasting, as well as correlation analysis and partial automated selection at some stage of the estimation process. For instance, as concerns the forecasting of the current quarter, for models relating to early months in a given quarter (*m*1 or, respectively, *m*2), we privilege balances dealing with the near future and based on *m*1 (resp. *m*2) subseries to define an initial subset of variables. Conversely, for models relating to *m*3 and, to a larger extent, to *m*4, we privilege balances relating to the recent past[41]. Note that, if we use forward-looking balances when working on "*m*3" or "*m*4" models, we privilege the subseries relating to *m*1 or *m*2, since the subseries relating to *m*3 or *m*4 refer to the next quarter more than to the current one. This stage leads to a subset of preselected variables that are, then, used for the determination of both the "automatic" and "manual" models.

For a given subset of manually preselected variables represented in level, first difference and lagged first difference, the automated selection procedure leads to the "automatic" model. In this model, however, some estimated coefficients may show some puzzling unexpected signs[42] or some variables may be pointed out as little reliable[43]. An iterative manual stage, then, occurs, which consists mainly in keeping the clearly reliable variables and sometimes adding some other variables until obtaining satisfactory results (among which coefficients of the expected signs). This stage leads to the "manual" model.

As concern the industry models estimated for the next-to-next quarter, the cumulated past experience in this respect is scarce, as it mostly suggests that the contribution of BTS at this horizon is hardly significant. Therefore, we have no operational forecast model at our disposal at this horizon as a basic benchmark to define a set of preselected regressors. Consequently, we limit ourselves to the estimation of two "automatic" models, with regressors derived from two different sets of balances: either $(PROI^{pa}, PROI^{ex}, OORI, DEM_i^{pa}, DEMI^{ex})$ or $(PROI^{ex}, FORI, GENI^{ex}, DEM_i^{pa}, DEMI^{ex})$[44].

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41 In forecasting models of the next quarter, conversely, we tend to privilege balances relating to expectations whatever the month in the quarter *m*1 to *m*4.

42 Such as, for instance, a negative sign of a variable relating to expected production.

43 The automatic procedure contains a reliability criterion for each regressor, based on the estimation on two sub-periods of the same length. A regressor is considered to be more or less reliable if it enters more or less significantly in both subperiod estimations.

44 The choice of the balances in the second set is very pragmatic. As the quarter to be forecasted is the next-to-next one, the second set of balances tends to privilege monthly balances relating to the near future. The balance relating to general expectations, therefore, replaces that relating to past production. In this context, the balance relating to foreign orders seems to be less redundant than that relating to overall orders. The shares of monthly and quarterly balances are kept unchanged so that they do not notably differ from those in the set of service balances.

The models based on industry and service variables are estimated in the same way as the "industry" models, but the preselected industry variables are those that appear in the selected industry models relating to the same month and step. In other terms, the selection process of service variables consists in determining which service variables may permit one to improve the best industry models. The selected variables within each model are presented in Appendix 1.

3.2.2 Variable selection in the case of VAR models

Due to the limited length of the time series, we restrict ourselves to VAR models with at most three variables: the GDP quarterly growth rate *g*, a variable relating to industry *IND*, and a variable relating to services, *SER*, to be compared, respectively, with VARs with two variables (*g* and *IND*) and, even, simple autoregressive models (ARs) of GDP growth *g* ([45]). Similarly, in order not to limit the number of degrees of freedom excessively, we cannot work on models with too many lags. An exploratory econometric analysis on several relatively "long" estimation periods (1988Q1 to either 2007Q3 or 2006Q4) shows that VARs with two lags are most often accepted against VARs with three or four lags on these periods. However, a check on shorter estimation periods suggests that, for the very shortest ones (especially those ending before the end of 2001), some fourth lags may be significant (depending on both the VAR and the equation in the VAR). An attempt to estimate unrestricted VARs with four lags proves to be quite unsatisfactory, as the high number of non significant coefficients, together with the occurrence of collinearity in some cases, leads to both mediocre adjustment properties and low power of subsequent tests. We, therefore, work on two kinds of VARs: unrestricted VARs with two lags, on the one hand, restricted VARs with four lags on the other end. The restrictions on the coefficients of the VARs with three variables (hereafter referred to as VAR3s) are defined so that they are accepted at any estimation period used in the out-of-sample analysis. The VAR with two variables (VAR2) (resp. the AR) to be compared with a given restricted VAR3 derives from the latter by imposing exclusion restrictions on the coefficients relating to service variables (resp. service and industry variables). In other terms, every set of VAR3, VAR2, AR models to be compared consists of nested models. By construction, this is the same for non restricted models with two lags (in this case, the benchmark AR has two lags too).

The selection of the industry and service variables included in the VARs partly results from a correlation analysis of every set of corresponding subseries relating to months *m*1, *m*2, *m*3, and *m*4 in three forms (current level, and quarterly lagged levels up to the fourth lag) with GDP growth. Not surprisingly, for a given variable, the more available piece of information (i.e. the higher index *i* in month *mi*, *i* = 1 to 4), the higher the correlations with GDP growth. Similarly, current levels show higher correlations than lagged variables. Moreover, the second, third and fourth lags show rather low correlations with GDP growth in most cases. As expected, balances relating to near future tend to be more highly correlated with GDP growth than the other balances in early months[46], while, in month *m*4, some balances relating to the recent past show

[45] In fact, VARs with four variables or more prove to lack from robustness in this context. We, therefore, prefered to focus on VARs with three variables, testing several possible VARs of this kind (i.e. several possible *IND* and *SER* variables) rather than to apply a general-to-specific method à la Krolzig (2001).

[46] Early (resp. late) months refer especially to *m*1 (resp. *m*4) and, to a lesser extent *m*2 (resp. *m*3).

higher correlations. Nonetheless, a few balances dealing with expectations still perform well, as well as their first lags (cf. table 3 below).

Table 3 Highest correlations of industry and service variables with GDP growth

	Month *m*1	Month *m*2	Month *m*3	Month *m*4
0.700<corr<=0.750		$PROI^{ex}$		$DEMI^{pa}$, $FACI^{q}$, $FACI^{m'}$, $FACI^{m}$, $PROI^{pa}$
0.650<corr<=0.700	$DEMI^{ex}$, $PROI^{ex}$	$FACI^{m}$	$PROI^{ex}$, $FACI^{m}$, $PROI^{pa}$, $FACI^{m'}$, $OPPS^{ex}$, $OORI$, $FORI$, $GENI^{ex}$	$GENI^{ex}$, $DEMI^{ex}$, $OPPS^{ex}$, $DEMI^{ex}_{-1}$, $OORI$, $FORI$, $PROI^{ex}$, $PROI^{ex}_{-1}$, $FACS^{q}$, $FACS^{m}$, $TOVS^{pa}$
0.600<corr<=0.650		$FACI^{m'}$, $OPPS^{ex}$, $PROI^{pa}$, $OORI$, $DEMS^{ex}$, $GENI^{ex}$, $FACS^{m}$, $FORI$	$FACS^{m}$, $DEMS^{ex}$, $TOVS^{pa}$, $TOVS^{ex}$, $OPPS^{pa}$	$DEMS^{ex}$, $TOVS^{ex}$, $OPPS^{pa}$, $GENI^{ex}_{-1}$
0.570<corr<=0.600	$FACI^{q}$, $DEMS^{ex}$, $GENI^{ex}$, $FACS^{q}$, $FACI^{m}$, $FACS^{m}$, $OPPS^{ex}$, $FACI^{m'}$, $TOVS^{ex}$	$TOVS^{ex}$, $OPPS^{pa}$		$FACI^{q}_{-1}$, $FACI^{m}_{-1}$, $DEMS^{ex}_{-1}$, $FACS^{q}_{-1}$, $FACI^{m'}_{-1}$, $FACS^{m}_{-1}$, $OPPS^{ex}_{-1}$

For the sake of notation simplicity, we do not mention that every variable appearing in column *mi* is a *mi* sub-series (*i* = 1 to 4). Note that series relating to *m*2 and *m*3 have been calculated for the quarterly service balances, which derive from regression on monthly service variables after June 2000 and interpolation using the SAS procedure EXPAND before. Sources: INSEE, industry and service surveys, French quarterly accounts, authors' calculations.

On average, the variables which show the highest correlations with GDP growth refer to industry. The balance concerning expected production proves to be quite regular in this respect, as well as that relating to expected demand, when it is available. The three common factors in industries are also rather highly correlated with GDP growth, especially in the late months. The service variables that show the highest correlations with GDP growth are the balance relating to expected operating profit and the two common factors in services. Some other balances perform relatively well too, although not as regularly well, notably the balances relating to expected turnover and expected demand and, in month *m*4, the balance concerning past turnover.

Table 4 Variables *IND* and *SER* included in VAR3s

Models	Month *m*1 *i* = 1	Month *m*2 *i* = 2	Month *m*3 *i* = 3	Month *m*4 *i* = 4
M*i*1	*IND* = $PROI_{m1}^{ex}$ *SER* = $OPPS_{m1}^{ex}$	*IND* = $PROI_{m2}^{ex}$ *SER* = $OPPS_{m1}^{ex}$	*IND* = $FACI_{m3}^{m}$ *SER* = $OPPS_{m1}^{ex}$	*IND* = $FACI_{m4}^{q}$ *SER* = $OPPS_{m4}^{ex}$
M*i*2	*IND* = $FACI_{m1}^{q}$ *SER* = $FACS_{m1}^{m}$	*IND* = $FACI_{m2}^{m}$ *SER* = $FACS_{m2}^{m}$	*IND* = $FACI_{m3}^{m}$ *SER* = $FACS_{m3}^{m}$	*IND* = $FACI_{m4}^{q}$ *SER* = $FACS_{m4}^{m}$
M*i*3	*IND* = $FACI_{m1}^{q}$ *SER* = $FACS_{m1}^{q}$	*IND* = $FACI_{m2}^{m}$ *SER* = $OPPS_{m2}^{ex}$	*IND* = $FACI_{m3}^{m}$ *SER* = $OPPS_{m3}^{ex}$	*IND* = $PROI_{m4}^{ex}$ *SER* = $OPPS_{m4}^{ex}$
M*i*4		*IND* = $PROI_{m2}^{ex}$ *SER* = $OPPS_{m2}^{ex}$	*IND* = $PROI_{m3}^{ex}$ *SER* = $OPPS_{m3}^{ex}$	
M*i*5		*IND* = $FACI_{m2}^{m}$ *SER* = $OPPS_{m1}^{ex}$	*IND* = $PROI_{m3}^{ex}$ *SER* = $OPPS_{m1}^{ex}$	
Sources: INSEE, industry and service surveys, French quarterly accounts, authors' calculations.				

We choose to privilege regularity over punctually higher correlation, as the use of relatively stable models permits one to better understand the reasons why forecasts change over time. Therefore, as for industry (resp. service) variables, we choose the balance relating to expected production (expected operating profit) and the monthly (*m*2, *m*3) or quarterly (*m*1, *m*4) common factor in industry (resp. services)[47]. Non-quarterly months (*m*2 and *m*3) raise a specific problem: true monthly service series are not observed on the whole estimation period (see above, sub-section 3.1). We have tested two kinds of solutions: either using the last available quarterly variable; or using the partly interpolated monthly variable. Obviously, there is a trade-off between using either less recent observations or partly interpolated ones. As was already stressed, this constitutes a potentially serious handicap for the service BTS, which should be kept in mind. Table 4 above defines the sets of models used in the simulation exercises.

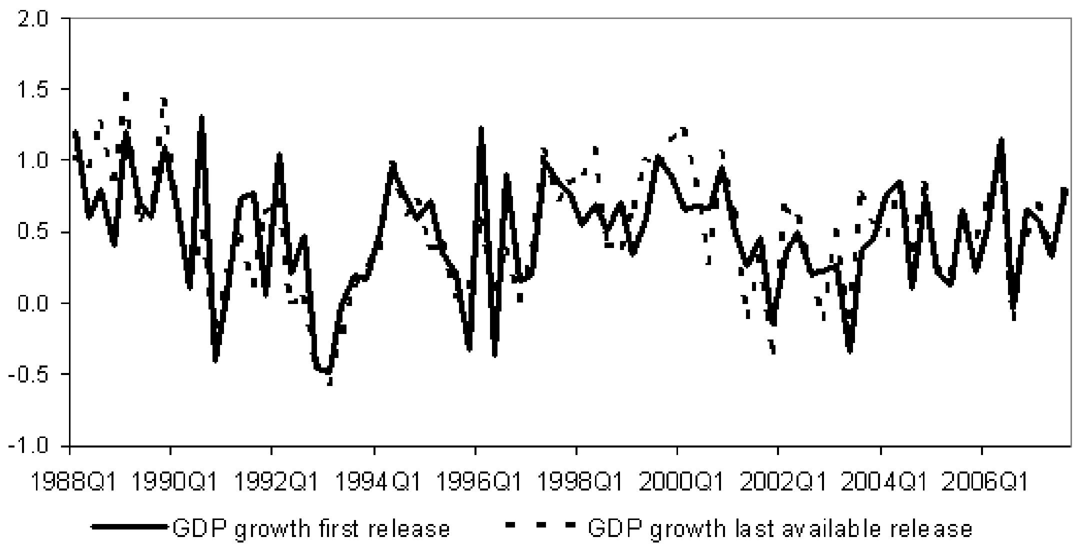
3.2.3 Other estimation and simulation characteristics

Real-time analysis was performed as far as possible. More precisely, GDP figures used within a model estimated at a given subperiod ending at month *n* of year *y* are those that were available at that time. Similarly, all common factors that appear in a model estimated on a given subperiod have been estimated without taking the posterior observations into account. The only

[47] Some further attempts have been made on other variables appearing in table 3, but which are not presented in table 4 as the corresponding models were only subjected to part of the systematic tests made on the basis of the models referred to in table 4.

variables that are not purely real-time are the underlying balances of opinion, whose successive releases are not easily accessible[48]. As a first approximation, we have used the truncated series derived from the last release at the moment when the empirical work was performed (i.e. that in November 2007). Intuitively, this should not significantly alter the results. In fact, raw balances are little revised over time[49]. The main source of revision lies in the seasonal adjustment procedure: every year, raw balances are seasonally adjusted using all available observations: this may change slightly some past values of seasonally-adjusted balances. However, on the whole, the revisions of balances are very limited, so that the main sources of revisions are taken into account in our out-of-sample analysis. If the common factors estimated on different subperiods do not differ notably, this is not the case of GDP figures, which can be more markedly revised over time, depending on the quarters - see Figure 3 below.

Figure 3 First and last releases of GDP growth



Sources: INSEE, French Quarterly Accounts. The two series are expressed in constant prices[50].

An almost-real-time out-of-sample analysis is necessary to shed light on how useful the industry and service surveys are for the forecasting of GDP growth in the short run. This analysis requires estimating and, then, simulating our selected forecast models on various subperiods within 1988Q1-2007Q3. There are two different ways of defining the various estimation subperiods: by carrying out either recursive or rolling estimations. As the literature does not conclude on the respective merits of either kind of estimations in the results, we carry out both kinds. Recursive estimation consists in successively estimating every selected model from an

48 They should be more easily accessible within one or two years, thus permitting pure real-time analysis.

49 Raw balances relating to month (quarter, for quarterly balances) *n* are revised once, at the end of the month (resp. quarter) following their first release, to take late responses into account.

50 The French quarterly accounts have been released since chained-prices in May 2007. Therefore, most GDP releases considered in this paper are defined as constant-price ones. That is why, for homogeneity purpose, we choose to work on constant-price series, which have still been available since May 2007.

initial quarter *q*0 to quarter *q*, for every *q* comprised between *q*1 and *q*2, q0 being given[51]. When rolling estimation is used, the estimations are successively carried out from quarter *q-L* to quarter *q*, for every *q* comprised between *q*1 and *q*2, *L* being given[52]. The relative advantages of recursive estimation are that the latter reflects short-term analysts' common practice and uses longer estimation periods on average. Rolling estimation, however, has advantages too: first, the length of all estimation periods is unchanged from one estimation to the other, which might intuitively lead to more homogenous forecast series as concerns predictive accuracy; above all, if some structural breaks occur within the period under analysis, rolling estimation may lead to better estimated models than recursive estimation, by allowing the estimated coefficients to evolve over time to a larger extent. Now, structural breaks have probably occurred between 1988Q1 and 2007Q3, notably due to major evolutions in France's international environment within the period. This might explain the presence of instability in the estimation results (such as the evolving significance of some fourth lags in the VAR models depending on the estimation subperiod mentioned above). This relative instability in forecasting models based on leading indicators is a current result in the literature. However, instability is considered to be less detrimental when the estimated coefficients evolve regularly and smoothly than when they experience strong variations. This is the case as concern our estimated models.

Whatever the estimation technique (recursive or rolling), multistep, unrestricted VARs and ARs were estimated using OLS, whereas restricted VARs were estimated using SURE[53]. The estimations of multistep models were performed using the GROCER package of the Scilab software (see above), while the VAR models where estimated using the SAS software. Then, forecasts at the one, two, three and four quarter horizons were carried out using our VAR and AR models (for those estimated on a subperiod ending at quarter *q*, for quarters *q*+1, *q*+2, *q*+3, and *q*+4). As for the multistep models, we restricted ourselves to the forecasting of the current, next and next-to-next quarters, which correspond to either the one-to-three or the two-to-four forecast horizons - cf. above, table 2 above. The comparison of these forecasts with the observed GDP growth rates published for the corresponding quarters leads to the calculation of series of forecast errors (one series per model, forecast horizon and GDP benchmark series). As concerns the GDP benchmark series, the first releases are the most interesting ones for short-term analysts, since they are accessible for comparison short after their forecasts are published. Therefore, they constitute the short-term analysts' privileged benchmarks[54]. Last available releases, however, are interesting too, as BTS might encompass leading enough

51 For multistep models and related ARs, *q*0 = 1989Q1 (1989Q1 was chosen to allow lags and to set aside the first observations of the service survey, which might be more fragile as they correspond to a stabilisation period for the newly created survey). For VARs and corresponding ARs, *q*0= 1988Q1 (as VARs are more demanding in terms of number of observations than univariate models, we preferred using the longest possible estimation periods, including the first releases of the service survey, which do not deteriorate the adjustment and forecast accuracy). For both kinds of models, *q*1=1999Q4 and *q*2=2007Q3.

52 *q*1 and *q*2 are the same as for the recursive estimations (see previous footnote). Depending of the number of lags in the different models, *L* varies between 43 and 47.

53 OLS = ordinary least squares. SURE = Seemingly Unrelated Regression Estimation.

54 Conversely, definitive results are published three years later.

pieces of information to allow one to forecast the definitive account releases on their basis[55]. Therefore, we consider both benchmark series systematically. At the moment when the empirical work was carried out, the last available GDP series consisted of definitive figures until the end of 2004Q4 and still provisional figures afterwards. Therefore, we carried out tests of predictive equivalence on both 2000Q1-20004Q4 and 2000Q1-2007Q3[56]. Besides, results of predictive performance tests are known to significantly depend on the simulation periods (cf. above, section 2). Carrying out such tests on two different periods may enable us to give a rough assessment of the degree of dependence of our results on the simulation period.

3.3 Tests of predictive accuracy

We calculate the mean-squared-forecast error (MSFE) of each series of forecast errors at our disposal and we compare the MSFEs of different sets of three models (one containing service and industry variables, one industry variables, and another no survey variable), for each month $m1$ to $m4$, forecast horizon h, benchmark GDP series (first or last available release), and out-of-sample simulation period (beginning in 2000Q1 and ending either in 2004Q4 or in 2007Q3). In the following paragraphs, we reason on given month mi, forecast horizon h, benchmark GDP series, simulation period, and set of three models.

In the case of three non-nested models, we test the hypothesis of equal predictive accuracy of one model with respect to another using the modified Diebold and Mariano (1995) test suggested by Harvey, Leybourne and Newbold (1997). To compare the forecast accuracy of two models among the three ones, we calculate the difference d between the MSFEs of the forecast series derived from the two models at stake. The test statistics is homogenous to the ratio of this difference to the root of its estimated variance, i.e. to a t statistic. The estimation of the variance requires some care, as the forecast errors are generally autocorrelated. Moreover, Harvey et al. (1997) recommend calculating the t statistic using a small-sample correction (even though the test remains an asymptotic one, with the resulting t statistic following a normal distribution with n-1 degrees of freedom, where n is the number of available forecasts). It is noteworthy that the test that we perform is a unilateral test, as we wish to know which model performs better if the null hypothesis of equal accuracy $t = 0$ is rejected. The direction of the inequality in the alternative hypothesis depends on the sign of the t statistic. If the latter is positive, then the alternative hypothesis is expressed as: $t > 0$; else it is expressed as: $t < 0$.

In case of nested models, Clark and West (2007) point out that both the Diebold and Mariano (1995) and Harvey et al. (1997) tests may be biased to the detriment of the less parsimonious model. In fact, under the null that the parsimonious model generates the data, the larger model introduces noise into its forecasts by estimating parameters whose population values are zero. The authors, thus, observe that the MSFE from the parsimonious model is expected to be *smaller* than that of the larger model. They describe how to adjust MSFEs to account for this noise. Instead of considering the previous difference:

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55 This is suggested by Hild (2004).

56 Note that, for “$m2$” models, not all quarters within these periods are available, since no forecasts are made in August.

$$d = MSFE_1 - MSFE_2 = n^{-1}\sum_q \left(y_{q+h} - \hat{y}_{1q,q+h}\right)^2 - n^{-1}\sum_q \left(y_{q+h} - \hat{y}_{2q,q+h}\right)^2$$

where 1 refers to the more parsimonious model, 2 to the larger model, *h* is the forecast horizon, y_{q+h} denotes the observed GDP growth figure at quarter *q*+*h*, and $\hat{y}_{iq,q+h}$ the forecast of GDP growth calculated at quarter *q* for quarter *q*+*h*, using model *i*, *i* =1, 2, they introduce a corrected $MSFE_2$:

$$MS\tilde{F}E_2 = n^{-1}\sum_q \left(y_{q+h} - \hat{y}_{2q,q+h}\right)^2 - adj., \quad \text{with } adj. = n^{-1}\sum_q \left(\hat{y}_{1q,q+h} - \hat{y}_{2q,q+h}\right)^2.$$

They divide the adjusted difference $\tilde{d} = MSFE_1 - MS\tilde{F}E_2$ by the root of its estimated variance, with the same care for variance estimation as in the case of the Diebold and Mariano (1995) and Harvey at al. (1997) tests, thus generating a *t* statistic.

As in the case of non-nested models, unilateral tests must be performed, with the specification of the alternative depending on the sign of the *t* statistic.

In order to test the robustness of the results, we calculate the test statistics in three different ways.

First, we use Newey-West (1987) estimated variances. The resulting test statistics are computed in the GROCER package of the Scilab software. From these *t* statistics, we perform unilateral tests using unilateral quantiles.

The main drawback of this way of proceeding is that it does not enable one to test the autocorrelation order of the error-term *u* of the underlying linear models:

$$d_q = \text{intercept} + u_q \qquad (1)$$

where d_q denotes the *q*th component of either d or $\tilde{d}$, depending on the test performed.

Therefore, we also estimate these models directly, using the AUTOREG procedure of the SAS software, allowing for, at most, six lags in the AR model of the error-term *u* and imposing the active option *Backstep*. The latter tests the significance of each autocorrelation term within the six possible ones and removes the non-significant ones. Yule-Walker estimates are derived from the AUTOREG procedure, as well as *t* statistics of the significance of the intercept. We use these *t* statistics to perform unilateral predictive accuracy tests on their basis.

The second testing device has two drawbacks: first, the Harvey et al. (1997) small-sample correction is not applied in case of non-nested-model comparisons; second, the distribution quantiles used are those of the normal distribution. As the lengths of forecast errors are rather short, especially those derived from the "*m*2" models, it seems to us that we should at least perform one set of "true" finite-sample tests. To do so, we transform the linear models (1) into models whose error-terms are non-autocorrelated, using a transformation *à la* Durbin:

$$d_q = \text{intercept}' + a_1 d_{q-1} + \ldots + a_r d_{q-r} + v_q \qquad (2)$$

where r is the autocorrelation order of the error-term u in model (1) and:

$$\text{intercept}' = (1 - \rho_1 - \dots - \rho_r) \times \text{intercept and } a_i = \rho_i \ \forall i = 1 \text{ to } r, \tag{3}$$

where the ρ terms denote the autocorrelation coefficients in the AR(r) model:

$$u_q = \rho_1 u_{q-1} + \dots + \rho_r u_{q-r} + v_q \tag{4}$$

As concern the autocorrelation terms, as we do not want to limit the number of degrees of freedom excessively, we restrict ourselves to $r \leq 6$ and we start with $\rho = (\rho_1, \rho_2, \rho_3, \rho_4, \rho_5, \rho_6)$ vectors satisfying the set of restrictions derived from the AUTOREG procedure previously carried out on model (1). Then, we check that the error terms v in the resulting models (2) can be considered as non-autocorrelated, using Durbin-Watson (DW) tests. If this is not the case, we modify the sets of non-zero terms in vectors ρ by iterations as long as the error-terms in the resulting models (2) can be considered as non-autocorrelated. Resulting models (2) can be estimated using OLS. We use the t statistics of the modified intercept to perform unilateral tests of predictive accuracy, reversing the inequality sign in the alternative in cases when the estimated $(1 - \rho_1 - \rho_2 - \rho_3 - \rho_4 - \rho_5 - \rho_6)$ (obtained from the estimation of the a_i parameters in (2) - cf. (3)) are negative. These are finite-sample tests: the degree of freedom is equal to n-p, when p is the total number of non-zero parameters in (2) (including the intercept) and the quantiles are those of the Student distribution.

It is noteworthy that none of the three ways of proceeding can be considered as strictly better than the two others. The second device determines the autocorrelation terms of the u terms endogenously, but does not apply any finite-sample correction, contrary to the first device. The latter device also reflects the state of art as concerns the variance estimation method, while the second one uses an older procedure. Last, the third device leads to a finite-sample test, but the DW statistic's "ideal" value of 2 is asymptotic[57]. Moreover, when calculated in models containing autoregressive terms, the DW statistics may be biased towards 2. In sum, our approach must be viewed as rather pragmatic. We aim by no means to find a better testing procedure than the standard one. Our approach consists above all in trying to slightly shock the test statistics in order to assess the robustness of our results. As will be shown in next section, the battery of tests that were performed (3 tests for each kind of estimation, rolling or recursive) indeed permits us to qualify our results, especially when they are ambiguous.

Last, we try to take into account the initial handicap of the service series with respect to the industry ones, notably due to the fact that a significant part of the monthly service series derives from interpolation[58], by considering (together with standard thresholds) higher thresholds as

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[57] We tried to take these properties into account and, since we worked on small samples, we accepted DWs comprised between 1.5 and 2.5.

[58] The fact that the service survey is much more recent than the industry survey and was subject to notable evolutions within the period under analysis, while the industry survey experienced less notable changes, may be considered to be another source of handicap as concern the tests of predictive accuracy for the service survey. This source involves both the monthly and quarterly data.

concerns the comparison of models including services with models excluding them. More precisely, we summarise the results of the tests using the following asymmetric classification:

1) If the sign of a *t* statistic suggests a possibly better forecast accuracy of a model including service variables with respect to a model excluding service variables, the contribution of the former model is considered to be:

H: Highly significant if the P-value of the test is lower than 0.005
S: very significant if 0.005 $<$ P-value $\leq$ 0.01
2: significant at the 2.5% threshold (but not at the 1% one: 0.01 $<$ P-value $\leq$ 0.025)
5: significant at the 5% threshold (but not at the 2.5% one: 0.025 $<$ P-value $\leq$ 0.05)
T: significant at the 10% threshold (but not at the 5% one: 0.05 $<$ P-value $\leq$ 0.10)
L: "limit 10%", i.e. close to significance at the 10% threshold (0.10 $<$ P-value $\leq$ 0.15)
A: ambiguous (0.15 $<$ P-value $\leq$ 0.20)
N: clearly non-significant

2) Else, with respect to the model excluding service variables, the model including service variables is considered to perform:

1: significantly less well at the 1% threshold
2: significantly less well at the 2.5% threshold (but not at the 1% one)
5: significantly less well at the 5% threshold (but not at the 2.5% one)
T: significantly less well at the 10% threshold (but not at the 5% one)
U: non-significantly less well (P-value $>$ 0.10).

4. Main Results

4.1 Comparing multistep and VAR models to AR models as well as industry models to industry + service models

As concern causality analyses involving industry and service data, similar in-sample analysis results can be found in Bouton and Erkel-Rousse (2003) and are not repeated here. Moreover, since the literature stresses that in-sample and out-of-sample results may differ significantly, we shall mainly focus on the out-of-sample ones. It is, nonetheless, interesting to glance at tables in appendices 2 and 3, in which the root-mean-squared-errors (RMSE) of the main estimated models (in-sample properties) are detailed. These tables show that the inclusion of industry data (respectively service data) results in a drop (resp. a slight decrease) in the RMSE with respect to AR models (resp. models including industry regressors, but no service ones).

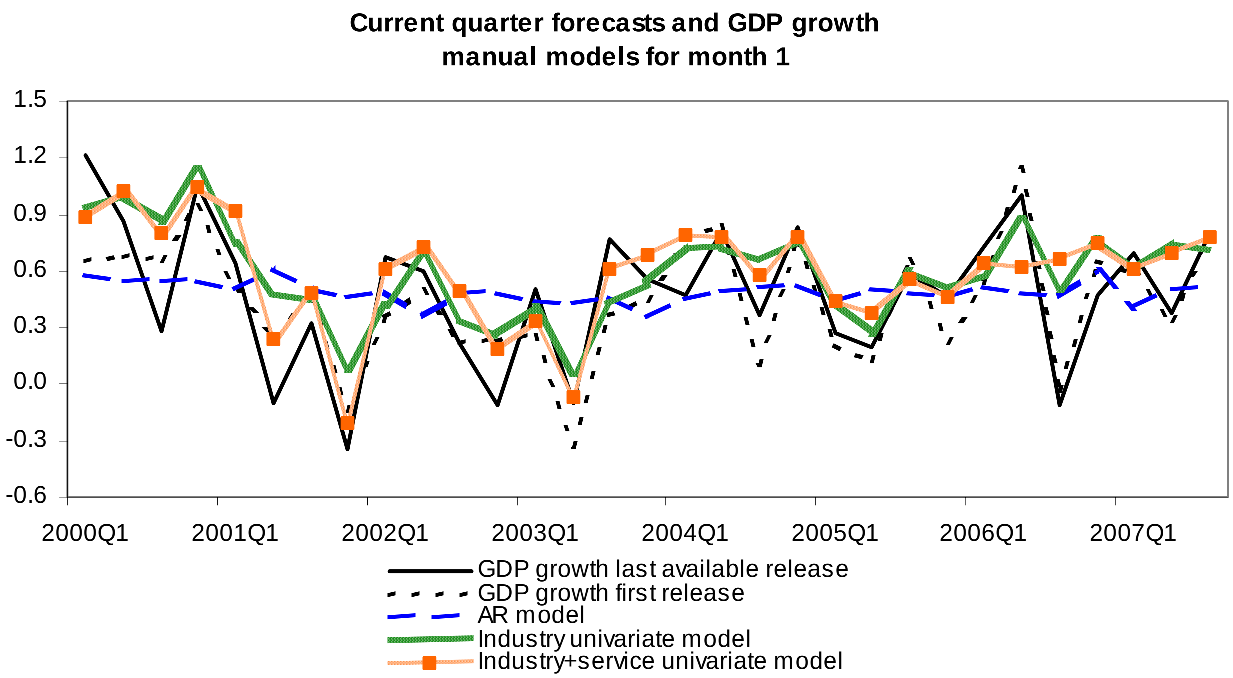
As concerns the out-of-sample analysis, let us first examine the RMSFEs of the models used. These RMSFEs tend to be slightly higher than the corresponding RMSEs. Above all, they tend to increase as the forecast horizon rises (even though not systematically). With respect to the magnitude of GDP growth's standard-error, the orders of magnitude of the MSFEs are high for the 3 and 4 quarter horizons and far from negligible at the 1 and 2 quarter horizons. This result is in line with other recent studies on the same kinds of data (e.g. Hansson et al., 2005, among many others).

At a close forecast horizon (1 or 2 quarter horizons), the models based on BTS variables always lead to lower MSFEs than AR models. At a more distant horizon (3 or 4 quarter horizons), the most parsimonious models often show lower MSFEs than the less parsimonious models. This is in line with Clark and West (2007)[59].

These results are observed for any kind of models as well as any estimation technique (both recursive and rolling). However, the simulations derived from rolling estimation often lead to slightly lower MSFEs than those obtained with recursive estimation. As for the VARs, the simulations on non-restricted VAR models with two lags often lead to slightly higher MSFEs than those on restricted VAR models with 4 lags. This result seems rather intuitive as the specifications of the restricted models with 4 lags have been optimized to a larger extent than the non restricted VAR models with 2 lags.

Figures 4 give a few illustrative examples of the different forecast series, depending on the models as well as on the month in the quarter[60]. The figures clearly suggest that the models including BTS perform significantly better than the AR models. The results of the horse-race between the models including services or not are less clear, at least at the end of the period. In this respect, we need to examine the results of the predictive accuracy tests. The latter are presented in appendices 4 B) and 5.

Figures 4.1 Multistep models



59 Cf. Appendix 4 A) for an illustration on multistep models. The same results are available for VARs upon request to the authors.

60 All figures relating to our forecasts are available upon request.

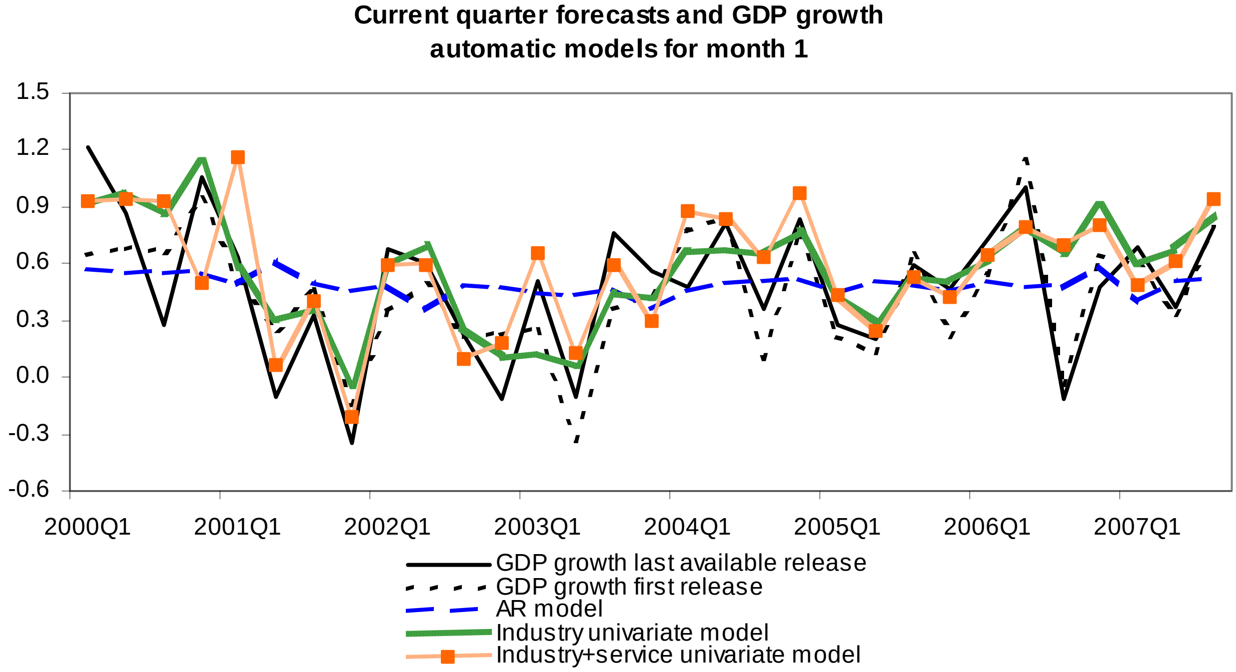
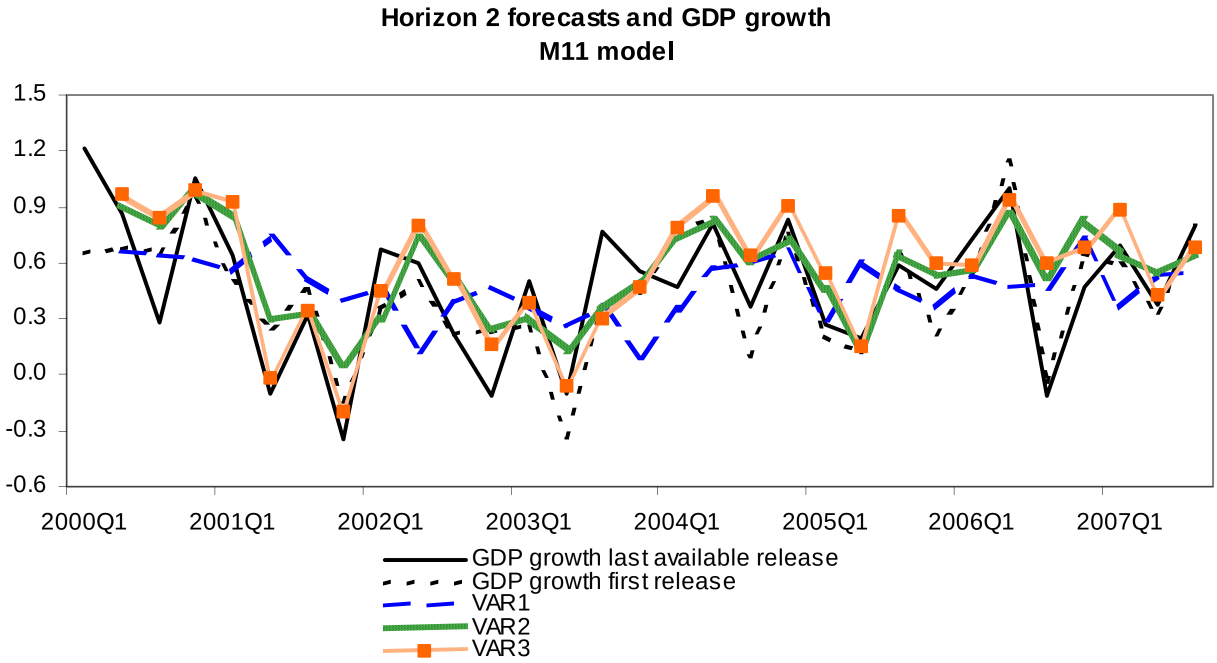


Figure 4.2 Example from unrestricted VAR models



The comparison tests (Modified Diebold-Mariano or Clark-West tests, depending on the type of models: nested or not) confirm that the performance of the models including BTS variables is higher than that of the AR models for every month in the quarter. In case of the univariate models, this result is especially true for the forecast of the current quarter whereas, for VAR models, it still lasts for more distant horizons.

The results also lead to overall encouraging conclusions as concerns the contribution of the service survey to the short-term forecasting of GDP in addition to the industry survey. Thus, for forecasts of the current quarter in “quarterly” months *m1* and, to a lesser extent, *m*4, models using both industry and service surveys are generally more accurate than models based on the industry survey only and this, whatever the kind of models used (multistep or VARs). It is not clear whether the contribution of the service survey is better established when the benchmark GDP series refers to the first results or, alternatively, the last available results. As for multistep models, it seems that the service survey contributes to the forecasting of last available results to a larger extent than to that of the first results, whereas the analysis carried out on the VARs suggests the opposite result. The simulation period does not help one to clarify the origin of this result. Multistep models sometimes show different results on the subperiod ending in 2004Q4 and on the total period ending in 2007Q3. However, the differences, then, appear on the first results as well, suggesting the occurrence of structural breaks. Surprisingly, however, the results derived from the VARs prove to be more robust with respect to the simulation period.

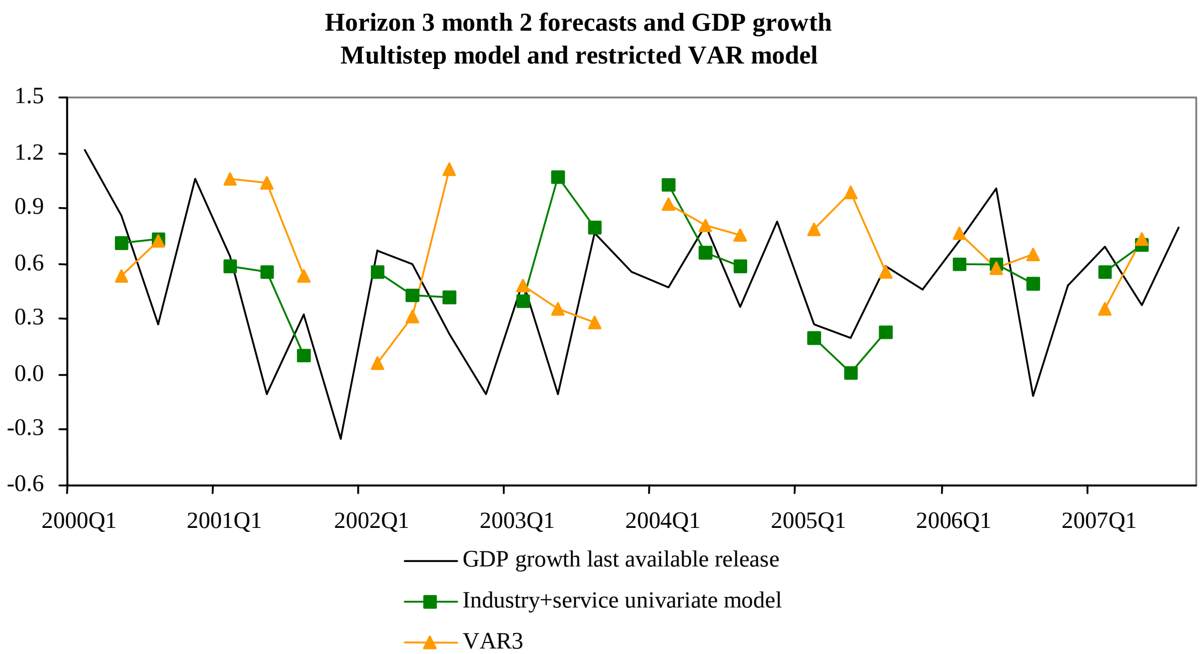
As concern the models relating to month *m*1, the contribution of a service variable to GDP growth forecasting, be it a peculiar balance of opinion or a common factor, proves to be generally more significant when the industry variable is a common factor rather than the balance relating to expected production. The opposite result tends to be observed for models relating to month *m*4. Similarly, the contribution of the balance of opinion relating to expected profit in services is generally more clearly significant than that of common factors in services used in case of models relating to month *m*1, but not in case of models relating to month *m*4. These results are in conformity with intuition. In fact, in month *m*1, the most possible leading indicators (such as balances relating to the near future) are needed to calculate the first forecast of GDP growth relating to the current quarter. Conversely, in month *m*4, indicators encompassing some piece on information on the recent past (such as the common factors) should enable one to better forecast GDP growth in the previous quarter. The results found, therefore, stem from the fact that the industry balance relating to expected production (resp. the service balance relating to expected profit) is more leading that the industry (resp. service) common factors used. This is consistent with our remark in sub-section 3.1: due to their construction, the common factors tend to be composite coincident indicators rather than CLIs. Things might be different if we had used composite indicators specifically elaborated to lead.

As was expected, for “non quarterly” months *m*2 and *m*3, the results are a little less clear as for the contribution of the service survey. The latter seems to significantly contribute to the forecasting of GDP growth in some models, but not in a majority of them. The positive results for the quarterly months suggest that this is probably due to serious methodological biases in the monthly analysis[61]. At this stage of the analysis, it is difficult to say whether the rough interpolation method used to alleviate the short length of monthly series in services should be questioned or whether the very fact of interpolating is at stake. In any case, a future study is needed when the monthly service series are long enough.

4.2 Comparing the best multistep and VAR models

Finally, it is interesting to try to assess whether our multistep models perform better than our VARs (which would be consistent with Marcellino, Stock and Watson, 2005) or not (in conformity with Hansson et al., 2005). Appendix 6 shows the main results of a comparison of the multistep models with the best VARs (as concerns forecast accuracy). The results suggest that no set of models perform systematically better than the other. We could have expected that the univariate models would lead to more accurate forecasts than the VARs for the current quarter. Similarly, we might have thought that the VARs would lead to better forecasts at later horizons. The results are consistent with intuition for the "*m*3" models only. In particular, multistep models sometimes prove to perform significantly better than VAR models at the 2 or 3 quarter horizon forecasts. - cf. figure 5 for an illustration.

Figure 5 Example of better predictive accuracy using a multistep model at horizon 3



61 Note that a majority of univariate multistep models use some interpolated service data, even in models relating to months *m*1 and *m*4, where some monthly first differences of service balances are used (cf. appendix 1). This might explain at least partly the better picture generally given by the service survey in the VARs relating to these months.

Conclusion

In this paper, we present the results of an almost real-time out-of-sample analysis, which shows the usefulness of the French BTS in industry and services carried out by INSEE for the short-term forecasting of GDP growth. The contribution of the service survey is clearly established in “quarterly” months, for which relatively long service series are available, especially for the calculation of the first forecast relating to the current quarter. This is less the case in “non-quarterly” months, probably due to the short length of the observed series in the sector and to the consequent use of interpolated service series. As concerns the imputation method of missing data in the service survey, some optimisations would probably be possible. The question whether such optimisations would significantly improve the results as concerns the contribution of the service survey to forecasting GDP growth has not been addressed in the paper and might deserve further investigation. An easy way of circumventing this problem would be to focus on quarterly date exclusively[62], which would suppress any controllable potential bias against the service survey from the analysis. By limiting the coverage of the study, this simplification would enable one to explore futher tracks for research which could not be dealt with in this paper due to the high number of cases to be treated. For instance, we have not addressed the question whether a pooling of our miscellaneous forecasts would enable one to better assess the contribution of the service survey for forecasting or not. As was stressed in section 2, the more diverse the sources of the forecasts the more efficient the pooling method. However, we also mentioned that the pooling of non-independent devices might also lead to interesting results. Therefore, even though not fundamental to our reflexion, this question might deserve some attention.

More importantly, it is noteworthy to stress that our assessment of the usefulness of the service survey is very demanding, much more than Gayer (2005)’s evaluation. In fact, Gayer (2005) compares the predictive accuracy of the confidence indicator in services from the European Commission with that of a naive model of Euro area’s GDP growth. On our data, we would undoubtedly find that the service survey *considered alone* contributes significantly to the forecast of GDP growth whatever the month considered (“quarterly” or not). Our point, however, is to go further by showing that the service survey adds some useful piece on information with respect to the industry survey that enables one to improve the forecasting of GDP growth. This very demanding goal should be kept in mind when considering the results. In future work, it might be interesting to test the opposite scheme as regard the two BTS, the service survey being used as the benchmark survey and the industry survey as the additive survey. In fact, this complementary exercice would probably show that, due to highly correlated business cycle fluctuations in the two sectors, the contribution of the additive survey would appear to be significant but always limited with respect to that of the benchmark survey whatever the latter might be (the industry or the service survey)[63]. In this paper, however, we privileged the industry survey as the benchmark survey, thus following the usual practice of empirical forecasters at a first stage, the exploration of the reversed scheme being of no practical impact.

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[62] This would require focusing on months *m*1 and *m*4 and estimating multistep models based on quarterly first differences of balances rather than monthly ones.

[63] This intuition was confirmed by Bouton and Erkel-Rousse (2003-2004), but in the context of an in-sample analysis only.

Another technical point deserves to be noted. We cannot completely exclude that some of our results might be subject to data snooping. As defined by White (2000), data snooping occurs when a given set of data is used more than once for purpose of inference or model selection; when such data reuse occurs, there is always the possibility that any satisfactory results obtained may be due to chance rather than to the merit inherent to the method yielding the results. White adds that this problem is practically unavoidable in the analysis of time series data. This author and subsequent Hansen (2004) propose two related methodologies based on resampling[64] that aim data snooping to be undertaken “with some degree of confidence that one will not mistake results that could have been generated by chance for genuinely good results” (White, 2000). However, these methodologies deal with the selection of the best possible model within a set of numerous models and privilege the comparison of the potential best model to a sole benchmark (the principle being to check whether the model selected as the best one does perform better than the benchmark). The issue addressed in our paper is different, as well as our testing scheme: for given month (*mi*) and forecast horizon (*h*), we aimed to assess whether a set of standard forecast models based on industry survey and representative of the kind of models used by short-term analysts could be outperformed either by a competing model encompassing service data or by a simple benchmark (each set of competing models, thus, consisted of at most three competing models). We, therefore, tried to limit the risks of data snooping differently, adopting a very pragmatic approach consisting in controlling the robustness of our results through the comparison of several methodologies, both in simulation (recursive and rolling estimation) and in testing (three tests per couple of forecasts to be compared). Even though this approach is without doubt imperfect, the strong homogeneity of the results derived from the six tests performed per couple of models tested in most cases is rather reassuring in so far as the repetition of a result should limit the risk of chance interference.

As was evoked in the previous paragraph, the question of model optimization was beyond the scope of our study: we intended by no means to find the best possible forecast model for GDP growth. In this respect, a lot of work would need to be done. Many important methodological issues have not been assessed in the paper which might be of importance in the perspective of model optimization, such as the quantification of the qualitative BTS surveys for instance.

Last but not least, our study focuses on the industry and service BTS. This approach is justified by Bouton and Erkel-Rousse (2003-2004)’s result according to which the BTS in other sectors of activity do not add any significant piece of information with respect to the industry survey in macroeconomic models of GDP growth. However, it would be interesting to check whether this result still holds on more recent data and in an out-of-sample context. This will be the object of future research.

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[64] The White (2000) methodology is known as “the reality check for data snooping”. Hansen (2004) refers to his methodology simply as a “test for superior predictive ability”.

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Appendix 1: Univariate multistep models: selected variables

Lagts(*n*, name of a quartely time serie) = n^{th} quarterly lag of the time series

Univariate Models used to forecast the current quarter

Month	Type of model	Industry	Industry+Services	Nested or not
1	Manual	Cte PROI_m1 DEMI^{ex}-lagts(DEMI^{ex})	Cte PROI^{ex}_m1 DEMI^{ex}-lagts(DEMI^{ex}) DEMS^{ex}-lagts(DEMS^{ex})	Nested
	Automatic	Cte PROI^{ex}_m1-lagts(PROI^{ex}_m3) Lagts(PROI^{ex}_m3)- lagts(PROI^{ex}_m2) DEMI^{ex}	Cte PROI^{ex}_m1-lagts(PROI^{ex}_m3) Lagts(PROI^{ex}_m3)- lagts(PROI^{ex}_m2) DEMI^{ex} TOVS^{pa}_m1-lagts(TOVS^{pa}_m3) TOVS^{ex}_m1-lagts(TOVS^{ex}_m3)	Nested
2	Manual	Cte PROI^{pa}_m2 PROI^{ex}_m1-lagts(PROI^{ex}_m3) DEMI^{ex}-lagts(DEMI^{ex})	Cte PROI^{pa}_m2 PROI^{ex}_m1-lagts(PROI^{ex}_m3) DEMI^{ex}-lagts(DEMI^{ex}) TOVS^{pa}_m2-TOVS^{pa}_m1 Lagts(OPPS^{pa})	Nested
	Automatic	Cte PROI^{pa}_m2 PROI^{pa}_m1-lagts(PROI^{pa}_m3) PROI^{ex}_m2 PROI^{ex}_m1-lagts(PROI^{ex}_m3) DEMI^{pa}	Cte PROI^{pa}_m2 PROI^{pa}_m1-lagts(PROI^{pa}_m3) PROI^{ex}_m2 PROI^{ex}_m1-lagts(PROI^{ex}_m3) DEMI^{pa} TOVS^{ex}_m1-lagts(TOVS^{ex}_m3) Lagts(OPPS^{pa})	Nested
3	Manual	Cte PROI^{pa}_m3-PROI^{pa}_m1 PROI^{pa}_m1-lagts(PROI^{pa}_m1) PROI^{ex}_m1	Cte PROI^{pa}_m3 PROI^{pa}_m3-PROI^{pa}_m1 PROI^{pa}_m1-lagts(PROI^{pa}_m1) DEMI^{ex}-lagts(DEMI^{ex}) TOVS^{ex}_m1	Not nested
	Automatic	Cte PROI^{pa}_m3 PROI^{pa}_m3-PROI^{pa}_m2 PROI^{ex}_m2 PROI^{ex}_m1-lagts(PROI^{ex}_m3) DEMI^{pa} Lagts(DEMI^{ex})	Cte PROI^{pa}_m3 PROI^{ex}_m2 DEMI^{pa} Lagts(DEMI^{ex}) Lagts(OPPS^{pa})	Not nested
4	Manual	Cte PROI^{ex}_m1 Lagts(-1,DEMI^{pa})-DEMI^{pa}	Cte PROI^{ex}_m1 Lagts(-1,DEMI^{pa})-DEMI^{pa} Lagts(-1, OPPS^{ex})	Nested
	Automatic	Cte PROI^{ex}_m2 Lagts(-1,DEMI^{pa}) DEMI^{pa}	Cte PROI^{ex}_m2 Lagts(-1,DEMI^{pa}) DEMI^{pa} Lagts(-1,OPPS^{ex})	

Univariate Models used to forecast the next quarter

Month	Type of model	Industry	Industry+Services	Nested or not
1	Manual	Cte Lagts(OORI_m1) Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(DEMI^{pa})-lagts(2,DEMI^{pa})	Cte Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(DEMI^{pa})-lagts(2,DEMI^{pa}) Lagts(OPPS^{pa})	Not nested
	Automatic	Cte Lagts(PROI^{pa}_m1)-lagts(2,PROI^{pa}_m3) Lagts(2,PROI^{pa}_m3)-lagts(2,PROI^{pa}_m2) Lagts(PROI^{ex}_m1) Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(2,PROI^{ex}–m3)-lagts(2,PROI^{ex}_m2) Agts(OORI_m1) Lagts(DEMI^{pa})-lagts(2,DEMI^{pa})	Cte Lagts(PROI^{pa}_m1)-lagts(2,PROI^{pa}_m3) Lagts(PROI^{ex}_m1) Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(2,PROI^{ex}_m3)-lagts(2,PROI^{ex}_m2) Agts(OORI_m1) Lagts(DEMI^{pa})-lagts(2,DEMI^{pa}) Lagts(OPPS^{pa})	Not nested
2	Manual	Cte Lagts(OORI_m2) Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(DEMI^{pa})-lagts(2,DEMI^{pa})	Cte Lagts(PROI^{ex}–m1)-lagts(2,PROI^{ex}_m3) Lagts(TOVS^{ex}_m2)-lagts(TOVS^{ex}_m1) Lagts(OPPS^{pa})	Not nested
	Automatic	Cte Lagts(PROI^{pa}_m2)-lagts(PROI^{pa}_m1) Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(OORI_m2) Lagts(DEMI^{pa}) Lagts(DEMI^{ex}) Lagts(DEMI^{ex})-lagts(2,DEMI^{ex})	Cte Lagts(PROI^{pa}_m2)-lagts(PROI^{pa}_m1) Lagts(PROI^{ex}_m1)-lagts(2,PROI^{ex}_m3) Lagts(TOVS^{pa}_m2)-lagts(TOVS^{pa}_m1) Lagts(TOVS^{ex}_m2)-lagts(TOVS^{ex}_m1) Lagts(OPPS^{pa})	Not nested
3	Manual	Cte Lagts(OORI_m3) Lagts(PROI^{ex}_m3)-lagts(2,PROI^{ex}_m2) Lagts(DEMI^{ex})-lagts(2,DEMI^{ex})	Cte Lagts(PROI^{ex}_m3)-lagts(2,PROI^{ex}_m2) Lagts(DEMI^{ex})-lagts(2,DEMI^{ex}) Lagts(TOVS^{ex}_m3)-lagts(TOVS^{ex}_m2) Lagts(OPPS^{pa})	Not nested
	Automatic	Cte Lagts(PROI^{ex}_m3) Lagts(OORI_m3) Lagts(DEMI^{ex}) Lagts(DEMI^{ex})-lagts(2,DEMI^{ex})	Cte Lagts(PROI^{ex}_m3) Lagts(DEMI^{ex}) Lagts(DEMI^{ex})-lagts(2,DEMI^{ex}) Lagts(TOVS^{pa}_m2)-lagts(TOVS^{pa}_m1) Lagts(TOVS^{ex}_m2)-lagts(TOVS^{ex}_m1) Lagts(OPPS^{pa})	Not nested
4	Manual	Cte Lagts(PROI^{ex}_m4) DEMI^{ex}-lagts(DEMI^{ex})	Cte Lagts(PROI^{ex}_m4) DEMI^{ex}-lagts(DEMI^{ex}) DEMSe^{x-}lagts(DEMS^{ex}) Lagts(OPPS^{pa})	Nested
	Automatic	Cte Lagts(PROI^{ex}_m4)-lagts(PROI^{ex}_m3) Lagts(PROI^{ex}_m3)-lagts(PROI^{ex}_m2) DEMI^{ex}	No services variables Same model as Industry alone	

Univariate Models used to forecast the next to next quarter (1)

Month	Type of model	Industry	Industry+Services	Nested or not
1	1st Automatic	Cte Lagts(2,$GENI^{ex}$_m1) Lagts(2,$GENI^{ex}$_m1)-lagts(3,GENIex_m3) Lagts(2,$DEMI^{pa}$)	Cte Lagts(2,$GENI^{ex}$_m1) Lagts(2,$GENI^{ex}$_m1)-lagts(3,$GENI^{ex}$_m3) Lagts(2,$DEMI^{pa}$) Lagts(2,$TOVS^{ex}$_m1) Lagts(2,$TOVS^{pa}$_m1) Lagts(2,$TOVS^{pa}$_m1)-lagts(3,$TOVS^{pa}$_m3) Lagts(2,$OPPS^{pa}$)-lagts(3,$OPPS^{pa}$) Lagts(2,$DEMS^{ex}$)-lagts(3,$DEMS^{ex}$)	Nested
	2nd Automatic	Cte Lagts(3,$PROI^{pa}$_m3)-lagts(3,$PROI^{pa}$_m2) Lagts(2,OORI_m1) Lagts(2,OORI_m1)-lagts(3,OORI_m3) Lagts(2,$DEMI^{pa}$)-lagts(3,$DEMI^{pa}$) Lagts(2,$DEMI^{ex}$)	Cte Lagts(3,$PROI^{pa}$_m3)-lagts(3,$PROI^{pa}$_m2) Lagts(2,OORI_m1) Lagts(2,OORI_m1)-lagts(3,OORI_m3) Lagts(2,$DEMI^{pa}$)-lagts(3,$DEMI^{pa}$) Lagts(2,$DEMI^{ex}$) Lagts(2,$TOVS^{ex}$_m1) Lagts(2,$TOVS^{pa}$_m1)-lagts(3,$TOVS^{pa}$_m3) Lagts(2,$OPPS^{pa}$) Lagts(2,DEMSex)-lagts(3,DEMSex)	Nested
2	1st Automatic	Cte Lagts(2,FORI_m2) Lagts(2,$GENI^{ex}$_m2)-lagts(2,$GENI^{ex}$_m1)	Cte Lagts(2,$GENI^{ex}$_m2)-lagts(2,$GENI^{ex}$_m1) Lagts(2,$TOVS^{ex}$_m2) Lagts(2,$TOVS^{ex}$_m2)-lagts(2,$TOVS^{ex}$_m1) Lagts(2,$TOVS^{pa}$_m2) Lagts(2,$TOVS^{pa}$_m2)-lagts(2,$TOVS^{pa}$_m1) Lagts(2,$OPPS^{pa}$) Lagts(2,$DEMS^{ex}$)-lagts(3,$DEMS^{ex}$)	Not nested
	2nd Automatic	Cte Lagts(2,$PROI^{pa}$_m2)-lagts(2,$PROI^{pa}$_m1) Lagts(2,$PROI^{pa}$_m1)-lagts(3,$PROI^{pa}$_m3) Lagts(2,OORI_m2) Lagts(2,OORI_m1)-lagts(3,OORI_m3) Lagts(2,$DEMI^{ex}$)	Cte Lagts(2,$PROI^{pa}$_m2)-lagts(2,$PROI^{pa}$_m1) Lagts(2,$PROI^{pa}$_m1)-lagts(3,$PROI^{pa}$_m3) Lagts(2,OORI_m2) Lagts(2,OORI_m1)-lagts(3,OORI_m3) Lagts(2,$DEMI^{ex}$) Lagts(2,$TOVS^{ex}$_m2) Lagts(2,$TOVS^{ex}$_m2)-lagts(2,TOVSex_m1) Lagts(2,$TOVS^{pa}$_m1)-lagts(3,$TOVS^{ex}$_m1) Lagts(2,$OPPS^{pa}$) Lagts(2,$OPPS^{ex}$) Lagts(2,$DEMS^{ex}$)-lagts(3,$DEMS^{ex}$)	Nested

Univariate Models used to forecast the next to next quarter (2)

Month	Type of model	Industry	Industry+Services	Nested or not
3	1st Automatic	Cte	Cte	Not nested
		Lagts(2,FORI_m3)	Lagts(2,TOVS^{ex}_m3)	
		Lagts(2,GENI^{ex}_m2)-lagts(2,GENI^{ex}_m1)	Lagts(2,TOVS^{ex}_m2)-lagts(2,TOVS^{ex}_m1)	
			Lagts(2,TOVS^{pa}_m3)	
			Lagts(2,DEMS^{ex})-lagts(3,DEMS^{ex})	
	2nd Automatic	Cte	Cte	Nested
		Lagts(2,PROI^{pa}_m2)-lagts(2,PROI^{pa}_m1)	Lagts(2,PROI^{pa}_m2)-lagts(2,PROI^{pa}_m1)	
		Lagts(2,OORI_m3)	Lagts(2,OORI_m3)	
		Lagts(2,DEMI^{ex})	Lagts(2,DEMI^{ex})	
			Lagts(2,TOVS^{ex}_m3)	
			Lagts(2,TOVS^{ex}_m3)-lagts(2,TOVS^{ex}_m2)	
			Lagts(2,TOVS^{ex}_m2)-lagts(2,TOVS^{ex}_m1)	
			Lagts(2,TOVS^{pa}_m3)	
			Lagts(2,OPPS^{pa})	
			Lagts(2,OPPS^{pa})-lagts(3,OPPS^{pa})	
			Lagts(2,OPPS^{ex})-lagts(3,OPPS^{ex})	
4	1st Automatic	Cte	Cte	Not nested
		Lagts(2,FORI_m4)	Lagts(2,PROI^{ex}_m4)-lagts(2,PROI^{ex}_m3)	
		Lagts(2,PROI^{ex}_m4)-lagts(2,PROI^{ex}_m3)	Lagts(2,TOVS^{ex}_m4)	
		Lagts(DEMI^{pa})-lagts(2,DEMI^{pa})	Lagts(2,TOVS^{ex}_m3)-lagts(2,TOVS^{ex}_m2)	
			Lagts(OPPS^{pa})	
	2nd Automatic	Cte	Cte	Not nested
		Lagts(2,PROI^{pa}_m4)-lagts(2,PROI^{pa}_m3)	Lagts(2,PROI^{pa}_m4)-lagts(2,PROI^{pa}_m3)	
		Lagts(2,PROI^{pa}_m3)-lagts(2,PROI^{pa}_m2)	Lagts(PROI^{ex}_m4)	
		Lagts(PROI^{ex}_m4)	Lagts(2,PROI^{ex}_m4)-lagts(2,PROI^{ex}_m3)	
		Lagts(2,PROI^{ex}_m4)-lagts(2,PROI^{ex}_m3)	Lagts(2,PROI^{ex}_m3)-lagts(2,PROI^{ex}_m2)	
		Lagts(2,PROI^{ex}_m3)-lagts(2,PROI^{ex}_m2)	Lagts(2,OORI_m4)	
		Lagts(2,OORI_m4)	Lagts(DEMI^{pa})-lagts(2,DEMI^{pa})	
		Lagts(DEMI^{pa})-lagts(2,DEMI^{pa})	Lagts(OPPS^{pa})	

Appendix 2: Univariate multistep models: In-sample results

Estimation period: 1989q1 - 2006q4 (full years)

PIB used: First release 2007Q3

Forecast = 1 (forecast of the current quarter)
Forecast = 2 (forecast of the next quarter)
Forecast = 3 (forecast of the next-to-next quarter)

		AR model		Manual model*				Automatic model			
				Industry		Industry +Services		Industry		Industry +Services	
Forecast	Month	R^2a	RMSE	R^2a	RMSE	R^2a	RMSE	R^2a	RMSE	R^2a	RMSE
1	*m*1	0.15	0.39	0.57	0.28	0.58	0.27	0.57	0.27	0.60	0.26
1	*m*2	0.15	0.39	0.59	0.27	0.62	0.25	0.64	0.25	0.68	0.23
1	*m*3	0.15	0.39	0.60	0.26	0.62	0.25	0.63	0.25	0.64	0.25
1	*m*4	0.15	0.39	0.63	0.26	0.64	0.25	0.61	0.26	0.62	0.25
2	*m*1	0.15	0.39	0.31	0.35	0.37	0.33	0.41	0.31	0.47	0.30
2	*m*2	0.15	0.39	0.31	0.35	0.39	0.33	0.38	0.32	0.49	0.29
2	*m*3	0.15	0.39	0.41	0.32	0.45	0.31	0.44	0.31	0.51	0.29
2	*m*4	0.15	0.39	0.57	0.28	0.60	0.26	0.57	0.27	0.57	0.27
3	*m*1	0.15	0.39	0.14	0.39	0.30	0.34	0.33	0.34	0.43	0.30
3	*m*2	0.15	0.39	0.15	0.39	0.38	0.32	0.37	0.32	0.47	0.28
3	*m*3	0.15	0.39	0.18	0.38	0.30	0.35	0.24	0.36	0.40	0.31
3	*m*4	0.15	0.39	0.30	0.35	0.42	0.32	0.41	0.31	0.47	0.30

(*) except for the next-to-next forecast: in this case, two automatic models are presented. R^2a = adjusted R^2.

Appendix 3: VAR models: In-sample results

Table A3.1 VAR models - Estimation Results

model	VAR	*Ind* (VAR 2, 3)	*Ser* (VAR3)	Nobs	GDP equation - RMSE Means*			
					VAR4 - Rec.	VAR4 - Rol.	VAR2 - Rec.	VAR2 - Rol.
M11	1	$PROI_{m1}^{exp}$	$OPPS_{m1}^{exp}$	32	0.450	0.435	0.434	0.423
M11	2			32	0.324	0.312	0.347	0.330
M11	3			32	0.302	0.300	0.322	0.321
M12	1	$FACI_{m1}^{q}$	$FACS_{m1}^{m}$	32	0.440	0.430	0.434	0.423
M12	2			32	0.340	0.327	0.386	0.369
M12	3			32	0.316	0.312	0.349	0.336
M13	1	$FACI_{m1}^{q}$	$FACS_{m1}^{q}$	32	0.440	0.430	0.434	0.423
M13	2			32	0.340	0.327	0.386	0.369
M13	3			32	0.316	0.304	0.345	0.333
M21	1	$PROI_{m2}^{exp}$	$OPPS_{m1}^{exp}$	24	0.445	0.428	0.429	0.418
M21	2			24	0.297	0.287	0.302	0.299
M21	3			24	0.279	0.280	0.285	0.293
M22	1	$FACI_{m2}^{m}$	$FACS_{m2}^{m}$	24	0.445	0.430	0.429	0.418
M22	2			24	0.304	0.291	0.326	0.319
M22	3			24	0.291	0.276	0.305	0.303
M23	1	$FACI_{m2}^{m}$	$OPPS_{m2}^{exp}$	24	0.445	0.430	0.429	0.418
M23	2			24	0.304	0.291	0.326	0.319
M23	3			24	0.283	0.281	0.296	0.300
M24	1	$PROI_{m2}^{exp}$	$OPPS_{m2}^{exp}$	24	0.445	0.430	0.429	0.418
M24	2			24	0.297	0.287	0.302	0.298
M24	3			24	0.272	0.275	0.277	0.286
M25	1	$FACI_{m2}^{m}$	$OPPS_{m1}^{exp}$	24	0.445	0.428	0.429	0.418
M25	2			24	0.300	0.288	0.326	0.319
M25	3			24	0.283	0.276	0.303	0.306
M31	1	$FACI_{m3}^{m}$	$OPPS_{m1}^{exp}$	31	0.448	0.433	0.432	0.421
M31	2			31	0.307	0.286	0.317	0.302
M31	3			31	0.285	0.273	0.297	0.291
M32	1	$FACI_{m3}^{m}$	$FACS_{m3}^{m}$	31	0.448	0.433	0.432	0.421
M32	2			31	0.307	0.287	0.317	0.302
M32	3			31	0.292	0.277	0.300	0.294
M33	1	$FACI_{m3}^{m}$	$OPPS_{m3}^{exp}$	31	0.445	0.436	0.432	0.421
M33	2			31	0.307	0.290	0.317	0.302
M33	3			31	0.288	0.281	0.297	0.295
M34	1	$PROI_{m3}^{exp}$	$OPPS_{m1}^{exp}$	31	0.417	0.405	0.432	0.421
M34	2			31	0.321	0.308	0.331	0.310
M34	3			31	0.295	0.299	0.305	0.301
M35	1	$PROI_{m3}^{exp}$	$OPPS_{m1}^{exp}$	31	0.417	0.405	0.432	0.421
M35	2			31	0.321	0.308	0.331	0.309
M35	3			31	0.302	0.300	0.314	0.301
M41	1	$FACI_{m4}^{q}$	$OPPS_{m4}^{exp}$	32	0.450	0.436	0.434	0.423
M41	2			32	0.308	0.284	0.315	0.297
M41	3			32	0.281	0.270	0.288	0.280
M42	1	$FACI_{m4}^{q}$	$FACS_{m4}^{m}$	32	0.450	0.436	0.434	0.423
M42	2			32	0.308	0.285	0.315	0.297
M42	3			32	0.290	0.274	0.294	0.281
M43	1	$PROI_{m4}^{exp}$	$OPPS_{m4}^{exp}$	32	0.450	0.436	0.434	0.423
M43	2			32	0.328	0.317	0.327	0.308
M43	3			32	0.277	0.276	0.300	0.293

* These columns present the simple averages of the RMSEs of the GDP growth equations estimated on all subperiods, using either the recursive estimation technique (Rec.) or the rolling one (Rol.). Grey tint= minimum RMSE for a given month *mi*, *i*= 1 to 4.

Appendix 4: Univariate multistep models: Out of-sample results

A) AR and univariate models: RMSFEs

Forecast = 1 (forecast of the current quarter), Forecast = 2 (forecast of the next quarter)
Forecast = 3 (forecast of the next-to-next quarter)

Table A4.1 Univariate models relating to month *m*1

			AR		Industry		Services	
Model	Forecast	End	1st result	Last result	1st result	Last result	1st result	Last result
M11	1	04Q4	0.32-0.31	0.38-0.37	0.22-0.19	0.27-0.24	0.22-0.19	0.22-0.20
M11	1	07Q3	0.32-0.31	0.35-0.34	0.23-0.21	0.26-0.24	0.26-0.24	0.25-0.24
M11	2	04Q4	0.32-0.31	0.37-0.36	0.34-0.33	0.42-0.41	0.34-0.34	0.40-0.40
M11	2	07Q3	0.32-0.32	0.34-0.34	0.35-0.34	0.39-0.38	0.36-0.35	0.39-0.38
M11	3	04Q4	0.34-0.33	0.38-0.37	0.34-0.33	0.43-0.44	0.51-0.50	0.53-0.55
M11	3	07Q3	0.33-0.33	0.35-0.34	0.34-0.33	0.40-0.40	0.45-0.46	0.45-0.48
M12	1	04Q4	0.32-0.31	0.38-0.37	0.20-0.20	0.25-0.24	0.30-0.27	0.30-0.27
M12	1	07Q3	0.32-0.31	0.35-0.34	0.24-0.23	0.26-0.25	0.29-0.27	0.29-0.27
M12	2	04Q4	0.32-0.31	0.37-0.36	0.40-0.39	0.44-0.42	0.37-0.36	0.39-0.36
M12	2	07Q3	0.32-0.32	0.34-0.34	0.37-0.36	0.39-0.38	0.35-0.34	0.36-0.33
M12	3	04Q4	0.34-0.33	0.38-0.37	0.36-0.33	0.41-0.39	0.41-0.47	0.39-0.43
M12	3	07Q3	0.33-0.33	0.35-0.34	0.37-0.33	0.41-0.37	0.40-0.45	0.39-0.43

Table A4.2 Univariate models relating to month *m*2

			AR		Industry		Services	
Model	Forecast	End	1st result	Last result	1st result	Last result	1st result	Last result
M21	1	04Q4	0.35-0.32	0.42-0.40	0.19-0.17	0.27-0.25	0.25-0.23	0.29-0.26
M21	1	07Q3	0.34-0.33	0.37-0.35	0.21-0.19	0.25-0.24	0.26-0.23	0.27-0.25
M21	2	04Q4	0.32-0.32	0.32-0.31	0.34-0.34	0.38-0.37	0.24-0.24	0.30-0.30
M21	2	07Q3	0.33-0.33	0.32-0.32	0.36-0.35	0.37-0.37	0.41-0.40	0.42-0.41
M21	3	04Q4	0.36-0.35	0.43-0.41	0.42-0.39	0.49-0.46	0.46-0.32	0.41-0.36
M21	3	07Q3	0.36-0.35	0.38-0.38	0.37-0.36	0.42-0.40	0.45-0.51	0.43-0.51
M22	1	04Q4	0.35-0.32	0.42-0.40	0.25-0.22	0.30-0.28	0.35-0.32	0.34-0.32
M22	1	07Q3	0.34-0.33	0.37-0.35	0.26-0.23	0.28-0.27	0.33-0.30	0.31-0.30
M22	2	04Q4	0.32-0.32	0.32-0.31	0.45-0.46	0.45-0.45	0.27-0.30	0.30-0.33
M22	2	07Q3	0.33-0.33	0.32-0.32	0.41-0.42	0.41-0.41	0.49-0.51	0.48-0.50
M22	3	04Q4	0.36-0.35	0.43-0.41	0.40-0.38	0.43-0.40	0.46-0.51	0.41-0.46
M22	3	07Q3	0.36-0.35	0.38-0.38	0.40-0.38	0.43-0.40	0.45-0.51	0.43-0.49

First figure = recursive estimation - second figure = rolling estimation.

Table A4.3 Univariate models relating to month *m*3

Model	Forecast	End	AR		Industry		Services	
			1st result	Last result	1st result	Last result	1st result	Last result
M31	1	04Q4	0.31-0.30	0.40-0.39	0.24-0.22	0.28-0.26	0.23-0.24	0.30-0.30
M31	1	07Q3	0.35-0.33	0.39-0.38	0.27-0.24	0.28-0.26	0.28-0.27	0.31-0.30
M31	2	04Q4	0.34-0.33	0.39-0.38	0.32-0.32	0.36-0.35	0.35-0.35	0.38-0.37
M31	2	07Q3	0.33-0.33	0.36-0.35	0.32-0.32	0.34-0.32	0.35-0.35	0.36-0.35
M31	3	04Q4	0.33-0.32	0.37-0.36	0.37-0.34	0.43-0.41	0.35-0.33	0.40-0.39
M31	3	07Q3	0.33-0.32	0.34-0.34	0.33-0.32	0.37-0.36	0.36-0.35	0.40-0.39
M32	1	04Q4	0.31-0.30	0.41-0.40	0.25-0.23	0.28-0.27	0.25-0.25	0.29-0.28
M32	1	07Q3	0.35-0.33	0.40-0.39	0.27-0.25	0.29-0.27	0.27-0.26	0.28-0.27
M32	2	04Q4	0.31-0.31	0.38-0.37	0.36-0.36	0.38-0.38	0.28-0.30	0.31-0.32
M32	2	07Q3	0.32-0.31	0.35-0.34	0.33-0.33	0.34-0.34	0.37-0.40	0.37-0.39
M32	3	04Q4	0.33-0.32	0.37-0.36	0.40-0.40	0.40-0.39	0.33-0.41	0.35-0.41
M32	3	07Q3	0.33-0.32	0.34-0.33	0.37-0.37	0.37-0.36	0.33-0.38	0.34-0.38

Table A4.4 Univariate models relating to month *m*4

Model	Forecast	End	AR		Industry		Services	
			1st result	Last result	1st result	Last result	1st result	Last result
M41	1	04Q4	0.31-0.30	0.41-0.40	0.22-0.21	0.26-0.25	0.31-0.29	0.33-0.31
M41	1	07Q3	0.35-0.33	0.40-0.39	0.27-0.26	0.28-0.27	0.33-0.31	0.32-0.31
M41	2	04Q4	0.31-0.31	0.38-0.37	0.22-0.20	0.27-0.24	0.22-0.22	0.21-0.19
M41	2	07Q3	0.32-0.31	0.35-0.34	0.23-0.21	0.26-0.24	0.27-0.27	0.25-0.24
M41	3	04Q4	0.33-0.32	0.37-0.36	0.33-0.33	0.38-0.39	0.41-0.41	0.37-0.37
M41	3	07Q3	0.33-0.32	0.34-0.33	0.35-0.34	0.38-0.37	0.43-0.41	0.39-0.37
M42	1	04Q4	0.31-0.30	0.41-0.40	0.25-0.22	0.28-0.27	0.31-0.28	0.33-0.31
M42	1	07Q3	0.35-0.33	0.40-0.39	0.28-0.27	0.29-0.28	0.33-0.31	0.33-0.31
M42	2	04Q4	0.31-0.31	0.38-0.37	0.21-0.20	0.24-0.23	0.21-0.20	0.24-0.23
M42	2	07Q3	0.32-0.31	0.35-0.34	0.24-0.23	0.26-0.25	0.24-0.23	0.26-0.25
M42	3	04Q4	0.33-0.32	0.37-0.36	0.33-0.34	0.40-0.41	0.43-0.43	0.42-0.42
M42	3	07Q3	0.33-0.32	0.34-0.33	0.33-0.32	0.36-0.36	0.44-0.43	0.41-0.40

B) AR and univariate models: Tests of predictive accuracy

Table A4.5 Univariate models relating to month *m*1

Model	Forecast	End	AR 1 vs Industry		AR 1 vs Industry+Services		Ind vs Ind+Serv	
			1st result	Last result	1st result	Last result	1st result	Last result
M11	1	04Q4	5 2 5 2 2 5	S H 5 H H 5	T T T 5 5 5	S H 5 H H 5	5 S 2 5 S L	S 2 2 S S 2
M11	1	07Q3	2 2 2 S S S	S H S H H 2	T T T 5 5 5	S L L S L A	N N N U U U	T T T L L L
M11	2	04Q4	U U U U U N	U-T U U-5 U	U U U U U U	U U U U U U	U U U U U U	N N N N N N
M11	2	07Q3	U U U U U U	-T-5-5-T-2-5	U U U U U U	U-T U-T-T-T	U U U U U U	N N N N N N
M11	3	04Q4	U U U U U N	U U U U U U	-1-1-1-1-2-5	-2-2-5-5-5-5	U U N U U U	N N N N N N
M11	3	07Q3	U U U U N N	U U U U U U	-1-5-5-1-1-2	-2-2-5-2-1-2	N N N N N N	L L L N N N
M12	1	04Q4	S 2 5 2 5 T	S H T S H T	N N N N N T	L L A T T T	2 S T S 5 5	2 5 T 5 T T
M12	1	07Q3	2 5 5 S 2 T	5 S T 2 S T	N N 5 L A 2	L A A T N T	2 S 5 S 2 2	2 5 5 5 T T
M12	2	04Q4	U-2-T-T-1-1	U-5-5 U-5-5	U-T U U U U	U U U N N N	A A A N N N	T T T T T T
M12	2	07Q3	U U U U U U	U-T-T U-T-T	U U U U U U	U U U N N N	N N N N N N	A L L L T T
M12	3	04Q4	2 T T 2 T T	A N N A N N	N N N U U U	N N N N N N	T T T N N N	2 2 5 T T T
M12	3	07Q3	S 2 5 S 5 5	N N N A N N	N N N U U U	N N U U U U	T L N N N N	S S 2 5 T L

Table A4.6 Univariate models relating to month *m*2

Model	Forecast	End	AR 1 vs Industry		AR 1 vs Industry+Services		Ind vs Ind+Serv	
			1st result	Last result	1st result	Last result	1st result	Last result
M21	1	04Q4	S S S 2 S T	A 2 2 A 2 5	T T L T T A	A T T A T T	T T T T T L	A A A A A A
M21	1	07Q3	H S S S S S	T 2 2 L 2 2	5 T T S 5 5	L T T L 5 T	A A A L L L	A A A A A A
M21	2	04Q4	U U U U U U	U U U-T-T-T	L A A A N N	N N N N N N	5 T T T T T	2 5 T T T T
M21	2	07Q3	U U U U U U	-T U U-T-T-T	U U U U U U	U U U U U U	U U U U U U	U U U U U U
M21	3	04Q4	U U U U U U	U-T-T U U U	U U U U U U	L L A A N N	N N N N N U	S S S 2 2 2
M21	3	07Q3	U U U U U U	U U U U U U	U U U U U-5	N N N U U U	U U U U U-T	L T N N N U
M22	1	04Q4	5 5 5 5 5 5	N T T N T T	U U U N N N	N N N N N N	N N N N N N	L L N L L L
M22	1	07Q3	S S 2 S S 2	A T T N T T	N N N N N N	A N N N N N	N U N N U U	T 5 T L L L
M22	2	04Q4	-T-T-T-T-T-T	U U U U U U	N N N N N N	N N N U U U	T L L L L L	5 T T L L L
M22	2	07Q3	-T-T-T-T-T-T	U-T U-T-T U	U U U-T U U	U U U-T U U	U U U U U U	U U U U U U
M22	3	04Q4	U U U U U U	U U U U U U	U U U U U U	N N N U U U	U U U U U U	N N N U U U
M22	3	07Q3	U U U U U U	U U U U U U	U U U-T-T-T	U U U U U U	U-5-T U-T U	N A A U U U

Last six columns: results of the 3 tests carried out on recursive estimations (first 3 results) and rolling estimations (last 3 results). For a set of 3 results, the first one refers to the test made using the Newey-West variance estimations, the second one to the test resulting from the AUTOREG procedure, the last one to the test derived from the Durbin approach. The classifications of the results are explained in sub-section 3.3. A negative sign preceding a result means that the corresponding test statistic is significantly negative, i.e. that the larger model performs significantly less well than the more parsimonious model. No negative sign: the test statistic is either positive, or non-significantly negative. **The same conventions are used for all tables relating to the predictive accuracy tests below.**

Table A4.7 Univariate models relating to month *m*3

Model	Forecast	End	AR 1 vs Industry		AR 1 vs Industry+Services		Ind vs Ind+Serv	
			1st result	Last result	1st result	Last result	1st result	Last result
M31	1	04Q4	T T L T T T	T 2 5 T 2 2	T L L L A A	L T T L T T	N N N U-T-T	-2-T-T-2-5-5
M31	1	07Q3	S 2 2 S S 2	2 H S S H S	S T T 2 T T	T S 2 T S 2	U U U-2-T-T	-1-1-2-1-1-1
M31	2	04Q4	N N U N N N	N N N N N N	U U U U U U	N N N N N U	U U U U U U	U U U U U U
M31	2	07Q3	N N U N N U	N N U N N N	U U U U U U	U N U U N U	U U U U U U	U U U U U U
M31	3	04Q4	U U U U U U	-T-T-T U U U	U U U U N N	U U U U-1 U	N N N N N N	N N N N N N
M31	3	07Q3	U U U U U U	U U U U U U	U U U U U U	-T-5-T-T-T-T	U U U U U U	U U U U U U
M32	1	04Q4	L T T T 5 T	5 5 5 5 5 5	T T T N A A	5 5 5 T 5 5	N N N U U U	U U U U U U
M32	1	07Q3	2 S S S S S	S 2 2 S 2 2	S 2 2 S 5 5	S 2 2 S 2 2	U U U U U U	N N N N U U
M32	2	04Q4	U U U U U U	N N N N N N	N N N N N N	T 5 T L T L	A A A N N N	5 S 2 L 2 N
M32	2	07Q3	U U U U U U	N N N N N N	U U U U U U	U U U U U U	U U U U U U	U U U U U U
M32	3	04Q4	-T-T-T-T-T-T	U U U U U U	-1-1-2-2-2-5	-2 U-T-1-2-2	U U U-T-T-T	U U U U U U
M32	3	07Q3	-5-5-5-T-T-T	-T-T-T U U U	-1-1-1-1-2-2	-1-T-2-1-2-T	U U U U U U	N N N U U U

Table A4.8 Univariate models relating to month *m*4

Model	Forecast	End	AR 1 vs Industry		AR 1 vs Industry+Services		Ind vs Ind+Serv	
			1st result	Last result	1st result	Last result	1st result	Last result
M41	1	04Q4	5 T T 2 5 5	5 2 2 5 S 2	N U U N N N	A L L L T T	-2-2-5-1-1-1	U U U-T-1-1
M41	1	07Q3	S 2 2 S 2 2	S S S 2 S S	N N N N N N	T T T 5 5 T	-2-2-2-1-1-1	U-5-5-T-1-1
M41	2	04Q4	2 5 5 2 2 5	S H H S H H	T T 5 T L T	S H S S H S	2 T T L A A	S 2 5 S S 2
M41	2	07Q3	2 2 5 S S S	S H S S H H	L A L L L L	2 A L S A L	U U U U U U	T T T T T T
M41	3	04Q4	N N N U U U	U U U U U U	U U N U U N	N N A U N N	U U N U U N	N N N N N N
M41	3	07Q3	U U U U U U	U U U U U U	-T-5 U-T-T U	U U U U U U	-T-T U U-T U	U U U N N N
M42	1	04Q4	L L L T T T	T 5 5 T 5 5	U U U N N N	N L A L T L	-T-T-2-5-5-1	U U U U U U
M42	1	07Q3	S 5 5 2 L L	2 2 2 5 2 2	N N N A L T	T T T T T T	-T-T-T-2-1-1	U U U-T-T-T
M42	2	04Q4	2 5 5 2 5 5	S H S S H S				
M42	2	07Q3	2 5 2 S 2 5	2 S S 2 S S				
M42	3	04Q4	U-T U U-5 U	U U U U U U	U U U U U U	N U-5 N N U	N N N N N N	L L L T T T
M42	3	07Q3	U U U U U U	U U U U U U	U U U U U U	U U U N N N	U U N N N N	N N N L T L

Appendix 5: VAR models: Out-of-sample results

AR and VAR models: Tests of predictive accuracy

Table A5.1 Restricted VAR models with 4 lags relating to month *m*1

			AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
Model	Horizon	End	1st result	Last result	1st result	Last result	1st result	Last result
M11	1	04Q4	S S S S S S	S S S S S S	2 S 2 S S 2	S H S S H S	N A A U U U	N N N U U U
M11	1	07Q3	H H H H H H	H H H H H H	S S S H H H	H H H H H H	N N N N N U	U U U U U U
M11	2	04Q4	H H S S S S	H S S S S S	H H S H H S	H 5 L H S S	5 T T L A N	N N N N N N
M11	2	07Q3	H H S H H S	H S S S S S	H H S H H H	H 2 T H H H	T A U T T T	N N N N N N
M11	3	04Q4	A L N L A N	U U U N N N	N N N N N N	U U U U U U	N N N U U U	N N U U U U
M11	3	07Q3	N A N A N N	U U U N N N	N N N N N N	U U U U U U	U U U U U U	N N U U U-T
M11	4	04Q4	N N N N N N	U U U U U U	U U U U U U	U U U U U U	N N N U U U	A L L N N N
M11	4	07Q3	N N N N A A	U U U U U U	U U U U U U	U U U U U U	N N N U U U	N A A N N N
M12	1	04Q4	H H S S S S	S S S S S 2	S S S S S S	S S S S H S	5 5 L T 5 L	N A A N N N
M12	1	07Q3	H H H H H H	H H S H H S	H H H H H H	H H S S H H	T 5 A 5 2 5	N A A N A A
M12	2	04Q4	H H S H S S	S 2 2 S 2 2	S S S S S S	S S 2 H S S	2 5 5 2 5 5	A A A N N N
M12	2	07Q3	H H H H H H	S S S S S S	S S S H H S	S S S H S S	5 5 5 2 5 5	A A A L A A
M12	3	04Q4	S 2 2 S S 2	N N N N N N	5 S S 5 S S	U U U U U U	5 T T T L L	N N N N N N
M12	3	07Q3	T T T 5 5 5	N N N N N N	L N N L N N	U U U U U U	2 5 5 T A L	T A L N N N
M12	4	04Q4	A A N L L L	U U U U U U	-T U-T U U-T	-2-2-5-2-2-5	U U U U U U	U U U U U U
M12	4	07Q3	T T T L L L	U U U U U U	U U U U U U	-T U U-T-T-T	U U U U U U	U U U U U U
M13	1	04Q4	H H S S S S	S S S S S 2	H H S S H S	H H S S H S	T 5 5 A L L	T T T N A N
M13	1	07Q3	H H H H H H	H H S H H S	H H H H H H	H H H H H H	T T T T 5 T	L T T A L L
M13	2	04Q4	H H S H S S	S 2 5 S 2 2	H H S H H S	H S S H H S	2 2 5 2 5 5	5 5 5 T T T
M13	2	07Q3	H H H H H H	S S S S S S	H H S H H S	H 2 T H S L	5 5 5 2 2 5	T 5 T 5 5 5
M13	3	04Q4	S H S S S 2	N N N N N N	S H S S S 2	N N N N N N	L A A N N N	N N N U U U
M13	3	07Q3	5 T T T T T	N N N U U U	5 5 5 5 5 5	N N N U U U	N N N 5 T T	U U U N N N
M13	4	04Q4	N N U N N N	-T U U U U U	A N N N N N	U U U U U U	L A A N N N	N N N N N N
M13	4	07Q3	A A A N N N	U U U U U U	T T T N N N	U U U U U U	A N N N N N	N N N N N N

M11: *Ind* = expected production, *Ser* = expected operating profit
M12: *Ind* = static quarterly common factor in industry, *Ser* = dynamic common factor in services
M13: *Ind* = same as in M12, *Ser* = static quarterly common factor in services.
The subseries included in the models refer to *m*1 exclusively.

Table A5.2 Restricted VAR models with 4 lags relating to month *m*2

			AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
Model	Horizon	End	1st result	Last result	1st result	Last result	1st result	Last result
M21	1	04Q4	S S S 2 2 2	S S S S S 2	S 2 2 2 2 2	S S 2 S S 2	L L A N N N	N N N U U U
M21	1	07Q3	S S S S H S	S S S S S S	S S S S H H	S S S S S S	N N N T L L	N N N N N N
M21	2	04Q4	2 2 2 S S 2	U U U N N U	2 2 5 S 2 2	N N N N N N	L L L U U U	5 T T L A T
M21	2	07Q3	S S S S S S	A A N N N N	S 2 S S S S	5 T T L N A	A A A U U U	T T T L T T
M21	3	04Q4	U U U N N N	-T U U U U U	U U U U U U	-T U U-T U U	N N N U U U	N N N N N N
M21	3	07Q3	U U U N N N	-T U U U U U	U U U U U U	U U U U U U	N N N U U U	N N U U U U
M21	4	04Q4	U U U N N N	N N U N N U	U U U N N N	N U U A N N	T L L N N N	L A A N N N
M21	4	07Q3	N N N N N N	N N N A N N	N N N N N N	N N N L A N	N N N U U U	N N N N N N
M22	1	04Q4	2 2 2 2 2 5	H H S H H S	2 2 5 2 5 2	S 2 2 S S 2	S H S S H S	N N N N N N
M22	1	07Q3	S H H S S S	H H H H H H	S S 2 S S 2	S S S S 5 A	2 2 A 2 2 5	N N A N N N
M22	2	04Q4	L L L T T L	-T U-2 U U-5	N N N A A A	U U U U U U	N N N N N N	U U U U U U
M22	2	07Q3	A A N T T T	U-5-5 U U U	N N N N N N	U U U U U U	N N N N N N	U U U U U U
M22	3	04Q4	T L L L L L	U U U U U U	N N N N N N	-T U U-T U U	-T-T-T-T-T-T	U U U-T-T-T
M22	3	07Q3	T T T T 5 L	U U U U U U	N N N N N N	-T U U U U U	U U U U U-T	U U U U U U
M22	4	04Q4	T L N L L N	T T N T T N	N N N N N N	N N N N N N	U U U U U U	U U U U U U
M22	4	07Q3	T T N T T N	T T N T T N	N N N L A A	A N N A N N	U U U N N N	U U U N N N
M23	1	04Q4	2 2 2 2 2 5	H H S H H S	2 2 2 2 2 5	S S S S S S	N N N N N N	U U U U U U
M23	1	07Q3	S H H S S S	H H H H H H	S S S S H H	S S S H H S	N N N N N N	U U U U U U
M23	2	04Q4	T T L T T T	-5-1-1 U U-5	N N N A A A	-1-1-1-2-1-2	U U U U U U	U U U-T-T U
M23	2	07Q3	2 5 5 5 5 5	U U U U U U	L A A T L L	U-T-T-T U-T	U U U U U U	-T-T-T-T U U
M23	3	04Q4	L A A L A A	U U U U U U	N N N N N N	U-T-T U U U	U U U U U U	U U U N N U
M23	3	07Q3	T L L L T L	U U U U U U	N N N N N N	U U U U U-T	-T-T-T U U U	U U U U U U
M23	4	04Q4	N N U N N U	N N U N N U	N N N N N U	T A A N N N	N N N N N N	N N A N N L
M23	4	07Q3	N N U N N U	A A U A N U	N N N N N U	L A A A N U	N N N N N N	N N A N N A
M24	1	04Q4	S S S 2 2 2	S S S S S 2	S S 2 S 2 2	S S S S S S	U U U U U U	N N N N N N
M24	1	07Q3	S S S S H H	S S S S S S	S S S S S S	S S S S H 5	U U U U U U	N N N N N N
M24	2	04Q4	2 2 2 S S 2	U U U N N U	S 2 5 2 2 5	N N N N N U	T T T N N N	S 2 N S 2 5
M24	2	07Q3	S S S S S S	A A N N N N	S 2 2 S S 2	T L T N N N	L T L N N N	S 2 2 5 5 5
M24	3	04Q4	U U U N N N	-T U U-T U U	U U U U U U	U U U U U U	N N N N N N	N N N A A N
M24	3	07Q3	U U U N N N	-T U U U U U	N N N U U U	U U U U U U	N N N N N N	N N N N N N
M24	4	04Q4	U U U N N N	N N U N N U	U U U U U U	N U U N U U	N N N N N N	N N N N N N
M24	4	07Q3	N N N N N N	N N N N N N	U U U U U U	N N U N N N	N N N U U U	N N N N N N
M25	1	04Q4	S S 2 S 2 2	H S S S S S	S S 2 S S 2	S S S S S S	T T T T L L	L L L 5 5 T
M25	1	07Q3	H H H S S S	H H H H H S	S S S S S S	H S S H H S	T T T 5 5 5	T S 2 S S S
M25	2	04Q4	T L L 5 T T	-5 U-2 U U-T	N N N L A A	-T U U U U U	N N N N N N	2 5 5 2 T 5
M25	2	07Q3	5 T T T T T	U U U U U U	T T T T T T	U U U U U U	N 5 T 5 2 5	S 5 2 S 2 S
M25	3	04Q4	A A A L L A	U U U U U U	N N N N N N	U-T-T U-T-5	-T-T-T-1-2-2	U U U U U U
M25	3	07Q3	A L A N L A	U U U U U-T	N N N N N N	U U U U-T-5	U U U U U U	U U U U U U
M25	4	04Q4	N N U N N U	N N U A A U	N N N N N U	A N N A A U	U U U U U U	N N N U U U
M25	4	07Q3	A N N A L N	N N U A A U	N N N A A N	A N N A A U	-T U U-T U U	U U U U U U

M21: *Ind* = expected production, *Ser* = expected operating profit derived from the last quarterly survey (*m*1)
M22: *Ind* = static monthly common factor in industry, *Ser* = dynamic common factor in services
M23: *Ind* = same as in M22, *Ser* = interpolated expected operating profit
M24: *Ind* = same as in M21, *Ser* = same as in M22. M25: *Ind* = same as in M22, *Ser* = same as in M21.

Table A5.3 Restricted VAR models with 4 lags relating to month *m*3

Model	Horizon	End	AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
			1st result	Last result	1st result	Last result	1st result	Last result
M31	1	04Q4	S S S S S S	S S S S S S	S T N S S 2	S S S S H S	T L T A A A	A A T N N N
M31	1	07Q3	H S 5 H H S	H H H H H S	S 2 T S S S	H H H S H H	N N N A A L	N L L A T T
M31	2	04Q4	S S S S S S	5 T T 5 T T	2 2 5 2 2 2	T L L T L L	N N N N U U	N N N N N N
M31	2	07Q3	S S S S S S	S H S 5 T T	S S S S S S	2 5 5 5 5 5	N N U N N N	N N N N N N
M31	3	04Q4	T T L T 5 N	U U U N N N	L A A L L N	N N N N N N	U U U-2-T-T	U U U U U U
M31	3	07Q3	T T T T T A	U U U N N N	L A A L T N	N N N N N N	U U U U U U	N N N N N N
M31	4	04Q4	N N N A A U	N N N N N U	N N N A A U	N N N N N N	S 5 2 T 5 5	S 2 S T A A
M31	4	07Q3	A N N L L N	N N N N N N	A N N T T T	N N N N N N	N N N T T T	T T L T A T
M32	1	04Q4	S S S S S S	S S S S S S	S T A S S 2	2 S 2 2 2 2	N N N N N N	N N N N N N
M32	1	07Q3	H S 5 H H H	H H H H H H	H S 5 S 2 T	S H S S H H	U U U N N N	U U U N N N
M32	2	04Q4	S S S S S S	5 T 5 T T T	5 5 5 5 5 5	L A L A N N	N N N N N N	U U U U U U
M32	2	07Q3	S S S S S S	2 S 2 5 T T	5 5 5 T 5 5	L A L A N N	N N N N N N	U U U U U U
M32	3	04Q4	T 5 T L T T	U N N-T N N	S 2 5 5 5 T	U N N U N N	U U U U U U	U U U U U U
M32	3	07Q3	L T T A T T	U U U-T N N	L T T A T T	U N N U N N	U U U U U U	U U U U U U
M32	4	04Q4	N L A U A U	U N U U N N	N N N U N N	U U U U U U	U U U U U U	-5-1-5-T-2-5
M32	4	07Q3	N T L U A A	U N U U N N	N N N U N N	U U U U U U	U U U U U U	U-5-T-T-5-5
M33	1	04Q4	H H S S S S	S H H S H H	S S S S S S	S S S S H S	N N N A L L	U U U N U U
M33	1	07Q3	H H 5 H S T	H H H H H H	H H H H S T	H H H S H H	U U U L T T	U U U N N N
M33	2	04Q4	S S S S S S	S S S 2 A N	S S 2 S S 2	2 S S 5 2 5	N N N N N N	U U U U U U
M33	2	07Q3	S S S S S S	S 2 S S 5 2	S S S S S S	S S S 2 S S	N N N N N N	U U U U U U
M33	3	04Q4	L T T T T T	N N N N N N	L T T T T T	U N N U N N	-T U U-T U U	-5 U U-5 U U
M33	3	07Q3	L T T L T T	N N N U N N	L T T L T T	U N N U N N	-5 U U U U U	-T U-T U U U
M33	4	04Q4	T L A A A N	N N N N N N	N N N A N N	N N N N N N	-2-2-2 U U U	-5 U U-T U N
M33	4	07Q3	S S 2 T T T	T T T A A A	2 2 5 2 H S	N N N N N N	-T U U U U U	-T U U U U U
M34	1	04Q4	H S S S H H	S H S S S S	S S S S S 2	S S S 2 S 2	-1-1-2-2-2-5	U U U U-T-T
M34	1	07Q3	H S S S S S	H H H S S S	S S S 2 2 2	S S S 2 S S	-2-1-2-2-2-2	U U U-T-T-T
M34	2	04Q4	S S S 2 2 2	S S S 5 L T	5 5 5 T 5 T	T L T L A A	U U U U U U	U U U U U U
M34	2	07Q3	H S S S S 2	H H H 2 5 2	2 2 2 5 5 5	5 S 2 T L L	U U U U U U	U U U U U U
M34	3	04Q4	U N N U N N	U U U-T U U	U N N U N N	U U U-T U U	-T-T U-T-T U	-5 U-T-T U-T
M34	3	07Q3	U N N U N N	U U U-T U U	U N N U N N	U U U-T U U	-T-T-T-5-5-5	-5 U-T-5-T-5
M34	4	04Q4	U U U U N U	U U U U U U	-5-T-T-T U U	U U U U U U	-1-1-1-1-1-2	-1-2-1-1-1-1
M34	4	07Q3	U N N U N N	U U U U U U	U U U-T U U	U U U U U U	-2-2-1-1-1-1	-5-T U-2-1-1
M35	1	04Q4	H S S S S S	S H S S S S	S S S 2 2 5	S H H S S S	-5 U U-T-T-T	U U U U U U
M35	1	07Q3	H S S S S S	H H H S S S	S S S 2 2 2	S H H S S S	-5-T-T-T-T-T	U U U U U U
M35	2	04Q4	H S S 2 2 2	S S S 5 T T	2 5 5 T 5 T	5 T T T L L	-T-T-T-T-T U	-T U U U U U
M35	2	07Q3	H S S S S S	H H H 2 5 2	S 2 2 5 5 5	S 2 S 5 T T	-T-T-T-5-T-T	U U U-T U U
M35	3	04Q4	N N N U N N	U U U-T U U	U N N U N N	U U U-T U U	-1-1-2-1-1-2	-2-1-1-1-5-T
M35	3	07Q3	U N N U N N	U U U-5 U U	U N N U N N	U U U-T U U	-2-2-2-1-2-2	-5-2 U-2-5-T
M35	4	04Q4	U N U U N N	U U U U N N	U U U U N N	U U U U N N	-5-2 U U U U	U-T U U U U
M35	4	07Q3	U N N U N N	U N N U N N	U U U U N N	U U U U N N	-5-T U U U U	-T U U U U U

M31: *Ind* = static monthly common factor in industry, *Ser* = expected operating profit from the last quarterly survey (*m*1)
M32: *Ind* = same as in M31, *Ser* = dynamic common factor in services
M33: *Ind* = same as in M31, *Ser* = interpolated expected operating profit (*m*3)
M34: *Ind* = expected production, *Ser* = interpolated expected operating profit (*m*3)
M35: *Ind* = same as in M34, *Ser* = same as in M31

Table A5.4 Restricted VAR models with 4 lags relating to month *m*4

Model	Horizon	End	AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
			1st result	Last result	1st result	Last result	1st result	Last result
M41	1	04Q4	H H H H H H	S H S S H S	S 2 N S S S	S S S S S S	N N N N N N	N L L N N A
M41	1	07Q3	H H H H H H	H H H H H H	H 2 T H H 5	H H S S H S	U U U U U U	N N N N N N
M41	2	04Q4	H S S S S S	S 2 2 S 2 2	H S S H S S	H 2 N H H H	S S 2 2 2 2	T T T L L L
M41	2	07Q3	H S S S H S	S S S S S 2	S 5 N H H S	H 2 N H 2 N	T T T 2 2 5	A A A L L L
M41	3	04Q4	2 2 2 5 2 5	A N N N N N	2 5 5 5 5 5	N N N N N N	L T T 5 2 5	L T T T T T
M41	3	07Q3	T T T T 5 L	N N N N N N	L L U T T T	N N N N N N	L T T 5 2 2	L T T L T T
M41	4	04Q4	2 5 T 5 T T	T T T L N N	S 5 5 T T T	T A A N N N	U U U U U U	N N N N N N
M41	4	07Q3	S 2 5 2 5 5	5 5 T L L A	S 2 2 2 5 5	T A A A N N	U U-5 U U U	N U U N N N
M42	1	04Q4	H H H H H H	S H S S H S	S 2 N S S S	S S S S S S	N N N N N N	N N N A N L
M42	1	07Q3	H H H H H H	H H H H H H	H S T H H 2	H H S S H S	U U U N 5 5	U U U L T 5
M42	2	04Q4	H H S H H S	S S S S S S	S S S S S S	H S S H S S	5 5 5 5 H S	L L A A L N
M42	2	07Q3	H H H H H H	H S S S S S	S T N S S S	S 5 N S A U	A N N L N N	N N N N A N
M42	3	04Q4	2 2 2 5 2 L	A N N N N N	S 2 2 2 2 5	N N N N N N	T L A T A A	U U U U U U
M42	3	07Q3	T 5 T T 5 L	N N N N N N	5 5 5 T 5 L	N N N N N N	5 L L T 5 T	N N N U U U
M42	4	04Q4	2 5 T T T T	A N N N N N	T A A N N N	U U U U U U	-T U-T U U U	U U U U U U
M42	4	07Q3	S 2 2 5 2 5	L A N N N U	5 T T L L L	U U U U U U	U U U U U U	U U U U U U
M43	1	04Q4	S S S S S S	H H S H H S	S S 2 S S 2	H H S S H H	U N N U U U	T L A N N N
M43	1	07Q3	H H H H H H	H H H H H H	S S 5 H H S	H H H H H H	U U U U U U	L L A A N N
M43	2	04Q4	H H H H H H	H H S H H S	H H H H H S	H 2 A H S S	5 5 5 T T T	A A N A A A
M43	2	07Q3	H H H H H H	H S T H H H	H H H H H H	H S T H H H	T 5 5 5 5 T	A A A T L 5
M43	3	04Q4	L T N T T N	N N N N N N	T T T L T L	N N N N N N	A A A N A N	N N N A A A
M43	3	07Q3	L L L T 5 A	N N N N N N	L L A L L L	N N N N N N	N N U U U U	N N N N N N
M43	4	04Q4	N N N N N N	U U U U U U	N N N N N N	U U U U U U	L T N A L N	L T N T T N
M43	4	07Q3	N N N A L L	U U U U U U	A A A N N N	N N N N N N	N A N N N U	A L N N A N

M41: *Ind* = static quarterly common factor in industry, *Ser* = expected operating profit in services

M42: *Ind* = static quarterly common factor in industry, *Ser* = dynamic common factor in services

M43: *Ind* = expected production in industry, *Ser* = expected operating profit in services

All variables refer to *m*4 subseries.

Table A5.5 Non-Restricted VAR models with 2 lags relating to month *m*1

Model	Horizon	End	AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
			1st result	Last result	1st result	Last result	1st result	Last result
M11	1	04Q4	H H H H H H	H H H H H H	S H H S H H	H H H H H H	U U U -T-T-T	N N N U U U
M11	1	07Q3	H H H H H H	H H H H H H	H H H H H H	H H H H H H	U U U U-T-T	N N N U U U
M11	2	04Q4	H H H H H H	H 5 N H 5 N	H T L H H H	H L A H A N	T L L N N N	L L L N N L
M11	2	07Q3	H H H H H H	H S T H S L	H H H H H H	H 5 T H T T	L L A N N N	L L L N N N
M11	3	04Q4	T T T 5 5 5	A A A A A N	T T L L A A	N A A N N N	-T U U -5-T-T	U U U N N N
M11	3	07Q3	N N N T T A	N N N N N N	N N N N N N	N N N N N N	U U U -T U U	N N N N N N
M11	4	04Q4	5 L L 2 L T	N N N N N N	T A L L N N	L A A A N N	U U U -T-T-T	N N N N N N
M11	4	07Q3	S 5 5 S T 5	L A A N N N	2 T T N N N	5 2 5 A N N	N N N -T U U	L L L N N N
M12	1	04Q4	H H H H H H	H H H H H H	S S S S H H	S H S S S S	L A A N N N	L L L A L A
M12	1	07Q3	H H H H H H	H H H H H H	S 2 T H H H	H H S H H S	U U U N U U	N N N N N N
M12	2	04Q4	H H H H 2 T	H H H H H H	H H H H S S	H L N H T N	S S 2 5 5 5	5 5 5 L T L
M12	2	07Q3	H H S H H S	H H H H H H	H S S H S S	H T A H T N	L L L L T T	L L L L L L
M12	3	04Q4	T T T 5 5 T	N N N A A A	5 5 T 5 T T	N N N N N N	U U U U U U	U U U U-T-T
M12	3	07Q3	L L L T T T	N N N N N N	T T T T T T	N N N N N N	N N U U U U	U U U U-T-T
M12	4	04Q4	S 5 5 S 5 5	T L A T A A	5 L L T L A	N N N N N N	-T-T-5 -5-T-5	-T-T-T -T-T-T
M12	4	07Q3	S 2 2 S 5 5	T L L L A A	2 T T T A A	A N N N N N	U U U -5-2-2	U U U -T-T-T
M13	1	04Q4	H H H H H H	H H H H H H	S H H S H H	S H S S H S	N N N N N N	L L N A A N
M13	1	07Q3	H H H H H H	H H H H H H	S S S H H H	H H S H H H	U U U U U U	N N N N N N
M13	2	04Q4	H H H H 2 T	H H H H H H	H H H H S S	H H 2 H T A	2 2 5 T T T	T 5 L L T A
M13	2	07Q3	H H S H H S	H H H H H H	H S S H S S	H 5 L H 5 A	A A A A L N	L L A A L A
M13	3	04Q4	T T T 5 5 T	N N N A A A	T L L T T T	N N N N N N	-5-5-5 U U U	-5-2-5 -5-T-5
M13	3	07Q3	L L L T T T	N N N N N N	A A A L L L	N N N N N N	-5-5-5 U U U	-5-5-5 -5-T-5
M13	4	04Q4	S 5 5 S 5 5	T L A T A A	5 L T 5 L L	N N N N N N	-5-T-T -T-T-T	-T-T U -T-T-T
M13	4	07Q3	S 2 2 S 5 5	T L L L A A	2 T 5 T A A	A N N N N N	-T-T-T -5-T-T	U U U -T-T-T

M11: *Ind* = expected production, *Ser* = expected operating profit
M12: *Ind* = static quarterly common factor in industry, *Ser* = dynamic common factor in services
M13: *Ind* = same as in M12, *Ser* = static quarterly common factor in services.
The subseries included in the models refer to *m*1 exclusively.

Table A5.6 Non-Restricted VAR models with 2 lags relating to month *m*2

Model	Horizon	End	AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
			1st result	Last result	1st result	Last result	1st result	Last result
M21	1	04Q4	S S S S S S	S S S S S S	S S S S S S	S S S S S S	U U U U U U	N N N N N N
M21	1	07Q3	S S S S S S	S S S S S S	S S S S S S	S S S S S S	N N N N N N	N N N L L L
M21	2	04Q4	S 2 2 S 2 2	L L A L L A	2 5 5 S 5 2	L L A L L A	-T U U -T-T-T	N N N L A T
M21	2	07Q3	S H H S H H	T T T T 2 2	S 2 S S S S	5 T T 5 T T	N N N N N N	T L T 2 S S
M21	3	04Q4	N N N N N N	U U U U U U	N N N N N N	N N N U U U	L A A U U U	T L L N N N
M21	3	07Q3	U U U U U U	U U U U U U	N N N U U U	N N N U U U	5 T T N N N	2 5 5 N N N
M21	4	04Q4	N N N N N N	A N N N N N	N N N N N N	N N N N N N	U U U U U U	U U U U U U
M21	4	07Q3	A N N N N N	A L L N A U	N N N N N N	A L L A T T	U U U N N N	U U U N N L
M22	1	04Q4	S S S S S S	H H S H H S	S S S S S S	S S S S S S	N N N N N N	N N N N N N
M22	1	07Q3	S S S S S S	H H S H H S	S S S S S S	S S S S S S	U U U N N N	N N N N N N
M22	2	04Q4	A N N A A A	U U U U U U	T H S A S N	U U U U U U	U U U U U U	U U U U U U
M22	2	07Q3	L A T L A L	N N N N N U	T T T A S 5	N N N U U U	U U U U U-T	U U U U U U
M22	3	04Q4	5 T T 2 T T	N N N N N N	L A L A N A	N N N U U U	-2-5-5 -2-2-5	-2-5-2 -5-5-5
M22	3	07Q3	T L L 5 T T	N N N N N N	L N L A N A	U U U U U U	-T-T-T -5-5-T	-T U U -T U U
M22	4	04Q4	N N N N N N	5 L T 5 L T	N N N N N N	5 2 5 2 5 T	-5-T-T -2-T-T	-2-5-5 -5-5-T
M22	4	07Q3	N N N N N N	T L L T A L	N N N N N N	5 2 5 T T T	-T U U -T U U	U U U -T-T-T
M23	1	04Q4	S S S S S S	H H S H H S	S S S S S S	S S S S S S	U U U U U U	U U U U U N
M23	1	07Q3	S S S S S S	H H S H H S	S S S S S S	H S S S S S	U U U U U U	U U U N N N
M23	2	04Q4	A N N A A A	U U U U U U	N N N N N N	U U U U U U	U U U -T U U	-2-T-5 -1-2-1
M23	2	07Q3	L A T L A L	N N N N N U	L H S N 5 T	N N U U U U	U U U U U-T	-5-T-5 -2-T-2
M23	3	04Q4	5 T T 2 T T	N N N N N N	T L T T L T	N N N N N N	-T-T-T U-T-T	U U-T U U-T
M23	3	07Q3	T L L 5 T T	N N N N N N	T A T T L T	N N N N N N	U U U U U U	U U-T U U-T
M23	4	04Q4	N N N N N N	5 L T 5 L T	U U U U U N	T N T A A L	-1-1-2 -2-5 U	-2-T-T -2-T-T
M23	4	07Q3	N N N N N N	T L L T A L	N N N N N N	L T T N A L	-1-2-2 U U U	-5-T-T -T U U
M24	1	04Q4	S S S S S S	S S S S S S	S S S S S S	S S S S S S	U U U U U U	U U U U U U
M24	1	07Q3	S S S S S S	S S S S S S	S S S S S S	S S S S S S	U U U U U U	U U U U U N
M24	2	04Q4	S 2 2 S S S	L L A L A A	S 5 2 S 2 2	A A N N N N	U U U -5-T-T	-5-T-T -2-5-5
M24	2	07Q3	S H H H H H	T T T T 2 2	S 2 S S H H	T L L T S S	U U U U U U	U U U U U U
M24	3	04Q4	N N N N N N	U U U U U U	L N A N N N	N N N N N N	N N N U U U	N N N N N U
M24	3	07Q3	U U U U U U	U U U U U U	N N N N N N	N N N U U U	A A A U U U	N N N N N U
M24	4	04Q4	N N N N N N	A N N N N N	N N N U U U	N A L N N N	-1-1-1 -1-2-2	-2-T-T -2-T-T
M24	4	07Q3	A N N N N N	A L L N A N	N N N N N N	N L N N N N	-1-5-5 -T U N	-T U U U U N
M25	1	04Q4	S S S S S 2	H H S H H S	S S S S S S	H S S H S S	N N N N N U	N N N N N N
M25	1	07Q3	S S S S S S	H H S H H S	S S S H S S	H H S H H S	N N N A A N	A A A L L L
M25	2	04Q4	A N N L A A	U U U U U U	N N N N N N	N N N U U U	U U U U-T U	U U U U U U
M25	2	07Q3	L A T T L T	N N N N N N	L A L T L T	N N N N N N	U U U N N N	U U U N N N
M25	3	04Q4	5 T T 5 T T	N N N N N N	5 T T 5 T T	N N N N N N	U U U U U U	N N N U U U
M25	3	07Q3	T L L T T T	N N N N N N	5 T T 5 T T	N N N N N N	U U U U U U	N N N N N N
M25	4	04Q4	N N N N N N	5 L T T A L	N N N N N N	5 L T L N L	-5-T-T U U U	-T U U -5-T U
M25	4	07Q3	N N N N N N	T L L L A L	N N N N N N	T L T T T T	-5-5-T N N N	-5 U U U U U

M21: *Ind* = expected production, *Ser* = expected operating profit derived from the last quarterly survey (*m*1)
M22: *Ind* = static monthly common factor in industry, *Ser* = dynamic common factor in services.
M23: *Ind* = same as in M22, *Ser* = interpolated expected operating profit
M24: *Ind* = same as in M21, *Ser* = same as in M22. M25: *Ind* = same as in M22, *Ser* = same as in M21.

Table A5.7 Non-Restricted VAR models with 2 lags relating to month *m*3

Model	Horizon	End	AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
			1st result	Last result	1st result	Last result	1st result	Last result
M31	1	04Q4	H H S H H S	H H H H H H	H H S H H S	S H H S H H	L L A N N N	A A N A A T
M31	1	07Q3	H H H H H H	H H H H H H	H H H H H H	H H H H H H	N N N N L A	N N N A A T
M31	2	04Q4	S H H S H H	2 S S S 5 2	S S 2 S S S	2 S 2 2 5 2	U U -T U U U	U U U N N N
M31	2	07Q3	S S S S S S	S S S S H S	S S S H S S	S H S S H S	N N N A A A	N N N T T T
M31	3	04Q4	T T T 5 T T	N N N N N N	T L L T L L	N N N N N N	U U U U U U	N N U N N U
M31	3	07Q3	T T T 5 T T	N N N N N N	T L L T T T	N N N N N N	U N U U U U	N N N N N N
M31	4	04Q4	T L L 5 A L	2 T T 5 T L	L A L 5 A T	5 T T 5 L T	U U U N N N	U U U U U A
M31	4	07Q3	S S 2 S 2 5	S 5 5 2 T T	5 2 5 S 2 2	2 T 5 5 T T	U U U N N N	U U U U U U
M32	1	04Q4	H H S H H S	S H H S H H	H H S H H S	S H H S H H	T T T T T T	N T 2 A N N
M32	1	07Q3	H H H H H H	H H H H H H	H H H H H H	H H H H H H	U U U N N N	U U U N N N
M32	2	04Q4	S H H S H H	S S S S 5 5	S S S S S 2	2 2 5 5 5 T	N L L N A A	U U U U U U
M32	2	07Q3	S S S S S S	S S S S S S	S S S S S S	S S S 2 2 5	N N N N N N	U U U U U U
M32	3	04Q4	T T T T T T	N N N N N N	5 5 T T T T	N N N N N N	U N N U U U	U U U U U U
M32	3	07Q3	L T T T 5 T	N N N N N N	T T T T T T	N N N N N N	U U -T U U U	U U U U U U
M32	4	04Q4	T L L T L T	5 T T T T T	T A A T N N	N N N N N N	U-T U -5-2-5	-5-5-5 -5-2-5
M32	4	07Q3	2 S 2 2 2 2	2 5 5 5 T T	S 2 5 5 L L	T A L N N N	U U U -5-2-2	U-T U -5-2-5
M33	1	04Q4	H H S H H S	S H H S H H	H H S H H S	S H H S H S	N N N N N U	U U U U U U
M33	1	07Q3	H H H H H H	H H H H H H	H H H H H H	H H H S H S	U U U U U U	U U U U U U
M33	2	04Q4	S H H S H H	S S S S 5 5	S S 2 S S 2	S 2 5 2 5 5	N N U U U U	U U U U -1-5
M33	2	07Q3	S S S S S S	S S S S S S	S S 2 S S S	S S S S S 2	U U U U U U	U-T-T U -2-5
M33	3	04Q4	T T T T T T	N N N N N N	T T T L T T	N N N N N N	-2 U U -2 U U	-T U U -5 U U
M33	3	07Q3	L T T T 5 T	N N N N N N	L L L L T T	N N N N N N	-5 U U -2 U U	U U U -5 U U
M33	4	04Q4	T L L T L T	5 T T T T T	A N N L A N	N N N N N N	-1-2-2 -2-2-2	-2-5-5 -5-5-5
M33	4	07Q3	2 S 2 2 2 2	2 5 5 5 T T	5 5 T 5 T T	L A L N N N	-5-5-5 -1-1-2	-T-T-T -5-T U
M34	1	04Q4	H H S H S 5	S H H S H H	H H S H H S	S H S S H H	-T-5-T -2-1-1	U U U U U U
M34	1	07Q3	H H H H S 5	H H H H H S	H H H H H H	S H H S H S	-5-2-2 -2-2-2	U U U U U U
M34	2	04Q4	H H H H H S	H H S H H S	H S S H S S	H H S H H S	N U U N U U	U U U U U U
M34	2	07Q3	H H H H 2 T	H H H H H A	H H S H 2 T	H H H H H L	U U U N U N	U U U U U N
M34	3	04Q4	N N N N N N	U U U U U U	L T T L T T	N N N N N N	S 5 2 A L L	L L T N N N
M34	3	07Q3	U N N N A A	U U U U U U	A L L L T T	N N N N N N	S 5 2 N N N	T T T N N N
M34	4	04Q4	5 L L 5 L L	N N N N N N	A N N T N A	U U U U N N	-2-5-2 -1-1-1	-5-5-2 -2-2-2
M34	4	07Q3	2 T 5 S T 5	N N N N N N	5 T T 2 T T	N N N N N N	U U U -5-2-5	U U U -5-5-5
M35	1	04Q4	H H S H S 5	S H H S H H	H S S H H S	S H H S H H	U U U -T U U	U U U U U U
M35	1	07Q3	H H H H S 5	H H H H H S	H S 2 H S 5	H H H H H S	U U U U U U	U U U N N N
M35	2	04Q4	H H H H H S	H H S H H S	H H S H S S	H L T H T T	A N L A A A	S S S 5 5 5
M35	2	07Q3	H H H H H H	H H H H H N	H 2 5 H H H	H H H H S 5	2 2 5 2 S 2	H H S S S S
M35	3	04Q4	N N N N A A	U U U U U U	N N N N A A	U U U U N N	5 T T T L A	2 S 2 L A A
M35	3	07Q3	U N N N L A	U U U U N N	N L N A L L	U N N N N N	S 2 S 5 H S	H H S T T T
M35	4	04Q4	5 L L 5 L L	N N N N N N	5 A L 2 L L	N N N N N N	N N N L A A	N N N L L L
M35	4	07Q3	2 T 5 S T 5	N N N N N N	S T 5 S 5 T	L A A L A A	N N N A A A	A A A A A A

M31: *Ind* = static monthly common factor in industry, *Ser* = expected operating profit from the last quarterly survey (*m*1).
M32: *Ind* = same as in M31, *Ser* = dynamic common factor in services.
M33: *Ind* = same as in M31, *Ser* = interpolated expected operating profit (*m*3).
M34: *Ind* = expected production, *Ser* = interpolated expected operating profit (*m*3).
M35: *Ind* = same as in M34, *Ser* = same as in M31.

Table A5.8 Non-Restricted VAR models with 2 lags relating to month *m*4

Model	Horizon	End	AR 1 vs VAR 2		AR 1 vs VAR 3		VAR 2 vs VAR3	
			1st result	Last result	1st result	Last result	1st result	Last result
M41	1	04Q4	H H S H H S	S S S S S S	H H S H H H	S H H S H H	N N N N N N	A N N N N N
M41	1	07Q3	H H H H H H	H H S H H H	H H S H H H	H H H H H 2	N N N N N N	N N N N A A
M41	2	04Q4	H H H H H H	H H H H H H	H H H H H H	H L N H H S	2 2 2 2 S S	A L L N A A
M41	2	07Q3	H S S H H H	H S N H H H	H S S H S S	H H 2 H T L	A A A T 5 A	N N N N N N
M41	3	04Q4	T T T T T T	N N N N N N	5 T T 5 T T	N N N N N N	N N N N N N	U U U U U U
M41	3	07Q3	A A A T T L	N N N N N N	L L A T T T	N N N N N N	N N N N N N	U U-T U U U
M41	4	04Q4	S 5 5 S 5 5	T A A T A A	2 T T S T 5	L A A T A A	U U U N N N	U U U N N N
M41	4	07Q3	S 2 2 S 2 2	T L L T L L	S 5 2 S 5 5	5 L L T L A	U N U N N N	N N N N N N
M42	1	04Q4	H H S H H S	S S S S S S	H H H H H H	H H H H H H	L L N A A A	5 5 5 5 T T
M42	1	07Q3	H H H H H H	H H S H H H	H H H H H H	H H H H H H	N N N N N N	N N N T A A
M42	2	04Q4	H H H H H H	H H H H H H	H H H H H H	H T N H T A	S S S S S S	5 2 5 5 5 T
M42	2	07Q3	H S S H H H	H S N H H H	S S S S S S	H T A H T A	T N N T T T	L L A L L A
M42	3	04Q4	T T T T T T	N N N N N N	2 5 5 2 5 5	N N N N N N	T L T T L T	U U U N N N
M42	3	07Q3	A A A T T L	N N N N N N	T T T 5 5 5	N N N N N N	5 T T T T T	N N N N N N
M42	4	04Q4	S 5 5 S 5 5	T A A T A A	2 T T S T T	N N N N N N	-T U-5 U U U	-T-T U U U U
M42	4	07Q3	S 2 2 S 2 2	T L L T L L	S 5 5 S T 5	L A N N N N	U U U U U U	U U U U U U
M43	1	04Q4	H H H H H H	S S S H H S	H H H H H H	S S S S S S	U U U U U U	U U U U U U
M43	1	07Q3	H H H H H H	H H H H H H	H H H H H H	H H H H H H	U U U U U U	U U U U U U
M43	2	04Q4	H H H H H H	H 5 N H H H	H H H H H H	H L N H T A	S 2 2 T L L	N N T N N L
M43	2	07Q3	H H H H H H	H H H H S T	H H H H H H	H H S H 2 T	L A A T T T	N U N N N L
M43	3	04Q4	L L L T T L	N N N N N N	5 T T T T T	N N N N N N	5 T T 5 5 T	N N U N N N
M43	3	07Q3	N N N L L L	U U U N N N	A A N T T T	U U U N N N	T L N T T T	N N U N N N
M43	4	04Q4	T N N T N N	U U U U U U	L N N T N N	N N N U U U	U U-T U U U	N N N N N U
M43	4	07Q3	2 L L S 5 2	N N N N N N	2 L T 2 T 5	N N N N N U	U U U U U U	N N N N N N

M41: *Ind* = static quarterly common factor in industry, *Ser* = expected operating profit in services

M42: *Ind* = static quarterly common factor in industry, *Ser* = dynamic common factor in services

M43: *Ind* = expected production in industry, *Ser* = expected operating profit in services

All variables refer to *m*4 subseries.

Appendix 6: Tests of the predictive accuracy of univariate models versus VAR models: Main results

Benchmark: univariate multistep models including services (1st and 2nd)
Competing forecast: the best corresponding VAR3 models

Forecast = 1 (forecast of the current quarter,
corresponding to the one or two quarter horizon for the VARs, depending on the months).
Forecast = 2 (forecast of the next quarter,
corresponding to the two or three quarter horizon for the VARs, depending on the months).
Forecast = 3 (forecast of the next-to-next quarter,
corresponding to the three or four quarter horizon for the VARs, depending on the months).

Table A6.1 Univariate models versus VAR models for month *m*1

			1st univ. vs VAR		2nd univ. vs VAR	
Model	Forecast	End	1st result	Last result	1st result	Last result
M11	1	04Q4	U U U-T-T-T	U U U-5-2-5	T 5 N L T N	N L U N N U
M11	1	07Q3	N N N N N N	U U U N N N	T 5 N 5 5 A	L A N A L N
M11	2	04Q4	U U U U U U	U-T-5 U U U	N N N U U U	U-T U-T-T-T
M11	2	07Q3	U U U U U U	U U-T U U U	U U U U U U	U U U-5-5-5
M11	3	04Q4	S 5 T 5 T T	2 5 T T T T	-T U U U U U	-T-T-T U U U
M11	3	07Q3	2 5 5 5 L N	5 5 5 5 T T	U U U U U U	U-T N U U U
M12	1	04Q4	-T-5-T U U U	-1-1-1-1-1-1	N N N L L L	-T-T-T-T-T-T
M12	1	07Q3	U-T U U U U	-5-2-2-5-2-5	U U U U U U	U U U-T-T-T
M12	2	04Q4	U U U U U U	-T-5-5-5-5-5	U U U U U U	-2-5-5-2-2-5
M12	2	07Q3	U U U U U U	U U U-T-T-T	U U U U U U	-T-5-T-2-2-2
M12	3	04Q4	N N N N N U	U U U U U U	-2-5-5-T U U	-2-T U-2 U U
M12	3	07Q3	N N N N N N	U U U U U U	-5 U U-T U U	-5 U U-5 U U
M13	1	04Q4	-T-T-T U U U	-1-1-1-1-1-1	N N N N A A	U U U U U U
M13	1	07Q3	-T-T-T U U U	-2-1-2-2-1-2	U N N U N N	U U U-T-T-T
M13	2	04Q4	U U U U U U	U-T-T U-T-T	U U U U U U	-T-5-5-T-5-5
M13	2	07Q3	U U U U U U	U U-T U-T-T	U U U U U U	-5-5-5-5-2-2
M13	3	04Q4	T A A L A N	N U U N N U	-5-1-2 U-5 U	-2-2-2-5-5-5
M13	3	07Q3	5 L T T L A	N N N N A N	-T U U U U U	-T-T U-T-T-T

Table A6.2 Univariate models versus VAR models for month *m*2

			1st univ. vs VAR		2nd univ. vs VAR	
Model	Forecast	End	1st result	Last result	1st result	Last result
M21	1	04Q4	U U U-T-T U	U-5-T U-1-2	N N N U U U	U U U U U U
M21	1	07Q3	U U U U U U	U-T-T U-1 U	N N N U U U	U U U U U U
M21	2	04Q4	-5-5-5-5-5 U	-2-5-5-2-2-5	U U U U U N	-5-5 U U-T N
M21	2	07Q3	N N N N N N	N N A N N L	A N L L N T	N N A A N L
M21	3	04Q4	-T-T-T-5-5-T	-1-1-2-1-1-2	-T-T-T U-T N	-5-2 U-5-5 U
M21	3	07Q3	-T-T-T U U U	-2-2-2-5-2-5	-T-T-T U U U	-5-5 U-T-T U
M24	1	04Q4	-T-T U-5-T-T	U-T-T U-1-5	U U U U U U	U U U U U U
M24	1	07Q3	-T-T-T-5-5-T	U-T-T U-1-2	U U U U U U	U U U U U U
M24	2	04Q4	-5-5 U-5-5 U	-5-5 U-5-5 U	U U U U U N	-T-5 U U U N
M24	2	07Q3	N N A N N N	N N A N N L	A N L L N L	N N A A N L
M24	3	04Q4	-T-T-T-T-T-T	-1-1-2-1-1-2	-T-T-T U U N	-5-2 U-T-5 U
M24	3	07Q3	U U U U U U	-2-2-5-T-5-T	U-T-T U U N	-T-5 U U U N
M25	1	04Q4	U U U U U U	U U U U U U	N N N N N N	N N U N N N
M25	1	07Q3	U U U U U U	U U U U U U	N N N N N N	N N N N N N
M25	2	04Q4	-2-5-T-5-T-T	-1-1-T-1-1-2	-T-T U U U U	-1-1-2-2-5-5
M25	2	07Q3	N N N N N N	N N N N N N	A N N L A A	N N N N N N
M25	3	04Q4	U U U U U U	-2-2-5-2-5-5	-T U U U U U	-1-1-2-5-5-5
M25	3	07Q3	U U U U U U	-5-5-5-T-T-T	-T U U U U U	-2-2-2 U-T U

Table A6.3 Univariate models versus VAR models for month *m*3

			1st univ. vs VAR		2nd univ. vs VAR	
Model	Forecast	End	1st result	Last result	1st result	Last result
M34	1	04Q4	-1-1-1-2-2-2	-T-T-T-T-T-T	-2-1-2-5-5-5	-5-5-5-T-5-T
M34	1	07Q3	-1-1-1-5-T U	-T-T-T U U U	-1-1-1-5-5-5	-2-2-2-T-5-5
M34	2	04Q4	5 5 T 2 5 5	N N N N N N	N N N T T T	U U U U U U
M34	2	07Q3	2 5 5 S 2 2	N N N L A A	5 T T S 5 T	N N N L L L
M34	3	04Q4	U-2-5-T-T-T	-T-1-1-T-1-1	2 5 5 5 5 5	N N N T T T
M34	3	07Q3	U U U U U U	U U U U U U	2 5 5 2 5 5	A N N 5 5 T
M35	1	04Q4	-1-1-1-2-2-2	-5-T-T U U U	-2-2-2-T-5-T	-2-2-2-5-5-5
M35	1	07Q3	-2-2-2 U-T-T	-T-T-T U U U	-2-1-2-T-T-T	-2-2-2-T-T-T
M35	2	04Q4	5 5 5 5 5 5	T T T T L T	A N N L L A	N N T N L L
M35	2	07Q3	S S 2 S S 2	2 L T 2 L T	2 5 T S 5 T	5 T T 5 5 5
M35	3	04Q4	-2-5 U-5-T-5	-5-5-5-5-5-T	2 2 5 2 5 5	N N N 5 5 T
M35	3	07Q3	U U U U U U	U U U U U U	2 2 2 2 2 2	L 5 5 2 2 2

Table A6.4 Univariate models versus VAR models for month *m*4

			1st univ. vs VAR		2nd univ. vs VAR	
Model	Forecast	End	1st result	Last result	1st result	Last result
M41	1	04Q4	U U U U U U	U U U U U U	U U U U U U	U U U U U U
M41	1	07Q3	-T-T-T U U U	-T-T-T U-T U	-T-T-T U U U	-5-5-5 U U U
M41	2	04Q4	N N N U N N	-1-1-5-1-1-2		
M41	2	07Q3	N N N L L L	-1-2-2-T-T-T		
M41	3	04Q4	N N-T N N-T	U U U U U U	U U U U U U	-2-1-1-2-5-5
M41	3	07Q3	N N U A A U	U U U U U U	U U U U U U	-2-1-1-2-2-5
M42	1	04Q4	U U U U U U	N N N U U U	U U U U U U	N N N U U U
M42	1	07Q3	-T-T-T U U U	U U U U U U	-T-T-T U U U	U U U U U U
M42	2	04Q4	5 T T T T T	-1-1-T-1-T U		
M42	2	07Q3	N N N N A A	-1-1-5-1-5 U		
M42	3	04Q4	N N-5 N N U	U U U U U U	N N N U U U	-5-T-T-2-5-5
M42	3	07Q3	N A U N N U	U U U U U U	U U U U U U	-2-5 U-2-2-2
M43	1	04Q4	-2-2-2-5-2-2	U U U U U U	-5-2-5-2-2-2	U U U U U U
M43	1	07Q3	U U U U U N	U U U U U U	U U U U U U	U U U U U U
M43	2	04Q4	T L L A A A	-5-T U-5-T-T		
M43	2	07Q3	2 2 2 2 2 2	U U U N N N		
M43	3	04Q4	N N U N N U	-T-2-2-T-2-2	N N N N N N	U U U-5-T-T
M43	3	07Q3	L T N L T N	U U U U U U	U U U U U U	-T-T-T-5-5-5